Which user-friendly model is the best for BASEL-III? An emerging market study

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Abstract： This paper explores backtesting Value-at-Risk (VaR) and Expected Shortfall (ES) considering ten standard and extended tests in the context of non-technical individual investors trading equities of twenty selected commercial banks listed at the Dhaka Stock Exchange (DSE) using their daily log return since last 11 years (from 2010 to 2020). Following a significant literature gap on investigating the efficacy of user friendly models quantifying market risk of Bangladeshi banks being a participant of emerging economy, this paper adopted Four user-friendly models that are relatively straightforward to understand, interpret and considered as representatives of zero, -one, -two, and -three parametric families of all risk models in the literature. The popular RiskMetrics^{TM} risk forecast model of JPMorgan, sweeping the world as the most user-friendly conditional alternative to unconditional Gaussian risk forecasts, under the framework of VaR, is found not to be adequate under the framework of ES that is recently recommended by Basel-III. The joint score value-based comparison finds the historical simulation (HS) model as the most appropriate model in Bangladesh when models are assessed under a practical user-friendly implementation design. Under this design the Trust Bank Ltd.(TBL), the bank managed and operated by Bangladesh Military, stands as the best investor friendly bank in terms of causing least frustration to its equity investors over 2010-20. Therefore, user friendly model is still successful to validate its uniformity being a best of the both worlds model in quantifying market risk over the globe.

Key words**:** Market risk; BASEL-III; Value at Risk; Expected Shortfall; Back-test

JEL Classification: C15, C32, C52, G28

1. Introduction

This study investigates the efficacy of four user-friendly models which are used in quantifying market risk under VaR (Value at Risk) and ES (Expected shortfall) in the emerging economy of Bangladesh. It then backtests the risk forecasts for twenty commercial banks that operate in Bangladesh. Different from the risk prediction and measurement in previous research perspectives (Lu et al., 2022; Sun et al., 2022; Medina-Olivares et al., 2022; Chai et al., 2019), the investigation is particularly from the perspective of individual investors (and not from institutions and enterprises) and from emerging economies (like Bangladesh) where investors' technical skills are certainly much poorer compared to those in the developed parts of the world (Islamaj et al., 2019). This surely has a bearing on an individual investor's sufferings, with serious consequences in their society. In fact, Bangladesh is not the only an emerging country with these features; most emerging countries reflect the same.

Emerging market banking often operates in less developed regulatory environments, where regulations may be more lenient or less strictly enforced compared to developed economies. This can lead to increased risks and vulnerabilities in the financial system. During the 1997 Asian Financial Crisis, many Asian emerging markets experienced banking sector vulnerabilities due to weak regulatory oversight and inadequate risk management practices (Agenor, P. 1999). In addition, Emerging market banks may face challenges in maintaining adequate capital levels and accessing funding compared to their counterparts in developed economies, which can affect their ability to absorb shocks and expand operations. During the 2008 global financial crisis, many emerging market banks faced difficulties in raising capital and accessing international funding, leading to liquidity shortages[1]. Moreover, Emerging market banks are often exposed to currency and exchange rate risks due to fluctuations in their local currencies. These risks can impact the stability of the banking sector and the ability of borrowers to repay loans denominated in foreign currencies. The 2018-2019

[1] "Capital Flows, Financial Crises, and Policies" by Carmen M. Reinhart, et al., NBER Macroeconomics Annual

Turkish currency and debt crisis resulted in significant stress on the Turkish banking sector, with many borrowers struggling to service their foreign currency-denominated debts (Güngen and Akcay., 2019).

However, Bangladesh, with a GDP of over USD 460 billion and being the world's 35th economy, is considered to be an emerging economy having a salient track record of consistent growth and development contributed to by robust demographic dividend, strong ready-made garments (RMG) export, resilient remittance inflows and stable macro-economic conditions prompting rapid growth over the past two decades.

The primary reason for choosing Bangladeshi banks in our investigation is to reveal the risk perception and risk-taking attitude of inadvertent ad-hoc contributors in the banking sector which is one of the few rising sectors driving the sustainable economic growth of this country. At present, Bangladesh faces global economic challenges such as rising commodity prices along with a surge in import payments, causing a widening balance of payment (BOP) deficit that results in mounting pressure on foreign exchange reserve. Moreover, Increasing Non-performing loans (NPLs) are a critical concern for the banking sector of Bangladesh, as they pose a threat to financial stability and economic growth. Inadequate credit assessment, monitoring, and recovery processes contribute to the accumulation of NPLs in Bangladeshi banks (Rahman and Khan., 2017). In addition, Political interference and weak regulatory oversight have been cited as significant factors leading to increased non-performing loans in Bangladeshi banks (Siddiqui and Hossain., 2018). Furthermore, A study (Rahman et al., 2020) explored the link between NPLs and financial stability in Bangladesh and proposed measures to enhance the resilience of the banking system. Effective regulatory reforms and supervision play a crucial role in controlling NPLs. Another recent investigation (Rahman and Ullah., 2022) examined the impact of regulatory changes on NPLs in Bangladesh and emphasized the need for a proactive regulatory approach. Despite these limitations in banking sector, Bangladesh is on track to graduate itself from the UN's least developed country (LDC) list by 2026. It is in the process of achieving this by emphasizing a number of initiatives such as diversifying exports beyond the RMG sector to create jobs or employment opportunities under a competitive business environment, increasing skilled labor force and human capital to build efficient infrastructure, generously supporting rural farming, impressively advancing fish culture and fisheries industries, etc. Bangladesh is also enhancing its policy environment to attract private investors, deepening the financial sector, and reinforcing public institutions including fiscal reformations to engender more domestic revenue for macro-economic development. The banking sector in Bangladesh plays a key role in its economic development by exerting the role of a financial intermediary which encourages and accelerates investments in both public and private sectors. This sector has experienced remarkable progress with several automation initiatives such as a market infrastructure module for automated auction and trading of government securities, an automated credit information bureau for ensuring effective risk management systems in banks, etc. In addition, this sector has introduced monitoring of L/C (letter of credit) openings along with export reports issued from AD (authorized dealer) branches of respective banks, providing an automated clearing house (BACH) facility to expedite instant inter-bank money transfer, implementing electronic fund transfer, etc. These facilitate making most payments instantly as a part of the core banking solution under a secured environment of online financial transactions. The banking sector of Bangladesh also delivers mobile banking services to accelerate faster secured monetary transactions along with full-fledged banking services to even the remotest corner of the country. In addition, BASEL-III has been introduced in 2015 in a phase-by-phase approach and fully implemented for Capital Adequacy Ratio (CAR) at the beginning of 2019. Guidelines on Stress Testing have also been issued to assess the resilience of banks and non-bank financial institutions under different adverse circumstances for ensuring comprehensive and intensive risk management. Despite all these initiatives individual investors are not participating in stock markets to the extent they used to, and when they do they make a total mess in the market causing utter frustration to their dependent families and thus their societies; unlike other sectors individual investors investing in bank equities on the stock markets are seen to behave and perceive thoughtlessly about market risk exposures of their investments.

Over the years, researchers have proposed various models and methodologies to estimate VaR and ES, catering to the evolving financial landscape and addressing shortcomings in existing approaches. The historical simulation method estimates VaR and ES by utilizing historical return data. Recent literature (Alexander, 2021) has focused on improving this approach through the use of advanced techniques such as asymmetric loss functions, fat-tailed distributions, and incorporating non-linear dependencies. Chen and Wang (2020) proposed a novel extension of historical simulation based on high-frequency data to improve accuracy during volatile market conditions. Despite its simplicity, the historical simulation approach is often criticized for its inability to capture dynamic market conditions and tail risk adequately. In contrast, the Parametric models, such as the Normal, Student's t, and Generalized Extreme Value (GEV) distributions, have been widely used for VaR and ES estimation. Researchers have proposed refinements to these models to better capture asset return characteristics, such as volatility clustering and skewness. For instance, Li et al. (2021) introduced a hybrid GARCH-Skewed t distribution model to address skewness and leptokurtosis, providing better tail risk estimation. Another investigation (Jiang and Zhu., 2022) introduced a hybrid GARCH-EVT model to incorporate volatility clustering and extreme value dependence. However, parametric models are limited by their underlying distributional assumptions, and their performance can suffer during periods of significant market stress. In addition, EVT has gained popularity in estimating tail risks of financial assets. EVT-based models, such as Peaks Over Threshold (POT) and Block Maxima (BM), have been applied to VaR and ES estimation. Huang and Wang (2022) proposed a hybrid EVT-GARCH model to capture extreme market risks effectively. Despite its benefits, EVT's reliance on a limited number of extreme observations can lead to estimation errors, particularly for assets with sparse extreme events. Furthermore, Monte Carlo methods involve generating random samples to simulate future asset returns and estimate VaR and ES. Recent studies (e.g., Boudreault and Gauthier, 2023) have explored the application of advanced variance reduction techniques, like antithetic variates and control variates, to enhance the efficiency of Monte Carlo simulations. Although this approach can be computationally intensive, it provides flexibility in modelling complex dependencies and allows for a more accurate estimation of extreme tail risks. Apart from this, another model namely Copula model enables the estimation of joint distributions, making them valuable for multi-asset portfolio risk assessment. Recent research (Song et al., 2022) focused on Vine Copulas and their application in VaR and ES estimation for diversified portfolios. Copula models provide a flexible framework to model complex dependencies, but selecting the appropriate copula structure remains challenging.

In this paper the adjective user-friendly covers four representative models from four classes of risk models having zero, -one, -two, and -three parameters. The selection of representative models from each class is also motivated by the familiarity and user-friendliness of the models in the literature which we assume drives individual investors' confidence in applying the models in practice. Of course, the institutional decision on model selection could be much more rigorous and need not be restricted to classes with zero, -one, -two, or –three parametric families; also it need not be driven by the user-friendly feature among the classes as financial institutions (banks) have presumably enough resource persons to weigh model performance over model user-friendly features.

