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Do econometric advances lead to more accurate VaR estimations when the legislation requirements are applied? The case of Turkish Lira FX Market.

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Abstract

This paper empirically tests the benefits of econometric advances in the field of Value at Risk (VaR) within the existing legal framework that regulates the Banking (Basel III) and Asset Management industry (CESR (2010)). We test several VaR models, from the simplest and the most easily applied, i.e. the Historical VaR (HVaR), Variance Covariance VaR (VCVaR), and the Exponential Weighted Moving Average VaR (EWMAVaR), to advanced models such as GARCH(1,1). We test these models by examining the extremely volatile FX market of the Turkish Lira (TRY) and we evaluate the models according to the criteria set by the legal framework on VaR. The empirical findings suggest that the HVaR model is a very reliable model if the goal of a risk manager is to satisfy the legislation requirements. However, we should mention that models that make use advances in econometrics lead to more accurate and more representative VaR estimations than the HVaR. The law should give incentives to adopt more representative models in the financial industry in order to take advantage of advances in financial modeling.

JEL Classification: C53; G15

Keywords: Value-at-risk; GARCH estimation; Historical VaR; Variance Covariance; Exponential Weighted Moving Average VaR; Back-testing; Legislation; FX Market

1. Introduction

Over the last years, the Turkish Lira (TRY) has suffered significant losses and many studies have tried to identify the reasons for this depreciation. Several explanations have been put forward in an effort to better understand the negative performance of the TRY. These include the impact of geopolitics (Kyriazis and Economou (2021)), central bank policies (Güney (2018)), the effect of cryptocurrencies (Ünvan (2021)) etc.. As opposed to examining in detail why the TRY depreciates so sharply, we opt to focus on the evaluation of the risk that TRY presents for investors, practitioners, and risk managers. Moreover, on a practical level, we examine whether risk managers who comply with the legal requirements are offered sufficient incentive to invest in advanced econometric models in order to produce more reliable risk estimations, particularly in the case of extremely volatile markets such as the TRY FX.

The increased volatility of an asset is linked to the increased risk of an investment, and accurate risk estimation is crucial for investment decisions. When an investor has to choose amongst many investment plans, at the very least s/he has to know what the expected profits will be and what the risk of the plan is. The dominant measure of risk estimation is the Value at Risk (VaR), which presents in a single number the expected losses of the worst-case scenario for an asset at a specific confidence level (c.l.). The significance and the necessity of VaR has increasingly come to the fore since the introduction of legislation that requires daily VaR estimations both in the banking sector (Basel Committee on Banking Supervision (1996)) and in the asset management industry (CESR (2010)).

The obligation for accurate and daily VaR estimation has also triggered the interest in VaR among researchers (Jorion (1996), Duffie and Pan (1997), Linsmeier and Pearson (2000)). Financial literature on VaR falls into two broad categories:

- studies that address the deficiencies of VaR legislation (Vasileiou (2016)) and the procyclicality caused by VaR legislation (Adrian and Shin (2014), Vasileiou and Pantos (2020)), and
- studies that try to apply advanced econometric models for more accurate VaR estimations: extreme value theory (GARCH family models (Engle (2004), Assaf (2009), Diamandis et al (2011)), Markov Switching Regime (Billio and Pelizzon (2000)), data filtering models (Vasileiou (2017, 2019), Extreme Learning Machine (Zhang et al (2017)) etc..

The importance of the TRY risk has been documented in several studies: Günay (2017), Yildirim (2015), Gün (2020) etc.. In this study, we examine conventional VaR models that are usually applied in the financial industry, such as the Historical, Variance Covariance, Exponential Weighted Moving Average1, and the widely applied GARCH model. We assume that we, the CIO of a bank or of an asset management firm, would like to decide whether to cover the additional cost of a VaR software that estimates VaR using a more advanced model, GARCH VaR in our case. This is an issue that is not usually examined in VaR studies.