It is the bitter experiences of inadvertent mass investors who didn't hesitate earlier to bet their inheritance and other properties to invest their fortune in stock markets, and mostly in the so-called robust banking sector (lured by the governments' enticing initiatives to declare the banking sector as robust); but who didn't but should have ideas of assessing their day-to-day investment risk with user-friendly models. The bottom line investors should be capable of grasping their investment potential to see sustainable stock markets developing that will bring genuine momentum to the stock markets[2] which will in turn save the entire society from being imprudent.

From the class of zero parametric (non-parametric) models for risk forecasts our selection is the historical simulation model; from the class of risk models with one parameter our selection is JPMorgan's RiskMetrics™ model commonly known as EWMA (exponentially weighted moving average) model. We keep the benchmark Black and Scholes dynamics as our representative selection of two parametric risk models. Finally, from the class of three parametric risk models, our selection is the student-t (with location scale) model.

Given the context and purpose of this study the risk measure ES, recommended by Basel-III, under no fixed distributional assumption needs to be backtested using the tests proposed by Acerbi et al. (2017) and Acerbi et al. (2014), which are free from distributional assumption. Other ES backtests relying on distributional assumptions will be conflicting in our context. We however consider two hypotheses for distributional assumption-free ES backtests, namely unconditional-normal and unconditional-T hypotheses. Though not consistent with Basel-III we consider backtesting for VaR as well with eight different tests. These are:

[2] one not fueled by arbitragers phony investment capitals.

Binomial (BIN), Traffic Light (TL), Proportion of Failure (POF), Time until First Failure (TUFF), Conditional Coverage (CC), Conditional Coverage Independence (CCI), time between failures (TBF) and time between failures independence (TUFI) tests.

Within the context of our research, it is also realistic to assume that individual investors do not have the propensity of applying their risk models with long time series of returns. With the default estimate of parameter λ in the RiskMetrics^{TM} model being that the return data older than 100 days have no role in risk forecasts, we in general apply the models with one-year rolling windows of return data and consider such dynamically forecasted risk estimates of VaR and ES in our backtest studies. This as well goes in favor of the choice of user-friendly models that we emphasize in this study. We backtest the models using over seven years (2013-2020) of returns. With our focus on user-friendliness, we consider the joint loss score function estimation of Fissler and Ziegel (2016) to obtain an order of preference among the four models when applied to all twenty banks in our selected emerging economy. The joint score function is based on both VaR and ES forecasts as well as corresponding return series; it considers both the frequency and severity of violations. This shows that with a one-year rolling window HS is a significantly better model with great user-friendly features for individual investors to consider in the emerging markets of Bangladesh. More significantly, though the RiskMetrics^{TM} model has achieved enormous popularity as a VaR forecast model, its performance as an ES forecast model has caused it to lose its initial attraction as the most user-friendly model for risk forecasts. HS consistently outperforms both the two-parametric and three-parametric user-friendly representative models in this study as well. To verify whether this has anything to do with our user-friendly selection of window length we repeated the same dynamic backtests for both VaR and ES using two years of rolling window forecasts; for a robustness study, we took a different start date for the backtest and then applied the tests over a three-year rolling window. Surprisingly with the increase in rolling window length[1], HS somewhat loses its relative superiority over the RiskMetrics^{TM} model though it distinctly fares better than the RiskMetrics^{TM} model and remains the best among the four user-friendly models in all cases. Two- or three-year rolling window-based forecasts and backtests can’t make any of the representative models of two and three-parametric classes of risk models best.

Finally, based on the above findings we consider HS and RiskMetrics^{TM} models to decide on a few top-performing investor-friendly banks in the emerging economy of Bangladesh based on ES and VaR forecasts efficiency[2] subject to our design of user-friendliness. This would help individual investors choose an investment bank in Bangladesh in terms of their market risk exposures. This ordering of the best investor-friendly banks is subject to our choice of user-friendly representative models of the classes of zero, -one, -two, and, -three parametric risk models. However, we cross-checked the validity of the ordering with alternative selections of rolling window lengths of two and three years on top of our backtest studies with a one-year rolling window[3]. We do not find the joint score function values based on both VaR and ES violations corresponding to alternative rolling window length indicating a different model as the best user-friendly model in the emerging market of Bangladesh. So, listing the best banks based on HS model and considering the backtest results of both VaR and ES works well from the user-friendly perspective in Bangladesh. This reveals a less attractive feature of the commonly known best user-friendly model of the RiskMetrics^{TM} model in the emerging markets of Bangladesh[4].

The remaining parts of the paper are as follows. Section 2 discusses the risk measures, models, data, and our user-friendly design. Section 3 presents the empirical analysis and the results of the study, while section 4 concludes the paper.

2. Data and Methods

We use log-returns of banks' daily equity share prices, as the shares get traded at Dhaka Stock Exchange, as the basis for our analysis:

$$\boldsymbol{r_t = log\left(\frac{S_t}{S_{t-1}}\right)} \tag{1}$$

The RiskMetrics^{TM} approach was developed by JP Morgan in 1994 with the detailed methodology published in 1996 (Longerstaey and Spencer, 1996; Christoffersen, 2012; Danielsen, 2012; Su and Knowles, 2006), it was adopted by the BASEL committee for banking supervision in 1998 which recommended all its member banks maintain capital reserve based on the estimate of VaR. Jordan and Mackay (1995) and

Linsmeier and Pearson (1996) first defined VaR as the maximum loss at a certain confidence level (α) with specific holding (h) as follows:

$$\boldsymbol{VaR_{h,\alpha}(X)} = \mathbf{inf}\{\boldsymbol{x}|\mathbf{P}(\mathbf{X}_{\boldsymbol{h}} < -x) \leq \boldsymbol{\alpha}\} \tag{2}$$

where X_t is the change in the value of an asset or portfolio after n days defined as $X_h = S_t - S_{t-h}$. The loss from this can be defined as $L_h = -X_h$.

ES can be defined as follows:

$$\boldsymbol{ES_{\propto}(X)} = \frac{\mathbf{1}}{\propto}\int_{\mathbf{0}}^{\propto} \boldsymbol{VaR_u(X)du} \tag{3}$$

Although VaR complies with the three major properties of risk measures which are Normalization, Translation invariance, and Monotonicity (Engvall, 2016; Dowd, 2005; Ender and Knowles, 2006), the drawback of not satisfying the subadditivity condition by VaR measure along with the failure of capturing the tail (extreme) risk (Artzner et al., 1997; Artzner et al., 1999; Acerbi and Tasche, 2002) causes it to be a non-coherent risk measure. This fact encourages financial institutions to use expected shortfall (ES). ES as a coherent risk measure upholds subadditivity property in estimating market risk (Rockafellar and Uryasev, 2000). As a consequence, the BASEL committee on Banking Supervision has replaced VaR with Expected Shortfall (ES) measure to estimate the market risk component of a financial institution. However, ES can't be attained as the unique minimizer of the expected loss function (Gneiting, 2011), although Fissler et. al.(2016) reveals that both VaR and ES are jointly elicitable that further navigates assessing the performance of ES jointly with VaR in a unified framework (Fissler and Ziegel, 2016).

Risk measures are understood as a way of quantifying risk exposure in the form of the capital amount which is required to defend against any future unexpected loss. For this paper, we have collected almost 2,500 observations of closing daily share prices of each bank to calculate the daily log returns of commercial banks listed on the Dhaka Stock Exchange (DSE) since 2010 for estimating the VaR and ES measures of each bank, followed by back-testing each VaR and ES measure to determine the efficacy of the user-friendly models. We found 20 listed commercial banks worth considering for this investigation.

To find the best user-friendly model based on backtest evidence and loss score values we considered the daily log return of each bank from January 2010 to August 2020. Estimation of VaR and ES for the 20 commercial banks involves the adoption of the following user-friendly approaches:

<u>I. Gaussian (Normal Distribution) Model</u>: The Black-Scholes model, also known as the Black-Scholes-Merton (BSM) model, is one of the most important concepts in modern financial theory. In this paper, we use BSM dynamics to assess the backtest-based performance of risk measures VaR and ES alongside our particular user-friendly design. This model is based on the geometric Brownian motion SDE, the so-called Black-Scholes SDE, from which one can deduce the Black-Scholes formula for option pricing (Black and Scholes, 1973; Merton, 1974). Asset's evolution in this model has the following form:

$$dS_t = \mu S_t dt + \sigma S_t dB_t \leftrightarrow \; S_{t+dt} = S_t + S_t \mu dt + S_t \sigma \sqrt{dt}\, z \sim N\left(S_t + S_t \mu dt, S_t \sigma \sqrt{dt}\right) \tag{4}$$

where both drift parameter μ and the diffusion parameter σ are constants[5] and $\sigma > 0$. The following analytic estimates of Value at Risk (VaR) and Expected Shortfall (ES) in this model are possible[6] only because the drift and diffusion coefficients in this model are not allowed to be stochastic[7] (McNeil et al., 2005):

$$VaR(\alpha) = -(\mu - \sigma \Phi^{-1}(1-\alpha)) \tag{5}$$

and [8]

$$ES(\alpha) = \frac{-(\mu - \sigma \varphi(\Phi^{-1}(1-\alpha)))}{\alpha} \tag{6}$$

where μ = mean of daily share price return

σ = standard deviation of daily share price return and

$\boldsymbol{\Phi}$ = standard normal distribution function

$\alpha = 0.025$, in our application, conforming to Basel-III.

VaR measures the quantile of the predicted distribution. ES is an alternative risk measure to VaR that is more conceptually appealing than VaR and is used in the field of financial risk measurement. As ES is more informative than VaR it is proposed by Basel (2013) to replace VaR. ES is more sensitive to the shape of the tail of the loss distribution, which is completely left unattended by VaR.

II. Historical Simulation model: Historical simulation is a model for VaR forecasts where past or historical data is used to estimate the quantile without requiring any explicit assumption regarding the shape of the return distribution (Taylor, 2003). It gets criticized due to utilizing past data to characterize the current return and future risk forecasts. Whether or not the data needs to be weighted may become necessary to explore any change in underlying market conditions (Haung, 2010). In addition, Hendricks (1996) identified that in historical simulations, a larger sample diminishes the variability of VaR estimates whereas the VaR measure is imprecise when applied with a short sample period.