In order to be able to make an informed decision on this matter, we follow the requirements laid down by the law, and we apply the aforementioned models to the volatile USD per TRY exchange rate (FX) for the period 2007-2021. This way we will be able to empirically show whether the legislation offers sufficient incentive to the banks and financial firms to encourage them to adopt more accurate VaR models whose estimations are closer to the real risk.The rest of the paper goes as follows: Section 2 outlines the methodology, Section 3 describes the data, Section 4 provides the empirical evidence, Section 5 discusses the results, and Section 6 concludes the study.

2. Methodology

The parameters of the VaR estimation in this study are set in accordance with legal guidelines: 250 observations[2] as inputs and 99% c.l.. Moreover, regarding the evaluation of the VaR models, we follow again the legal requirements: if there are more than 4 VaR overshootings in the last 250 VaR estimations (250 observations are roughly equal to one trading year), the model is considered inaccurate (hereafter we call this threshold the “4-overshooting rule”).

This is not the first study to examine the financial risk in several FX pairs and evaluate the accuracy of several VaR models. Hendricks (1996) tests the Historical VaR (HVaR), the Variance-Covariance VaR (VCVaR), and the Exponential Weighted Moving Average VaR (EWMA VaR) and reaches the conclusion that there is no specific model that is consistently more accurate than the others because it depends on several conditions such as the financial trend.

Setting a minimum number of 250 observations is not without drawbacks because the number of observations that are used as input is crucial to the accuracy of VaR estimations. Vasileiou et al (2021) show that HVaR is a very accurate approach when fewer than 250 observations are used for the VaR

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[1] These models are considered the most widely applied according to VaR legislation documents: Basel Committee on Banking Supervision (2006, p. 115) and CESR (2010, p.26).

[2] A 250-observation (or 250-day) period is the minimum number of data inputs that should be included in a model and 99% is the c.l. that the VaR legislation (Basle Committee on Banking Supervision (1996), CESR (2010)) requires.

estimations. On the other hand, the EWMA VaR model requires periods equal to or more than 250 trading days (250-day) in order to produce more accurate VaR estimations at the 99% c.l.. Similarly, requiring more than 250 observations may be beneficial for models such as the GARCH family models because a small sample size may lead to lack of convergence in the estimation algorithms (Angelidis, Benos, and Degiannakis (2004)).

HVaR shorts the last 250 daily returns and assumes that the VaR at the 99% is the average value between the second and the third worst value. The 250-day VCVaR uses rolling standard deviations of the last 250 observations and the VaR is estimated by the formula

$$\boldsymbol{VCVaR_t = 2.326 \times \sigma_t} \qquad \textbf{(1)}$$

, where 2.326 is the VaR coefficient at the 99% c.l. and σ_t denotes the standard deviation on day t using the last 250 daily returns for the following formula

$$\boldsymbol{\sigma_t = \sqrt{\frac{\sum_{t=1}^{250}(Daily\ Returns_t - \mu)^2}{249}}} \qquad \textbf{(2)}$$

, where μ is the mean return of the last 250 days.

The EWMA model assumes that recent observations have a greater impact than older ones, and it is estimated by the formula

$$\boldsymbol{\sigma_t = \sqrt{(1-\lambda)\cdot r_{t-1}^2 + \lambda \cdot \sigma_{t-1}^2}} \qquad \textbf{(3)}$$

, where λ is the decay factor which means that recent observations have a greater influence than the previous ones. In our study, we adopt the λ=0.94 suggestion that is usually used in VaR studies[3].

As far as the GARCH models are concerned, the GARCH(1,1) rolling model is described by the following equations

$$\boldsymbol{Daily\ Returns_t = \mu + \varepsilon_t} \qquad \textbf{(4)}$$

, where μ is the mean of the returns, and ε_t is the error term $\varepsilon_t \sim N(0, \sigma_t)$.

Thus, HVaR increases significantly when a crisis comes, but it may overestimate the risk for a long period of time because for almost a year VaR will not change. The VCVaR model will not incorporate the increased risk instantly because each new observation has an impact equal to 0.4%. The EWMA model resolves this

[3] Most VaR studies adopt the λ=0.94 because it was used by JP Morgan in its popular Risk Metrics system https://www.msci.com/documents/10199/5915b101-4206-4ba0-aee2-3449d5c7e95a .

issue because the last observation has an impact of 6%, the previous day is at 5,64% (=0.6*0.94), etc.. The GARCH model, which was developed by Bollerslev (1987), captures the widely known volatility clustering effect and this could yield better results in terms of the accuracy of VaR estimations. Even in the case of the GARCH family models, some models may be more accurate than others, but overall, GARCH VaR models are considered as very reliable and representative (So and Philip (2006), Degiannakis, Floros, and Livada (2012), Orhan and Köksal (2012) etc.).

3. Data

We use daily data from yahoo finance for the period 2005-2021 and the performance of the USD per TRY (TRYUSD) is presented in Figure 1. The daily returns are calculated by the formula

$$\boldsymbol{Daily\ Returns_t} = \frac{\mathbf{TRYUSD_t}}{\mathbf{TRYUSD_{t-1}}} - \mathbf{1} \tag{5}$$

, where *Daily Returns*$_t$ is the Daily Return on day t, and TRYUSD$_t$ and TRYUSD$_{t-1}$ is the TRYUSD Price on the current and on the previous day respectively. Table 1 presents the descriptive statistics of our sample. We observe that the time series is leptokurtic (leptokyrtosis>3), the Skewness is not equal to zero, and it does not follow the normal distribution (Shapiro-Wilk statistical significance), which means that a linear model, e.g. the VCVaR, is not appropriate for our data sample. The Augmented Dickey-Fuller test shows that the time series does not need further modification. The histogram below Table 1 is a graphical indication that our time series does not follow the normal distribution.

Table 1: Descriptive Statistics of the Daily Returns of TRYUSD for the time span 2005-2021.

Statistics	**TRYUSD Daily Returns**
Mean	-0.045%
Standard Deviation	1.094%
Min	-18.566%
25%	-0.470%
50%	0.000%
75%	0.431%
Max	23.250%
Kurtosis	74.817
Skewness	0.790
Shapiro-Wilk normality test	0.777*
Augmented Dickey-Fuller Test	-13.126*