For a series of historical observations$\{r_{t-i}\}_{i=0}^{m-1}$; this simply means that

$$VaR_{t+1}(\alpha) = -percentile\left\{\{r_t, r_{t-1}, r_{t-2}, \dots \dots, r_{t-(m-1)}\}, 100\alpha\right\} \tag{7}$$

and the ES[9]

$ES_{t+1}(\alpha) = -\frac{1}{\alpha m}\sum_{i=0}^{m-1} r_{t-i} \;\; I_{\{r_{t-i} < -VaR_{t+1}(\alpha)\}}$. In our application $\alpha = 2.5\%$.

III. RiskMetrics™ Method: Unlike the previous model, this model doesn't assign equal weights to past returns. Instead, it assigns unequal weights which follow an exponentially decreasing pattern[10] assigning higher weights to the most recent returns (as they contain significant current market information for future movements (Christoffersen, 2012) compared to previous returns of assets as revealed below:

$$\widehat{\boldsymbol{\sigma}_t^2} = \frac{\mathbf{1}}{\boldsymbol{c}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{w_e}} \boldsymbol{\lambda^{i-1} r_{t-i}^2} \tag{8}$$

Where c is a normalizing constant followed by notation:$c = \sum_{i=1}^{w_e} \lambda^{i-1} = \frac{1-\lambda^{w_e}}{1-\lambda}$ And λ, in practice, is the decay factor showing the relative importance of past data observing a default value of 0.94[11], as proposed by JPMorgan.

A simplification (Christoffersen, 2012) yields the recursive volatility updating rule in this model as:

$$\widehat{\sigma_{t+1}^2} = \lambda \widehat{\sigma_t^2} + (1 - \lambda) r_t^2 \tag{9}$$

from which getting the estimates of risk measure VaR turns out to be methodical ($VaR_{t+1}(\alpha) = -\widehat{\sigma_{t+1}}\Phi_{\alpha}^{-1}$) (Longerstaey and Spencer, 1996; McMillian et al., 2009). Once VaR is obtained ES can be obtained as an average of VaR's on the tail (Engvall, 2016; Emmer et al., 2015; Dowd, 2005).

<u>IV. Student-t-location-scale Distribution:</u> Many researchers also find that VaR measures based on normal or simple student's *t*-distribution underestimate variance and are subject to upward bias because return distributions are fat-tailed (Longin, 1996; Wu et al., 2020; Lee and Poon, 2015). For quantifying market risk, we have also adopted a student *t*-distribution with location and scale allowing us to specify the mean and standard deviation of log returns distribution while characterizing VaR on degrees of freedom (ν), confidence level (cl) and holding period (hp):

$$VaR(hp, cl) = -hp\mu_{returns} + t_{cl,,v}^{-1} \sqrt{hp}\sqrt{\frac{v-2}{v}}\sigma_{returns} \tag{10}$$

Following the estimations of VaR for the 20 banks at 97.5% level under the BASEL-III accord, the expected shortfall (ES) can also be estimated considering the four user-friendly models. As ES is defined as an integral of VaR according to Eq. (2) above, this integral can be approximated as a sum of different VaR's corresponding to different VaR levels:

$$ES_{\propto}(X) = \frac{1}{\propto}\int_0^{\propto} VaR_u(X)du \approx \frac{1}{N}\sum_{k=1}^{N} VaR_{\frac{k\propto}{N}}(X) \tag{11}$$

The approximation suggested by Emmer and Tasche (2015)

$$\boldsymbol{ES}_{\propto} = \frac{\mathbf{1}}{\mathbf{4}}[\mathbf{VaR}_{\boldsymbol{\alpha}}(\mathbf{X}) + \mathbf{VaR}_{\mathbf{0.75}\boldsymbol{\alpha}}(\mathbf{X}) + \mathbf{VaR}_{\mathbf{0.50}\boldsymbol{\alpha}}(\mathbf{X}) + \mathbf{VaR}_{\mathbf{0.25}\boldsymbol{\alpha}}(\mathbf{X})] \quad (12)$$

However, Engvall (2016) applied the following approximation to integration and found it to be more precise when used for VaR estimated with Historical Simulation (HS):

$$\boldsymbol{ES}_{\propto} = \frac{\mathbf{1}}{\mathbf{5}}[\mathbf{VaR}_{\boldsymbol{\alpha}}(\mathbf{X}) + \mathbf{VaR}_{\mathbf{0.80}\boldsymbol{\alpha}}(\mathbf{X}) + \mathbf{VaR}_{\mathbf{0.60}\boldsymbol{\alpha}}(\mathbf{X}) + \mathbf{VaR}_{\mathbf{0.40}\boldsymbol{\alpha}}(\mathbf{X}) + \mathbf{VaR}_{\mathbf{0.20}\boldsymbol{\alpha}}(\mathbf{X})] \quad (13)$$

So here we unwind the main attraction of our user-friendly design that recently individual investors at DSE, as well as many asset management firms in Bangladesh, started adopting to make ES a familiar- not too complicated- risk measure (compared to VaR) by using equation (12) which shows ES as a simple average of four VaR's at four VaR levels. Of course, ES as an average of five VaR's at five different VaR levels (as in Eq. (13)); and as an average of infinitely many VaR's at infinitely many VaR levels (as in Eq. (11)) are supposed to be slightly better than the ES estimates we obtain with our user-friendly design. However, in this study, we stick to the practice that non-technical individual investors in Bangladesh prefer and so we consider the ES as the average of four VaR's in our empirical analysis[12].

After estimating VaR and ES for each of the 20 commercial banks of Bangladesh for the four user-friendly models under the user-friendly design of individual investors as discussed above, we are set to apply the following tests, eight for VaR and two for ES, to explore the popular and extended hypotheses of backtesting both VaR and ES. The ultimate goal is to figure out which user-friendly model is most adequate under our design of user-friendliness from an individual market participant's perspective. Every hypothesis has some particular focus and tests whether observed real losses comply with what the model predicts.

(1) **POF-test:** This test statistic, also known as the Kupiec test, verifies whether there is a large difference between the observed failure rate and model predicted failure rate as:

$$\boldsymbol{LR}_{\boldsymbol{uc}} = -\mathbf{2}\,\mathbf{ln}\frac{(\mathbf{1}-\boldsymbol{P})^{\boldsymbol{T}-\boldsymbol{x}}\boldsymbol{p}^{\boldsymbol{x}}}{\left[\mathbf{1}-\left(\frac{\boldsymbol{x}}{\boldsymbol{T}}\right)\right]^{\boldsymbol{T}-\boldsymbol{x}}\left(\frac{\boldsymbol{x}}{\boldsymbol{T}}\right)^{\boldsymbol{x}}} \quad (14)$$

where p = failure rate and T = total number of risk forecasts used in backtest

(2) **Christoffersen's Interval forecast test**: Following test statistic will be applied to test the independence hypothesis i.e., whether VaR failures (violations) are statistically clustered or not:

$$\boldsymbol{LR_{ind}} = -\mathbf{2}\ \mathbf{ln}\frac{(\mathbf{1}-\boldsymbol{\pi})^{\boldsymbol{Too+T1o}}\boldsymbol{\pi}^{\boldsymbol{Too+T11}}}{[\mathbf{1}-\boldsymbol{\pi_{01}}]^{\boldsymbol{Too}}\boldsymbol{\pi_{01}^{To1}}(\mathbf{1}-\boldsymbol{\pi_{11}})^{\boldsymbol{T1o}}\boldsymbol{\pi_{11}^{T11}}} \qquad (15)$$

where $\pi_{01}$is the probability of having a violation tomorrow given that today has no violation

π_{11} is the probability of tomorrow being a violation given today is also a violation;

This test statistic follows a chi-squared distribution with one degree of freedom, $\boldsymbol{LR_{ind}}\sim\boldsymbol{\chi 2}$

(3) **BASEL Traffic Light Approach**: This test depends on the excess ratio followed by notation α expressed as:

$$\widehat{\boldsymbol{\alpha}} = \frac{\mathbf{1}}{\mathbf{N}}\sum_{\mathbf{t=1}}^{\mathbf{N}}\mathbf{I_t} \qquad (16)$$

where I_t is either zero or one based on whether a forecast is a violation or not and N is the total number of forecasts considered in the backtest.

The responses of this test have been classified into the three categories of Green Zone, Yellow Zone, and Red Zone, signifying there is no problem, potential problem, and severe problem respectively with the predictive accuracy of the model. It uses the following formula:

$$\mathbf{F(I_t)} = \sum_{\mathbf{k=0}}^{\mathbf{I_t}}\binom{\mathbf{N}}{\mathbf{K}}\mathbf{p^k(1-p)^{N-k}} = \boldsymbol{\alpha}\begin{Bmatrix}\textbf{Red zone}: & \boldsymbol{\alpha}\geq\mathbf{0.999}\\ \textbf{Yellow zone} & \mathbf{0.999}>\boldsymbol{\alpha}\geq\mathbf{0.975}\\ \textbf{Green zone}: & \mathbf{0.975}>\boldsymbol{\alpha}\geq\mathbf{0.950}\end{Bmatrix} \qquad (17)$$

(4) **Binomial (bin) Test:** Comparing the observed number of exceptions (violations), say x, to the expected number of exceptions is the easiest test to do. We can formulate a confidence interval for the anticipated number of exceptions based on the characteristics of a binomial distribution. The test employs either exact probabilities from the binomial distribution or a normal approximation. We can calculate the likelihood of incorrectly rejecting a good model when *x* exceptions occur by computing the probability of observing *x* exceptions which is the p-value for the observed number of exceptions, *x*. If *x* is outside the test confidence range for the predicted number of exceptions, the VaR model should fail as a simple accept-or-reject result in this scenario for a particular test confidence level. The usual Z-score calculation for this test statistic is:

$$\boldsymbol{Z_{bin} = \frac{x - Np}{\sqrt{Np(1-p)}}} \tag{18}$$

where *x* is the number of failures, *N* is the number of risk forecasts used in backtest, and *p* = 1 – VaR level.