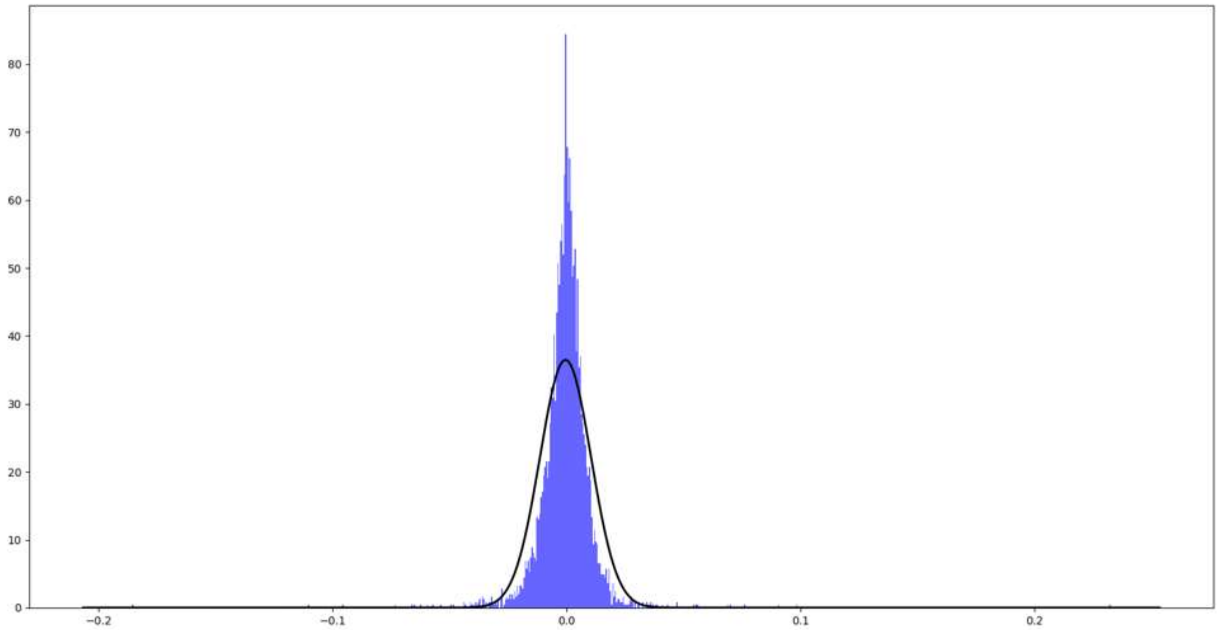
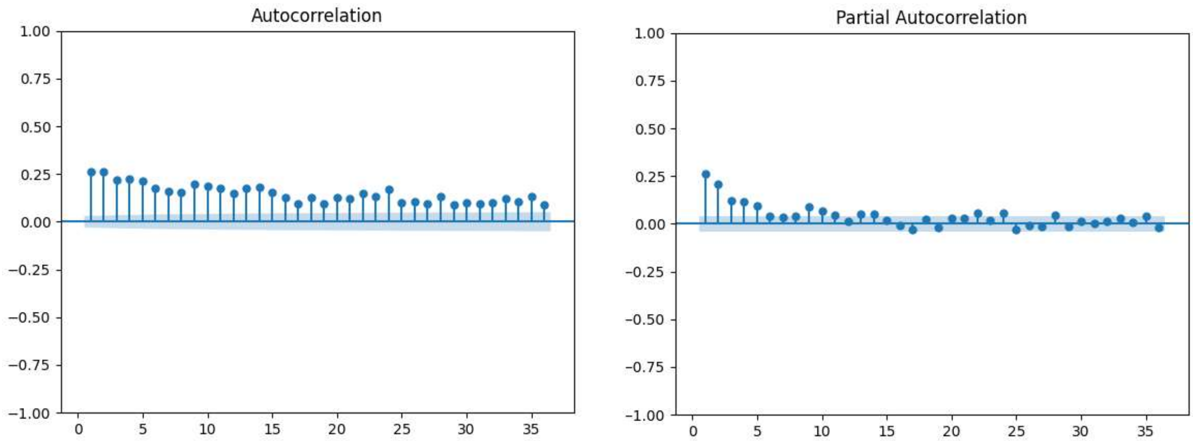


Figure 1: The performance of TRYUSD during the period 2005-2021.

The daily returns in Figure 1 show that volatility appears in bounces, which is an indication of volatility clustering. Figure 2 presents the autocorrelation and partial autocorrelation of the absolute values of the daily returns, and the statistical significance of these values confirms that there is volatility clustering in the time series; thus, a GARCH family model may be beneficial for more accurate VaR estimation.

Figure 2: Autocorrelation and Partial Autocorrelation of Absolute Values of Daily Returns of TRYUSD: the statistical significance confirms the presence of volatility clustering.



4. Empirical Results

The descriptive statistics suggest that linear models are not appropriate for our study due to the non-linearity and the volatility clustering. These findings are, in theory, in favor of the HVaR and GARCH models. What do the empirical findings show? Table 2 presents the backtesting results of our study. Shaded cells indicate the years in which the overshootings are more than 4. The results confirm our assumption that linear models are not appropriate for our dataset. When we define the parameters in the model to conform to legal regulations (250 observations and 99% c.l.), the VCVaR model is considered inappropriate in 11 out of 15 years. The EWMA version of this model fails in 12 out of the 15 tested years. As previous studies suggest, amongst the popular and widely applied models, the HVaR model is the most accurate and fails to meet the 4-overshooting rule in 4 out of 15 backtesting evaluations (Vasileiou et al (2021)).

The GARCH(1,1) models are considered inappropriate 5 and 3 times when the rolling data inputs observations are 250 and 500 respectively. These findings confirm that GARCH models need an increased number of observations for more accurate fat tail estimations (Angelidis, Benos and Degiannakis (2004)). Thus, when we adhere to the legal framework, the backtesting procedure shows that advanced modeling slightly improves the accuracy of the VaR models compared to the HVaR model.

Table 2: Backtesting report

Year	HVaR	VCVaR	EWMA	250-day rolling GARCH	500-day rolling GARCH(1,1)
2007	3	8	6	6	6
2008	6	10	12	5	5
2009	0	1	2	2	2
2010	3	6	8	4	3
2011	4	7	7	3	3
2012	0	1	3	0	0
2013	9	11	9	5	4
2014	2	2	5	1	2
2015	2	7	5	3	3
2016	3	10	11	4	4
2017	1	7	6	2	2
2018	6	14	9	3	4
2019	0	4	4	2	3
2020	3	11	10	5	2
2021	5	12	9	6	6
Violations of the "4-overshooting rule"	**4**	**11**	**12**	**5**	**3**

5. Discussion

The empirical findings show that the VCVaR and the EWMA VaR models generate too many inaccurate VaR estimations, and are thus considered inappropriate; so we focus on the two models that outperform against all the other: the HVaR and the GARCH (1,1) model. We should always take into consideration that VaR departments are cost centers and the increased cost for VaR software, the need for long-term data[4], and the expertise of the user increase this cost (Vasileiou (2016)).

Hence, a risk manager that examines the findings of Table 2 may suggest that the advanced GARCH family models do not significantly improve the risk accuracy of the simple and easily applied HVaR model. A significant drawback of the current legislation governing risk analysis is that it does not examine if the VaR model overestimates the risk; therefore, in some cases, a model may be conservative, but not always representative of the real financial risk (Vasileiou (2017)).

For the aforementioned reasons, we examine the 250-observation GARCH(1,1) model and the HVAR (in order to use the same number of observations in both models (*ceteris paribus*)). Figure 2 shows the daily returns and the VaR estimations of the HVaR and 250-day GARCH (1,1) and we can observe that even though the HVaR fails to meet the 4-overshooting rule 4 times and the 250-day GARCH(1,1) 5 times:

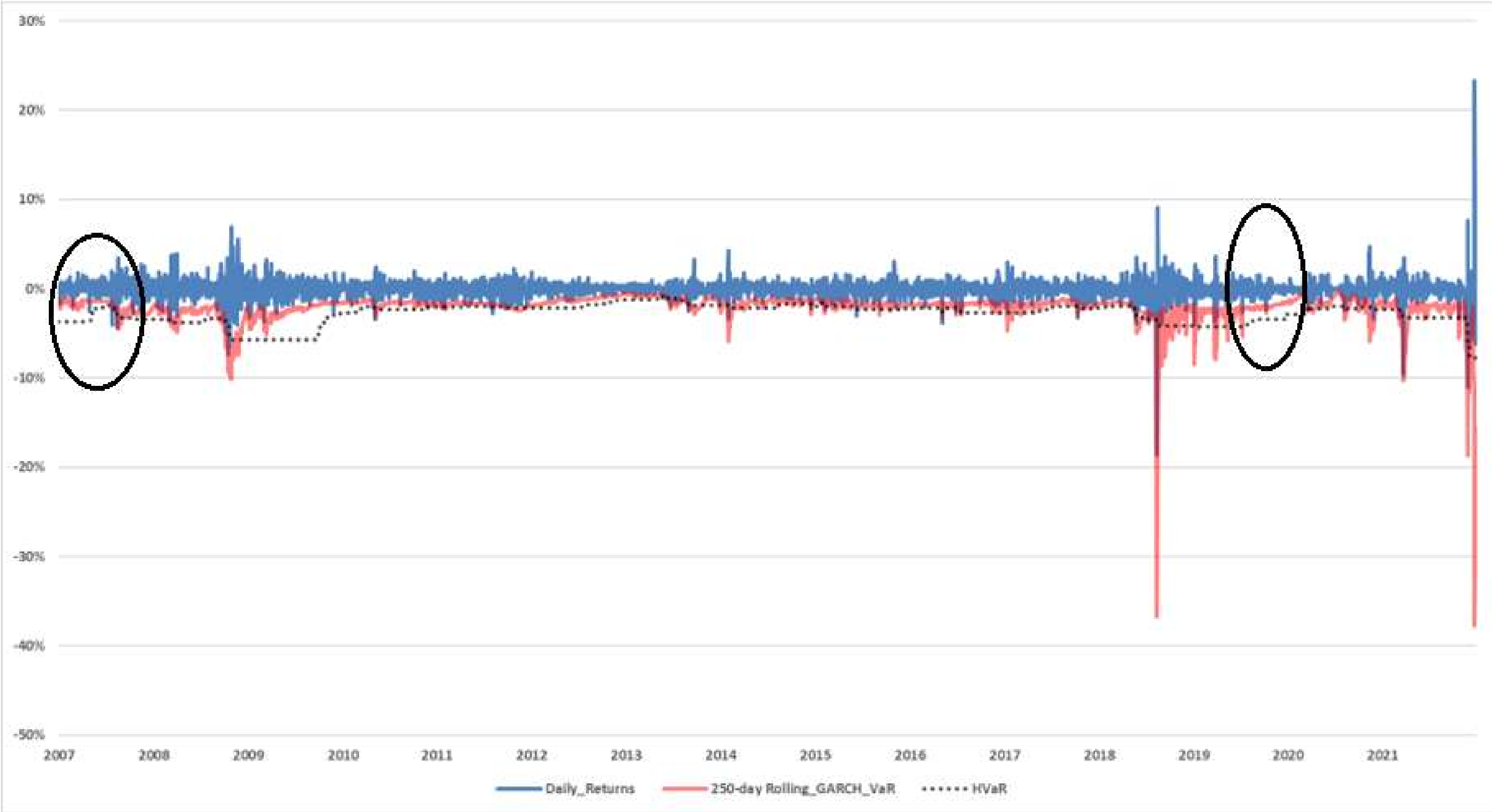
- the HVaR in many cases is more conservative than the 250-day GARCH(1,1), and
- the HVaR is not as flexible as the 250-day GARCH(1,1) which more accurately captures the changes in financial trends, and