(5) **Time Until First Failure (TUFF) Test:** Looking beyond the conventional test framework, Kupiec suggested a second test, in a somewhat controversial framework, known as the time until first failure (TUFF). The TUFF test examines the timing of the initial rejections. The VaR model fails the test if violations occur too quickly. Only checking the first exception leaves out a lot of information, as anything that occurs after the first exception is disregarded. The TBFI test expands on the TUFF strategy by taking into account all failures (in an extended framework of the TUFF test).

The underlying distribution for the TUFF test is a geometric distribution and is also based on a likelihood ratio. The test statistic is asymptotically distributed as a chi-square variable with 1 degree of freedom as below, where n is the number of days until the first exception:

$$\boldsymbol{LR_{TUFF} = -2\log\left(\frac{p(1-p)^{n-1}}{(\frac{1}{n})(1-\frac{1}{n})^{n-1}}\right)} \tag{19}$$

(6) **TBF and TBFI Test:** TBF, and further extension of TBF to independence- TBFI, standing for Time between Failures incorporates the time information among all failures in the sample. This test statistic implements the TUFF test with each violation in the sample and accumulates the time between failures (TBF). The test statistic is asymptotically distributed as a chi-square variable with *x* degrees of freedom, where x is the number of failures, p = 1 – VaR level and n_i is the number of days between failures i-1 and i (or until the first exception for i = 1); and it has the following expression:

$$\boldsymbol{LR_{TBFI} = -2\sum_{i=1}^{x}\log\left(\frac{p(1-p)^{n_i-1}}{(\frac{1}{n_i})(1-\frac{1}{n_i})^{n_i-1}}\right)} \tag{20}$$

The TBF mixed test combines the TBFI test with the frequency test POF; such mixing is also known as Haas's mixed Kupic Test. Obviously, it is asymptotically distributed as a chi-square variable with x+1 degrees of freedom:

$$\boldsymbol{LR_{TBF} = LR_{POF} + LR_{TBFI}} \tag{21}$$

In addition, the following unconditional test statistic of backtesting ES has also been considered in our study:

$$\boldsymbol{Z_{unconditional} = \left(\frac{1}{N_{pVaR}}\right)\sum_{t=1}^{N}\frac{X_t I_t}{ES_t} + 1} \tag{22}$$

Where N is the number of time periods in the test window (number of risk forecasts). X_t is the portfolio outcome, that is, the portfolio returns or portfolio profit and loss for period t. p_{VaR} is the probability of VaR failure defined as 1-VaR level. ES_t is the estimated expected shortfall for period t. I_t is the VaR failure indicator on period t with a value of 1 if $X_t < -\mathrm{VaR}_t$, and 0 otherwise.

This test statistic usually has an expected value of 0 and it produces a negative value when the risk of underestimation happens. The critical values are required to decide how negative it (test statistic value) should be to reject the model. Though the test is free of any distributional assumption the critical values can be determined based on distributional assumptions for the corresponding outcomes of X_t being a proxy for real portfolio return or portfolio profit and loss for period t. ES (expected shortfall) backtest consists of two sets of critical value tables. The first set assumes that X_t follows a standard normal distribution for executing the unconditional Normal test whereas the second critical value table assumes that X_t follows a t-distribution for executing the unconditional-T test.

After that we have another section that navigates a predictive relationship between market capitalization and risk management process of banks estimated with Normal, Historical, Student-T (location based) and EWMA VaR and ES forecasts considering two econometric models[3] estimated with different approaches including fixed effect, random effect, pooled OLS (ordinary least square) and GLS (generalized least square) method. We have regressed log of market capitalization against four VaR forecasts depending on the daily market capitalization data along with daily four VaR forecasts data found from our empirical section of the paper for the periods covering from January 2015 to August 2020 to estimate the models. Following table reports the list of variables included in the models:

(Insert Table 1 here)

(Table 1: List of Variables included in the model)

Following econometric models have been adopted to investigate the relationship between market capitalization and risk management of banks:

$$MarketCap_{it} = \alpha_{it} + \sum_{k=1}^{4} \delta_{it} VaR_{itk} + \varepsilon_{it} \dots \dots \dots \dots (23)$$

$$MarketCap_{it} = \alpha_{it} + \sum_{k=1}^{4} \delta_{it} VaR_{itk} + u_{it} + \varepsilon_{it} \dots \dots \dots \dots (24)$$

$$MarketCap_{it} = \alpha_{it} + \sum_{k=1}^{4} \delta_{it} ES_{itk} + \varepsilon_{it} \dots \dots \dots \dots (25)$$

$$MarketCap_{it} = \alpha_{it} + \sum_{k=1}^{4} \delta_{it} ES_{itk} + u_{it} + \varepsilon_{it} \dots \dots \dots \dots (26)$$

Here, market capitalization is going to be regressed against four VaR and ES forecasts where α_{it} = constant; VaR_{it} = four VaR forecasts including Normal, HS, StuT and EWMA daily VaR forecasts collected from previous section; ES_{it}= four expected shortfall forecasts including Normal, HS, StuT and EWMA daily ES

[3] One model measures the predictive relationship between Market capitalization and VaR measures and another model corresponds between market capitalization and ES measures.

forecasts also adopted from the calculation of previous section; δ_{it}= coefficient of explanatory variable; ε_{it} = error term / within entity error; u_{it} = between entity error.

We have adopted pooled OLS, fixed effect, random effect and GLS method to estimate the co-efficient of the models as per these four equations to incorporate the robustness of the models. In addition, several diagnostic checks such as test of multicollinearity, heteroscedasticity, auto-correlation and model specification test have been executed to ensure the performance of the models.

3. Empirical Results with Discussion

The entire banking sector of the emerging economy of Bangladesh is represented in this study by the twenty selected commercial banks operating in Bangladesh and trading their shares on the DSE. We use the maximum amount of data available in the country's SEC's (securities and exchange commission) electronic database and make a selection of twenty banks - as a representative sample of the economy - which have better data records and discarding only a few handfuls of banks among all the banks which trade their shares on the DSE[13]. Our sample includes PCB's and NCB's as conventional and Islamic banks too. We use the dataset of daily closing share prices. The data series covers the period from 1st January 2010 to 31st August 2020 for the banks: Al-ArafaIslami Bank Ltd (ABL), Bank Asia Ltd (BA), BRAC Bank Ltd (BRAC), The City Bank Ltd (CBL), Dutch Bangla Bank Ltd (DBBL), Eastern Bank Ltd (EBL), Export-Import Bank Ltd (EXIM), First Security Islami Bank Ltd (FSIBL), Islami Bank Bangladesh Ltd (IBBL), IFIC Bank Ltd (IFIC), Jamuna Bank Ltd (JBL), Mutual Trust Bank (MTBL) Ltd, Mercantile Bank Ltd (MBL), National Credit and Commerce (NCC) Bank Ltd, ONE Bank Ltd (ONE), Prime Bank Ltd (PBL), Premier Bank Ltd (PRBL), Rupali Bank Ltd (RBL), Standard Bank Ltd (SBL), and Trust Bank Ltd (TBL).

Since two out of our four user-friendly models are virtually non-parametric (HS using the empirical distribution of historical returns and RiskMetrics™ model using a default value for its sole parameter as proposed by JPMorgan) we do not concentrate on any in-sample estimation performance analysis for the remaining two models, namely two-parametric Gaussian model and three-parametric student-t-location-scale model. Moreover, as we believe the risk is in the future and not in history, we put our best efforts into backtesting based inference towards configuring the most adequate user-friendly model when future risk forecasts are made, conforming to our user-friendly design. Our inference is based on the combined data from eight VaR and two ES backtests which consider out-sample returns; VaR and ES forecast corresponding to each such return; all triplets of out-sample (return, VaR, ES) together over the entire backtest period yield loss score value using the score function of Fissler and Ziegel (2016) which is based on accuracy and adequacy of each VaR and ES forecast over the entire backtest period. The lower the loss score value the better the model's risk forecast ability. Using this loss function in ordering the models' performances in risk forecast accuracy is also partly due to our utmost concern of being user-friendly.

3.1 Estimations of VaR and ES with user-friendly models

As part of our user-friendly design, we have adopted a 250-trading day window each time throughout the dynamic forecasts of VaR and ES, considering 2,460 returns data of each bank where the length of test windows corresponding to different banks consists of somewhere between 1,200 to 1,600 VaR and ES forecasts for out sample-observations. The total data set for each bank was cleaned up, for repeated closing share prices for a number of consecutive days, so the length of test windows varies from one bank to another. Thus the expected number of tail events varies from bank to bank, e.g., a bank with 1,600 forecasts will have 40 tail events expected at 2.5% of the tail as per the BASEL-III accord.

Fig. 1 shows the daily VaR's of twenty commercial banks in Bangladesh, from the 1st of January 2013 to the 31st of August 2020, that have traded their equity share prices on the DSE regularly since 2010. We consider 97.5% VaR as in Basel-III accord and for each plot, we include VaR's from four of our user-friendly models. The VaR's in figure1 are all out-sample forecasts with a one-year rolling window of immediate past return series as the basis of each forecast. This is in line with our user-friendly design which takes into account that individual investors at DSE often do not have more than one-year data to review; and even if some of the investors have they do not like to consider those older observations while making forecasts dynamically based on one year rolling window calibrations for Normal and Student-t with location and scale (the other two models do not require any calibration as HS uses empirical distribution and EWMA uses default estimate of JPMorgan). Corresponding ES forecasts are presented in Fig. 2.

(Insert Figure 1 here)

Figure 1. The daily VaR's of twenty commercial banks in Bangladesh,

Over 1st January 2013 to 31st August 2020

(Insert Figure 2 here)

Figure 2. The daily ES Estimates for all models for each bank from 1st Jan.2013 to 31st Aug.2020

3.2 Estimation of loss score value jointly under VaR and ES

Fissler and Zeigel (2016) developed a family of loss functions where each function jointly assesses the associated VaR and ES forecast series corresponding to a model and helps infer a model's capacity to generate adequate VaR and ES forecasts that leads to the lowest loss score value. Such loss score values corresponding to a number of alternative models can be used to obtain a performance order of models based on their relative adequacy in appropriately forecasting both VaR and ES.