If we combine the outcomes of Table 2 and Figure 2 the difference in favor of HVaR models is in years 2007 and 2020 (years that HVaR is considered accurate and GARCH is not). The cycles in the Figure show that HVaR was not as flexible as the GARCH (1,1) model, and it was too conservative compared to the GARCH model. Thus, in this case HVaR may be more accurate (according to the law), but it does not provide more representative VaR estimations than the GARCH model. Moreover, in 2018 when the GARCH model was accurate and the HVaR was not, the GARCH model was more representative, was not more conservative than the HVaR. Therefore, the choice that managers have to make is whether the advantages of the GARCH model are worth its additional cost. In some cases, especially in small sized institutions, this

[4] At this point, we should note that an increased number of observations may lead to practical issues in the financial industry. For example, when a portfolio manager includes in his/her portfolio an asset that did not exist prior to the last 500 days, e.g. a new stock, reliable proxies should be estimated to ensure that risk estimations are as reliable as possible; the longer the historical observation time period, the longer these proxies will be used.

cost could be prohibitive and the managers may decide to adopt the HVaR model which is reliable enough to meet legal standards. Therefore, a conclusion could be that although the literature points to the direction of more representative and reliable models than the conventional ones, the law does not examine how representative the VaR estimations are and, as a result, the law does not create a strong incentive that would accelerate a wider transition to more sophisticated modeling systems.

Figure 2: Accurate vs representative VaR estimations: HVaR and 250-day GARCH(1,1) model.



6. Conclusions

The aim of this paper is to examine the benefit of using advanced financial econometrics methods in the field of financial risk. We use data from the extremely volatile TRYUSD FX rate from the last 15-year period (2007-21). Our findings suggest that if we follow the legal requirements (VaR estimations at the 99% c.l., at least 250 observations as data inputs, and the "4-overshooting rule"), the HVaR model is the most appropriate amongst the popular and widely applied models in the financial industry. The use of GARCH family models leads to more representative VaR estimations because these models capture the volatility changes faster than the HVaR models. However, as we present, managers in the finance industry have little incentive to adopt advanced models, opting instead to rely on conventional and reliable models, such as the HVaR model. Advanced models, such as the GARCH (1,1), are more representative, but managers tend to avoid them because of the additional costs.

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