The loss score value based on a particular model's VaR and ES forecast series is estimated as:

$$\boldsymbol{S}[\mathbf{y},\, \boldsymbol{VaR},\, \boldsymbol{ES}] = (\boldsymbol{I}{-}\propto)\boldsymbol{VaR} - \boldsymbol{I} * \boldsymbol{y} + \mathbf{exp}(\boldsymbol{ES}) * \left(\boldsymbol{ES} - \boldsymbol{VaR} + \left(\frac{\boldsymbol{I}}{\propto}\right)(\boldsymbol{VaR} - \boldsymbol{y})\right)$$

$$- \mathbf{exp}(\boldsymbol{ES}) + \mathbf{1} - \mathbf{log}(\mathbf{1}{-}\propto) \tag{23}$$

where *S* is the loss function score or value found from jointly assessing the VaR and ES forecasts from a model, *y* is out-sample log-returns, α = 1- VaR Level, *I* = 1 when *y*<VaR and 0 otherwise.

(Insert Table 2 here)

Table 2. VaR and ES Joint loss function values

(Insert Table 3 here)

Table 3. Robustness Check- VaR and ES Joint loss function values

3.3 Back-Testing VaR and ES forecasts

The out-sample VaR and ES forecasts, together with their corresponding returns, are the basis for implementing and analyzing VaR and ES backtests; as well as for obtaining loss score values of each model for each bank using the Fissler and Zeigel (2016) methodology. The loss score value method is a straightforward technique to determine the best and/or better-performing models from a list of alternatives in a user-friendly fashion. Table 1 includes information on the best and the second-best models for each of the twenty banks in this study. This table includes two panels. The upper panel is based on the VaR and ES forecasts as in Fig. 1 and Fig. 2, respectively, according to our user-friendly design of one-year (250-days) rolling window-based estimates. However, in the lower panel we replicate the entire experiment over exactly the same period of backtesting as in the upper panel but now consider two-year rolling window estimations. It is obvious EWMA loss scores remain exactly the same under one- and two-year rolling window cases (since JPMorgan's default estimate of λ, by default, allows the model to consider only the last one hundred observations in making the risk forecasts). However, in Table 3 we conduct a robustness study by slightly shifting the starting point for the backtesting window so that EWMA loss score values also get changed and we consider a three-year rolling window-based estimation for this table.

For every bank in our sample, and for every window size we consider in rolling calibration and dynamic risk forecasts, HS always stands best or second best. Moreover, in all three window size experiments the proportion for HS as the best is significantly higher than it is as second best (95% vs. 5% for 250-days; 85% vs.15% for 500-days; and 65% vs. 35% for 750-days). Corresponding odds for the RiskMetrics^{TM} model are 10% vs.15% for 250 days; 15% vs. 60% for 500 days; and 15% vs. 45% for 750 days. So that's the comparative feature of HS and RiskMetrics^{TM} models as the best and second-best models among the four user-friendly models of our consideration as investigated with our user-friendly design. Though the student *t* has never come up as the best model in any of our window size experiments its odds as second best (65%) corresponding to our main user-friendly design of implementing models with only 250-day rolling window estimation is significantly higher than the odds of both HS (5%) and RiskMetrics^{TM} (15%) models.

Fig. 3 presents the 'observed' and 'expected' number of VaR violations and the average severity ratios over all violations. It includes this information for all twenty banks and for all four user-friendly models. This information crucially determines the outcome of ES backtests, under both hypotheses (unconditional-*N* and unconditional-*T*).

Table 4 includes the results of all ten tests that we consider with VaR and ES. Except for the TL test, all tests are shown as either pass ('*P*') or fail ('*F*') with corresponding *p*-values in parenthesis, for all twenty banks. With the TL test, instead of reporting '*P*' or '*F*' we report each bank's performance zone as Green (*G*), Yellow (*Y*), or Red (*R*) based on Eq. (16) which assigns one of the three zones to each bank based on the extent of violation that characterizes the fraction α. Obviously, α is the highest (0.999) for the red zone assignment and lowest (0.995) for the green zone assignment. There should not be any confusion between the p-values of the TL hypothesis test (as reported in Table 4) and α bands (that remain the same for all banks). Therefore, we just report the TL zone for each bank in Table 4 but not the zone fraction α. However in general the higher the *p*-values the lower the α.

Table 2 and Table 3 reflect the accuracy and adequacy of VaR and ES forecasts, as presented in figure 1 and figure 2, respectively, corresponding to each of the twenty banks; so do the loss scores reported in Table 3. Any comment on bank's investor-friendliness based on their market risk exposure must consider the findings in both Table 2 and Table 4.

Twenty banks that trade equity shares at the DSE make a good representation of the banking sector of Bangladesh, which is viewed as an emerging economy in the world in the last decade or so. Standard and featured tests applied with VaR and ES backtests covering a number of user-friendly alternative models confirm that very few banks in Bangladesh are genuinely investor-friendly. Based on all ten tests considered, two for ES and eight for VaR, only four banks were found to pass all ten tests under some models (one or two of the four user-friendly models), those were TBS, AIBL, JBL, and PRBL. When these four banks are further investigated under the best or second-best model, out of four, we get only two banks (TBL and AIBL) passing all ten back tests applied with both VaR and ES. The determination of best and second-best models is based on score values obtained with a joint performance of both VaR and ES forecasts dynamically made over a long period. This reveals a contrast to the reputation of the most user-friendly model in the literature[14]; namely the RiskMetrics™ model. RiskMetrics™ model performs second worst, only better than Gaussian risk forecasts, under the consideration of the joint performance of both VaR and ES with the design of our user-friendly facets. The bank that passes all ten VaR and ES backtests corresponding to the best model (based on the joint score values) is TBL; surprisingly TBL passes all ten VaR and ES backtests corresponding to the second best model (student-*t* with location scale, based on joint score values) as well. Moreover, it is the only bank, out of the twenty banks in this study, that passes all ten VaR and ES backtests corresponding to both best and second-best models; while the RiskMetrics^{TM} model performs appallingly with TBL (failing half of the VaR and all the ES backtests).

As a consequence, holding a 15.6% share of total market capitalization in the capital market of Bangladesh, these 20 commercial banks in our sample must receive attention from the regulatory bodies, namely Bangladesh Bank and BSEC (Bangladesh Securities and Exchange Commission) to ensure effective implementation of policy recommendations regarding the capital adequacy in accordance with risk-weighted assets and maintenance of high-quality assets to minimize classified or non-performing loans. In addition, the specific implementation of policy recommendations must be ensured for effective provisioning against non-performing loans with deferral conditions, in order to stabilize the capital adequacy ratio for being eligible to declare dividends for shareholders. Moreover, these policies will also ensure sound management with robust corporate governance guidelines to create sustainable earnings capacity for banks in order to uphold shareholders' dignity with maximization of their wealth. Apart from creating a sound liquidity management system for banks (in order to avoid any unexpected circumstance), strategies for creating a separate risk management division (especially to address market forces affecting the share price of the respective bank) must be implemented by the regulators so that any period of instability in capital markets would be tamed with a purpose of protecting micro investors' interest.

(Insert Table 4 here)

Table 3. VaR and ES Back-Testing Outcomes at 97.5% level amid forecasting

period of 1st Jan. 2013 to 31st Aug. 2020

(Insert Figure 3 here)

Figure 3. Average Severity Ratio (ASR) and number of VaR Failures across Banks and Models

This will save the entrepreneurial investors from the bitter experiences that earlier investors faced (Bi. et. al.(2020)); experiences that discourage investors from participating in the capital market including the so-called robust (!) banking sector. Policy enactment should be there to help investors assess their day-to-day investment risk, plausibly with user-friendly models, that's where our study will turn handy. We recommend Bangladesh Bank, in collaboration with the management of the four banks (TBL, AIBL, JBL, and PRBL) that passed all ten backtests under some model in our study, arrange training sessions to help nontechnical baseline investors grasp their investment risk at least with the HS simulation model (if not with Student-t (with location scale) model due to its parameter estimation challenges for nontechnical investors). Helping the baseline investors by providing an excel-sheet coded with ES forecast under the HS method using at least a one-year share price data of their chosen banks (whose share they plan to buy from the DSE/CSE[4]) will pre-warn them of their investment prospect. Such training can be made easy[5] even for investors with low or no technical expertise. Keeping vast non-technical investors in dark about their investment risk can only seduce arbitrageurs to bet more on the naive entrepreneurs who come to reality only when the foreign arbitrageurs get done with their predatory arbitrage success (Atilgan et. al. (2020)) leading to a massive siphoning off cash to foreign destinations and causing untoward social unrest to the individual and family lives of so-called entrepreneurial preys. The bottom line investors should be enlightened, no matter how non-technical they are, regarding the genuine relative risk-return prospects of their investments; that will help see the capital markets sustaining in the long run. This will bring genuine momentum to the stock markets by at least partially saving naive investors from being targeted as gamblers' pawns. Like our study on the banking sector, other studies should come up with user-friendly risk assessment tools for other sector investments.

Now, for establishing a predictive relationship between market capitalization and risk management process, the following table reveals the descriptive statistics of both dependent and independent variables of the model estimated using daily observations covering from January 2015 to August 2020 depending on the availability of data as described earlier in the data and methods section:

(Insert Table 5 here)

Table 5. Descriptive statistics of variables included in the model

[4] Chittagong stock exchange.

[5] At least with HS method.

According to the estimated parameters reported in the table 06, there is a significant statistical relationship exists between market risk management measured with four different VaR forecasts being explanatory variables and market capitalization of banks being explained variable. The primary rationale behind this scene is that risk management practices can influence the perceived and actual stability with prospects of a bank which then could impact its stock price and consequently, its market capitalization. Moreover, Effective risk management can enhance investor confidence, leading to increased demand for the bank's stock and potentially a higher stock price. If risk management is perceived to be poor, it could reduce investor confidence, potentially leading to a decrease in stock price. This significant statistical relationship infers that static risk management can prevent significant financial losses, safeguarding the bank's assets and profitability, both of which can influence stock price and, by extension, market capitalization. Another annotation is any bank that effectively manages its risks is less likely to face regulatory penalties which can negatively impact its financial performance and its stock price and thereby market capitalization. Additionally, a bank that manages its risks well is less likely to require bailouts or face other systemic challenges, which can have direct implications for its market value.

(Insert Table 6 here)

Table 6. Parameter Estimation of Econometric model

The R^2 value of 0.6140 followed by 0.9958 measured reveals that 61.40% and 99.58% variation in market capitalization has been caused by four VaR forecasts including Normal-VaR, Historical-VaR, Student-T-VaR (location based) and EWMA-VaR under both pooled OLS and Fixed effect models respectively. Moreover, the F-value estimated under both models is also evidencing the joint significance of all explanatory variables in affecting the market capitalization of banks. The intraclass correlation measured with rho value of 0.8831 followed by 0.6098 accounts for 88.31% and 60.98% variation in market capitalization estimated under both fixed effect and random effect method respectively due to the differences across the panels.

Several diagnostic checks of the model have been executed to validate the result. The mean VIF[6] (variance inflation factor) value reveals very low pairwise correlation existing between the explanatory variables in the model. So, the model doesn't suffer from the problem of multicollinearity. Moreover, regression error specification test (RESET)[7] has been performed to check the specification bias of the model and found that model is free of specification bias as null hypothesis of no specification error is not rejected according to the estimated F ratio at 5% level of significance. In addition, we have also performed Hausman test[8] to choose between fixed effect and random effect. This test statistic is statistically significant at chosen level of significance that rejects the null hypothesis of preferring fixed effect than random effect. So, it infers that random effect method is better than fixed effect method. After that BP/LM[9] (Breusch Pagan Lagrangian Multiplier) test has been also executed to choose between random effect and pooled OLS method and found that pooled OLS is better estimates than random-effect method as the test statistic is not statistically significant at 5% level so that the null hypothesis of no significant difference across units or no panel effect can't be rejected and therefore suggesting pooled OLS is better than random effect. The modified Wald test[10] for groupwise heteroscedasticity has been executed to check whether the model holds a constant error variance. The test statistic is statistically significant which infers that the model suffers from the non-constant error variance. At last, we have also executed the serial autocorrelation test considering Wooldridge[11] test statistic and found that model suffers from autocorrelation problem. As a consequence, we have also estimated the coefficient of corresponding explanatory variables using cross-sectional GLS (generalized least square) method that assumes no heteroscedasticity and no-autocorrelation in the model.

[6] Mean VIF value for all explanatory variables is found 1.32 which is obviously less than 5. Usually VIF value greater than 5 is a sign of causing high collinearity among the variables in the model.

[7] F value of RESET is 2.79 which is statistically insignificant as its corresponding p-value is 0.127

[8] χ^2 value is 26.485 and its corresponding p-value is 0.017 for Hausman Test.

[9] χ^2 value is 1.492 and its corresponding p-value is 0.263 for BP/LM Test.

[10] χ^2 value for Wald test is 129.459 and its corresponding p-value is 0.000 where the H_o is constant error variance across the panels

[11] F-value of Wooldridge test is 37.394 and its corresponding p-value is 0.001 that rejects null hypothesis of no serial autocorrelation in the model.

According to the estimated coefficients reported in table 07, all four ES measures are individually statistically significant in explaining the changes in market capitalization of banks. Moreover, the F-value along with chi-square value estimated under respective models is also evidencing the joint significance of all explanatory variables in impacting the market capitalization of banks. The R^2 value of 0.5571 followed by 0.6127 under pooled OLS and fixed effect method respectively divulge that 55.71% variation followed by 61.27% variation in market capitalization has been explained by all independent variables such as Normal-VaR, Historical-VaR, Student-T (location based)-VaR and EWMA-VaR forecasts. In addition, the intraclass correlation measured with the value of rho shows that 90.56% and 80.66% variability in market capitalization under both fixed effect and random effect method respectively are explained by differences across panels.

(Insert Table 7 here)

Table 7. Parameter Estimation of Econometric model

Several diagnostic checks of this model have been also executed to validate the result. The mean VIF[12] (variance inflation factor) value reveals very low pairwise correlation existing between the explanatory variables in the model. So, the model doesn't suffer from the problem of multicollinearity. Moreover, regression error specification test (RESET)[13] has been performed to check the specification bias of the model and found that model is free of specification bias as null hypothesis of no specification error is not rejected according to the estimated F ratio at 5% level of significance. In addition, we have also performed Hausman test[14] to choose between fixed effect and random effect. This test statistic is statistically significant at chosen level of significance that rejects the null hypothesis of preferring fixed effect than random effect. So, it infers that random effect method is better than fixed effect method. After that BP/LM[15] (Breusch Pagan Lagrangian Multiplier) test has been also executed to choose between random effect and pooled OLS method and found

[12] Mean VIF value for all explanatory variables is found 1.79 which is obviously less than 5. Usually VIF value greater than 5 is a sign of causing high collinearity among the variables in the model.

[13] F value of RESET is 2.571 which is statistically insignificant as its corresponding p-value is 0.102

[14] χ^2 value is 32.927 and its corresponding p-value is 0.011 for Hausman Test.

[15] χ^2 value is 2.015 and its corresponding p-value is 0.237 for BP/LM Test.

that pooled OLS is better estimates than random-effect method as the test statistic is not statistically significant at 5% level so that the null hypothesis of no significant difference across units or no panel effect can't be rejected and therefore suggesting pooled OLS is better than random effect. The modified Wald test[16] for groupwise heteroscedasticity has been executed to check whether the model holds a constant error variance. The test statistic is statistically significant which infers that the model suffers from the non-constant error variance. At last, we have also executed the serial autocorrelation test considering Wooldridge[17] test statistic and found that model suffers from autocorrelation problem. As a consequence, we have also adopted cross-sectional GLS (generalized least square) method to estimate the coefficient of corresponding explanatory variables assuming no heteroscedasticity and no-autocorrelation in the model.

4. Conclusion

HS, RiskMetric™, Gaussian risk measures of Black and Scholes (GBM)-SDE, and Student-*t* (with location and scale) models are the simplest user-friendly models of, respectively, zero, -one, -two, and -three parametric families of all risk models in the literature. Nontechnical investors in the emerging economy of Bangladesh, along with observing the banks' equity prices for a year or so and having good regard for ES risk measure (not VaR alone), should consider one of HS and/or student-*t* (with location and scale) risk models as part of their user-friendly toolkit to analyze market risk. They should not be enticed by the common narrative that RiskMetrics™ is the most user-friendly model for risk forecasts. When the ES risk measure is considered, the RiskMetrics™ model with its default parameter is not the best user-friendly model that passes the ES backtests (certainly not in Bangladesh).

Both HS and student-*t* (with location scale) models find Trust Bank Ltd. (TBL) as the best bank in terms of causing the least frustration to its equity investors - in a crisis market - based on all ten backtests we looked at for VaR and ES. None of the other banks in this study passed all ten backtests of VaR and ES with

[16] χ^2 value for Wald test is 163.028 and its corresponding p-value is 0.000 where the H_o is constant error variance across the panels

[17] F-value of Wooldridge test is 35.629 and its corresponding p-value is 0.001 that rejects null hypothesis of no serial autocorrelation in the model.

HS; and other than TBL, only Al-Arafa-Islami-Bank Ltd. (AIBL) passed all ten tests with the student-*t* model. So AIBL stands as the second best model for equity investors under the same criteria as TBL. In fact, only four banks, out of twenty, pass all backtests even when passing all ten tests is required under at least one of the four user-friendly risk models of this study. The dominance of HS model as found in this investigation is also espoused by Palaro, H. P., & Hotta, L. K. (2006) illustrating how Historical Simulation could be tailored to capture specific characteristics of Brazilian Market. Moreover, Gencay, R., & Selcuk, F. (2004) in another investigation found that HS model provided a good balance between simplicity and effectiveness in the Turkish market for forecasting market risk. In another investigation of the Greek financial market contributed by Kenourgios, D., Samitas, A., & Paltalidis, N. (2011), the authors found that the Historical Simulation model captured the contagion effects during financial crises effectively. While Greece is not classified as an emerging market, this study might be relevant to emerging economies with similar financial characteristics. However, another investigation contributed by Diebold, F. X., Gunther, T. A., & Tay, A. S. (1998) applied Student-t distribution to forecast density in the context of U.S. stock returns and highlighted the efficacy of the student-t (with location scale) model in capturing the tail behaviour of the returns' distribution. Moreover, Haas, M., Mittnik, S., & Paolella, M. S. (2004) applied the student-t (with location scale) distribution to capture the leptokurtic feature commonly observed in financial returns in the context of the German stock market. In addition, Fujii, Y. (2005) in another investigation applied applies both the Historical Simulation (HS) and Student-t (location scale) model to estimate VaR in the Japanese market that acknowledged the benefits of both models depending on the underlying characteristics of the data. In contrast, Dowd, K., & Blake, D. (2006) applied different methods, including HS to the U.K. equity market and presented strong insights into the applicability as well as efficacy of Historical Simulation (HS) model in developed markets like the U.K. After 2008 GFC, one of the papers contributed by Kupiec, P. (2010) found that Historical Simulation (HS) model remains a popular method for estimating VaR among top asset managers in the U.S. In another study by Nawrocki, D., & Harding, B. (2011) applied a combination of a combination of GARCH and HS to estimate VaR in European markets and found to perform well reflecting the advantages of HS in modelling market risk. Bekiros, S., & Uddin, G. S. (2013) analysed high-frequency data for the S&P 500 and concluded that the

Student-t distribution can model the returns more effectively than other distributions, emphasizing the tail behaviour. Allen, D. E., Singh, A., & Powell, R. (2013) applied the student-t (location scale) to the U.K. market and found it effective in capturing extreme equity market shocks. In addition, Rombouts, J. V. K., & Stentoft, L. (2014) employed the student-t (location scale) distribution for innovations, highlighting its appropriateness in capturing market risk.

For Bangladesh Bank being the Central bank of Bangladesh and the Bank for International Settlement (BIS), incorporating models like the Historical Simulation (HS) and the Student-t (location scale) models into the framework for estimating market risk can lead to better risk management for retail investors of bank stocks. Central Bank should ensure there's a robust system for the collection, processing, and dissemination of high-quality financial market data which is quite absent right now due to high confidentiality and poor corporate governance of Bangladeshi banking industry. This would enable the implementation of HS and Student-t (with locations scale) models that rely on historical data and allow market participants to better evaluate risks. Banks and financial institutions should be also encouraged to use a combination of different models to estimate market risk of their trading portfolio. This would enhance the reliability of risk measures by incorporating the strengths of each model. For example, HS can be used to capture the empirical features of the return series, while the Student-t model can better capture tail risks. Moreover, Regular stress tests, guided by both HS and Student-t models, could be conducted to estimate potential losses under extreme market conditions. The results should then be reported to regulatory authorities to ensure proper risk management. Apart from this, Bangladesh Bank should ensure rigorous model validation practices are in place. This includes back-testing, sensitivity analysis, and scenario analysis to ensure the models are performing adequately and to assess their limitations. In addition, Bangladesh Bank and the BIS should facilitate the sharing of best practices, research findings, and other information related to the use of HS and Student-t (with location scale) model for market risk estimation.

Bangladesh Bank could enforce policies that encourage banks to disclose risk management procedures and their impact on financial performance. The disclosure of such information could provide investors with a more comprehensive view of a bank's value, thereby influencing market capitalization. Moreover, Bangladesh

Bank and BIS could establish policies to regulate excessive risk-taking activities that might inflate market capitalization artificially. Such regulations could help maintain the stability of the financial system and ensure that market capitalization reflects the true value of firms. In addition, Bangladesh Bank along with BIS could develop policies aimed at educating investors and the public about the relationship between risk management and market capitalization as in this investigation a significant relationship is already established between market capitalization and risk management process of banks. Increased understanding could lead to more informed decision-making by investors, potentially leading to more accurate market capitalization of banks. Moreover, Policies could be established that require regular auditing of a bank's risk management strategies and their impacts on market capitalization. Such audits could ensure that banks are adequately managing their risks and that their market capitalization is a true reflection of their value.

It is our further recommendation that Bangladesh Bank along with the top management of these four banks, succeeding to pass ES backtests in our study, form a policy with a view to informing the investors regarding the implications of user-friendly models considered in this paper. We contend that these relative efficacy studies of user–friendly models could help non-technical retail investors more in predicting maximum possible loss (that could result from holding shares of listed commercial banks during adverse market movements) provided they use them with standard backtesting guidelines of ES as a tool to quantify their market risk exposure, and provided central bank (Bangladesh Bank) enacts policy encouraging ordinary investors to receive a short risk-management training of the type we recommend. These may also lessen the likelihood that a stock market bubble may cause a capital market crash or unrest as a result of an unanticipated swindle in the future.

We end our analysis with an excerpt from Christoffersen (2012) which says: "*Taking the model-free approach (HS) is sensible in that the observed data may capture features of the returns distribution that are not captured well by any standard parametric model*". The spirit is upheld in the banking sector in particular, see Escanciano et.al. (2012).

Notes

1 Deviating from our user-friendly design.

2 Analyzed on the basis of backtesting evidence.

3 Gaussian and student-T location scale models are continuous models and using just one year rolling data in dynamic estimation is likely to catch criticism no matter how practical it may seem from the perspective of individual investors in emerging markets.

4 However, there is no study available in the literature confirming that based on joint performance of VaR and ES RiskMetricsTM is even an acceptable model; though based on VaR alone its appeal as an acceptable most user-friendly model has been found strong, see [IRFA paper and the references therein].

5 B_t is a standard Brownian motion and so $dB_t = z\sqrt{dt}$, z being a standard normal random number.

6 If daily log-returns are used to estimate μ and σ and dt=$\frac{1}{252}$ is used in estimation, instead of dt=1, then μ and σ should be replaced by μdt and $\sigma\sqrt{dt}$, in the VaR and ES formulas.

7 Which requires applying Ito's formula to derive the distribution of log-returns of the asset, see McNeil (2005).

8 Though we do not use this expression in our user-friendly design.

9 Again unfortunately we do not use this with our user-friendly design.

10 Hence this model is more popularly known exponentially weighted moving average (EWMA).

11 This choice of lambda ensures that return observations older than the previous 100 have no effect in risk forecasts, see Christoffersen (2012).

12 However we compare our user-friendly design with ES as five VaR average and infinitely many VaR average in loss score computations separately, as in section 3.2. We do not include those results here because except for slight changes in p-values corresponding to ES backtests alternative ES valuations have no effect in loss-score value-based ordering of user-friendly models compare to those obtained with our user-friendly design as presented in next section. This is precisely due to the fact that any extra precision obtained with alternative ES estimation as 'five VaR average'

and ‘infinitely many VaR average’ applies uniformly to all user-friendly models of our consideration. So that doesn’t affect the preference order we use with our user-friendly design.

13 When we find the data is seriously corrupt, especially at the peak of COVID 19, DSE saw a virtual closure; so those data over that period are virtually non-representative and nonexistent for banks and were discarded from our analysis.

14 Based, however, on VaR alone.

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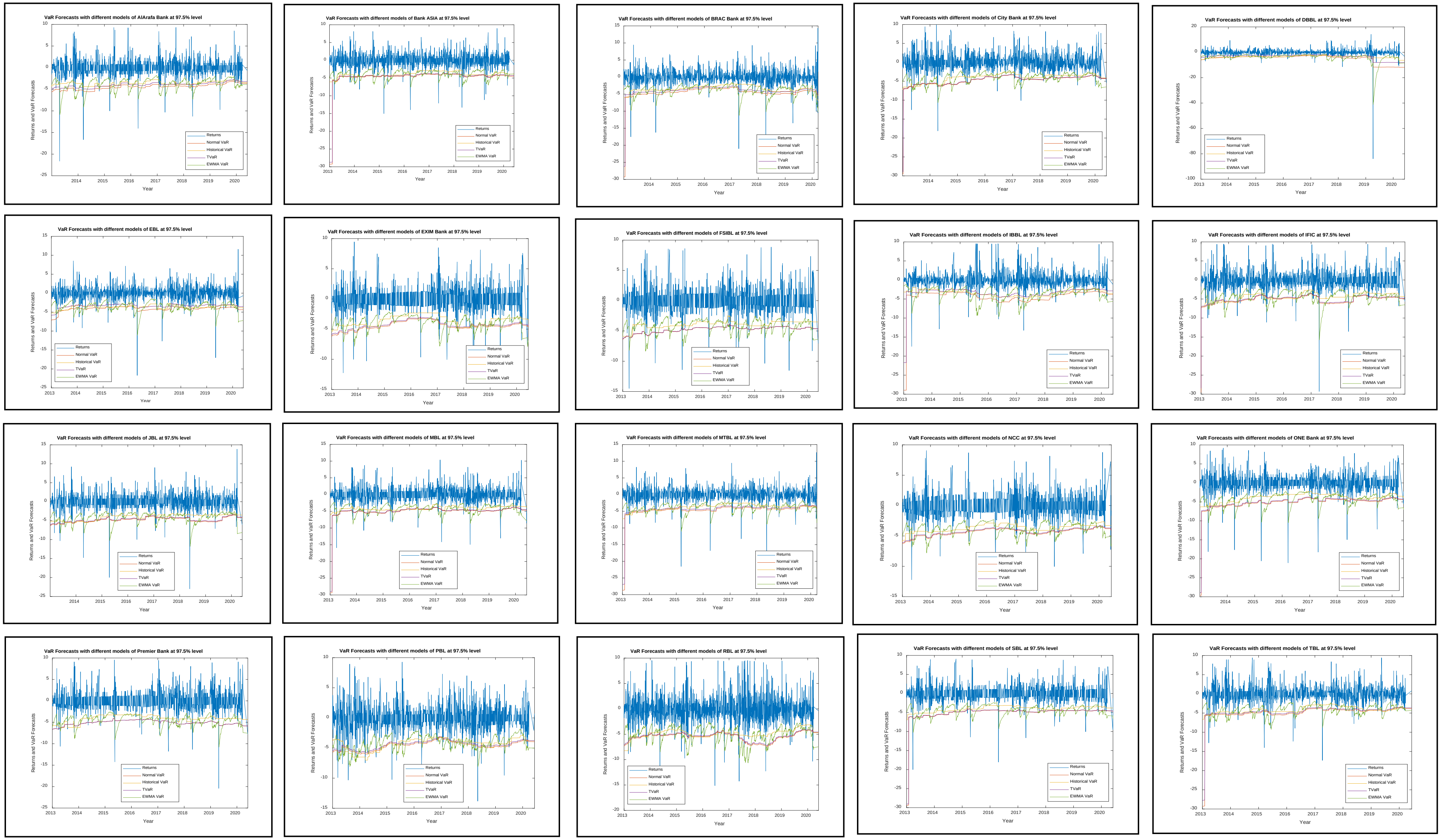

Figure 1. Daily VaR estimates at 97.5% level for all twenty banks and for all models for each bank from 1st Jan.2013 to 31st Aug. 2020. The total number of forecasts varies from bank to bank due to data cleaning, particularly over the pandemic period. User-friendly models considered from zero, -one, -two, and –three parametric families of all risk models are implemented under a particular user-friendly design.

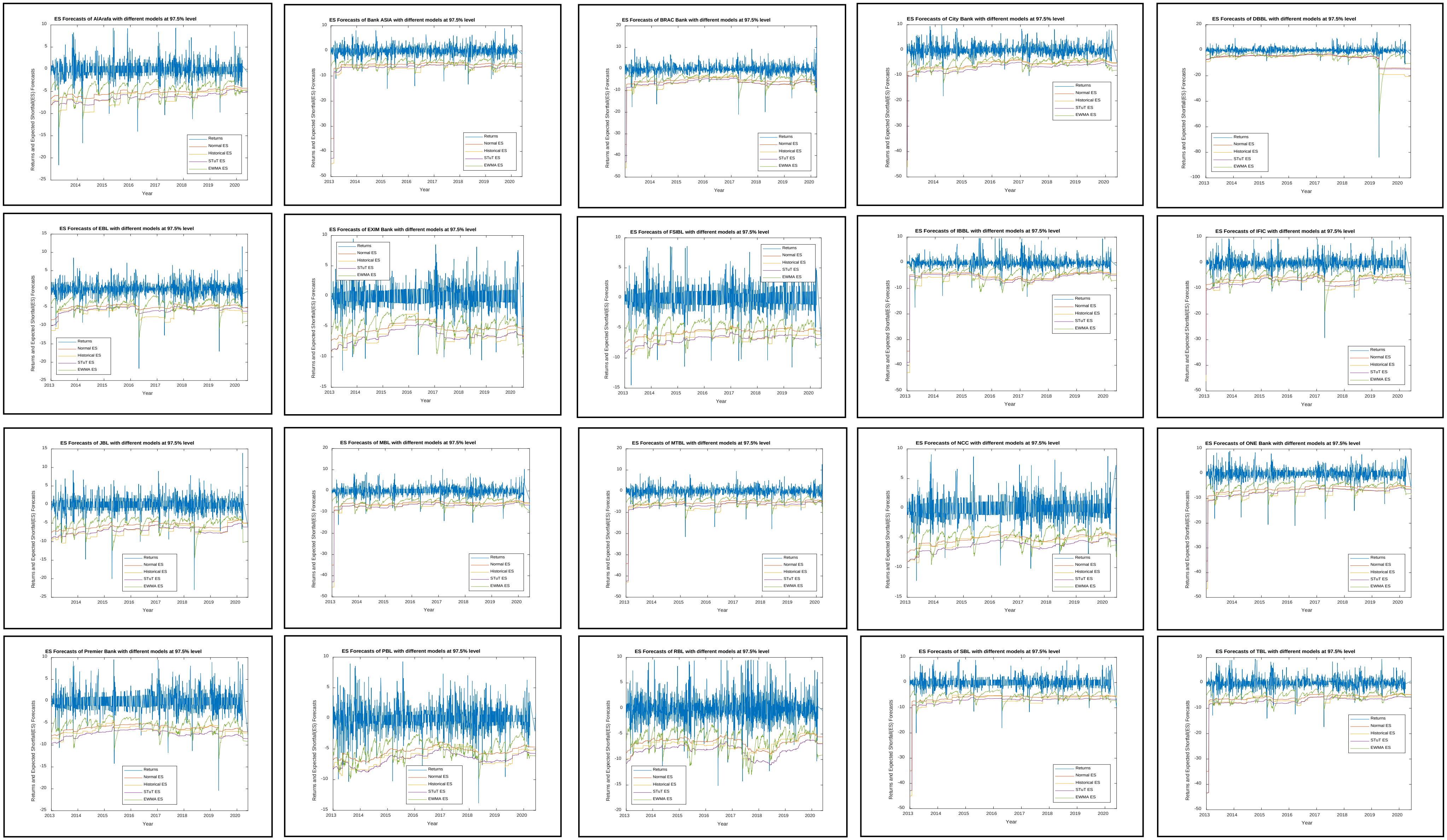

Figure 2. Daily ES estimates at 97.5% level for all twenty banks and for all models for each bank from 1st Jan.2013 to 31st Aug. 2020. The total number of forecasts varies from bank to bank due to data cleaning, particularly over the pandemic period. User-friendly models considered from zero, - one, -two, and –three parametric families of all risk models are implemented under a particular user-friendly design.

Figure 3. Average Severity Ratio (ASR) and a number of VaR Failures across Banks and Models. Across banks the performance of all four user-friendly models under user-friendly design in backtesting the adequacy of making ES forecasts can be further clarified by observing the average severity ratios. The ASR's determine the outcome of the ES back-testing under unconditional normal as well as unconditional T hypotheses. The loss scores estimated across all twenty banks and four models consider both ASR as well as the extent of VaR violations.

Table 1: List of Variables included in the model

Variables	Notation	Measures	Source
Market Capitalization	MarketCap	Log (Number of outstanding share x daily closing share price)	Dhaka Stock Exchange, Bangladesh
Normal-VaR	Normal-VaR	Estimated in empirical section	Collected from empirical section
Historical-VaR	HS-VaR	Estimated in empirical section	Collected from empirical section
Student-T-VaR	StuT-VaR	Estimated in empirical section	Collected from empirical section
EWMA-VaR	EWMA-VaR	Estimated in empirical section	Collected from empirical section
Normal-ES	Normal-ES	Estimated in empirical section	Collected from empirical section
Historical-ES	HS-ES	Estimated in empirical section	Collected from empirical section
Student-T-ES	StuT-ES	Estimated in empirical section	Collected from empirical section
EWMA-ES	EWMA-ES	Estimated in empirical section	Collected from empirical section

Source: Authors' estimations

Table 2. VaR and ES Joint loss function values considering Eq. (22) across the markets, α = 0.025

Estimation Window	Models	Banks																			
		AIBL	BASIA	BRAC	CBL	DBBL	EBL	EXIM	FSIBL	IBBL	IFIC	JBL	MBL	MTB	NCC	ONE	PRM	Prime	RBL	SBL	Trust
250	Normal	1609	1748	1917	1794	2013	*1781*	1536	1510	1738	1772	1693	1698	1789	1487	1728	1539	*1745*	1978	1533	1774
	Historical	1599	1726	1881	1779	1982	1773	1525	1502	1715	1760	1680	1679	1763	1475	1702	1524	1742	1962	1512	1754
	Student-t	*1604*	*1743*	*1910*	*1795*	2015	1782	*1530*	*1508*	*1735*	*1770*	*1689*	1694	*1780*	1485	*1723*	*1538*	1761	*1974*	*1530*	*1771*
	EWMA	1639	1767	1918	1777	*2003*	1818	1525	1509	1780	1776	1703	*1687*	1833	*1484*	1763	1545	1767	1982	1542	1822
500	Normal	1620	1839	1998	1888	2101	1796	1548	1521	1826	1864	1696	1775	1879	1509	1801	1544	1765	2068	1618	1859
	Historical	1609	1735	1906	*1789*	2000	1783	*1540*	1506	1728	1764	1681	1682	1775	*1487*	1712	1532	1746	1971	1521	1765
	Student-t	*1612*	1830	1976	1886	2066	*1789*	1542	1519	1795	1855	1691	1770	1861	1507	1792	*1543*	*1762*	2060	1613	1848
	EWMA	1639	*1767*	*1918*	1776	*2003*	1818	1524	*1509*	*1780*	*1776*	*1703*	*1687*	*1833*	1484	*1763*	1545	1767	*1982*	*1542*	*1822*

Note: For individual models considering each estimation window or rolling window, the sky blue box indicates the most favored model and italicized box second best. The above Table reveals the loss function values followed by notation S estimated using Eq. (22) for jointly assessing the accuracy of each model's VaR and ES forecasts considering two different estimation windows including 250 days and 500 days amid the forecasting period from 2013 to 2020. In these estimations, the historical simulation model along with EWMA or Risk Metrics model's forecasts are found as the best or favored model to estimate VaR and ES measures during this forecasting period.

Table 3. Robustness Check- VaR and ES Joint loss function values considering Eq. (22) across the markets, α = 0.025

Estimation Window	Models	Banks																			
		AIBL	BASIA	BRAC	CBL	DBBL	EBL	EXIM	FSIBL	IBBL	IFIC	JBL	MBL	MTB	NCC	ONE	PRM	Prime	RBL	SBL	Trust
750	Normal	1391	1593	1748	1613	1831	1554	1314	1307	1584	1588	1470	1537	1622	1304	1548	1323	1497	1766	1388	1603
	Historical	1379	1503	*1662*	*1532*	*1746*	1540	*1305*	1278	1492	*1503*	1454	*1447*	1545	*1269*	1467	1313	1475	1694	1292	1521
	Student-t	*1382*	1584	1729	1612	1801	*1546*	1309	1305	1549	1580	1466	1532	1608	1302	1541	1322	1493	1759	1384	1594
	EWMA	1389	*1536*	1650	1510	1744	1571	1287	*1280*	*1513*	1502	*1460*	1441	*1591*	1255	*1505*	*1314*	*1484*	*1710*	*1296*	1560

Note: For individual models considering each estimation window or rolling window, the sky blue box indicates the most favoured model and italicized box second best. The above table has also revealed the loss function values using the same equation to jointly assess the accuracy of each model's VaR and ES forecasts considering an estimation window of 750 days amid the forecasting period from 2014 to 2020 for all these 20 commercial banks. We have changed the Test window or forecasting period by one year as the initial forecasts of VaR and ES require 750 observations that fall short in case of using an earlier test window because of cleaning up the total data set for each bank due to repeated closing share price for several consecutive days as explained earlier. Moreover, changing this Test window or forecasting period enables a robustness check of each model forecasting VaR and ES for all these 20 banks. In this estimation of robustness check, both EWMA and Historical Simulation model's forecasts are still found the favoured model amid this forecasting period.

Table 4. VaR and ES Back-Testing Outcomes at 97.5% level amid forecasting period of 1st Jan. 2013 to 31st Aug. 2020.

		VaR Back-testing								ES Back-testing	
		TL	BIN	POF	TUFF	CC	CCI	TBF	TBFI	UCN	UCT
	Normal	G (0.99)	F (0.01)	F (0.01)	P (0.71)	F (0.00)	F (0.04)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
AIBL	Historical	G (0.32)	P (0.30)	P (0.61)	P (0.80)	P (0.50)	P (0.36)	F (0.00)	F (0.00)	P (0.27)	P (0.29)
(1362)	Student-t	G (0.83)	P (0.19)	P (0.36)	P (0.80)	P (0.23)	P (0.15)	P (0.07)	P (0.06)	P (0.50)	P (0.50)
	EWMA	G (0.90)	P (0.11)	P (0.20)	P (0.78)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F (0.03)	F(0.06)
	Normal	G (0.99)	F (0.01)	F (0.01)	P (0.94)	F (0.03)	P (0.39)	P (0.06)	P (0.15)	P (0.50)	F (0.50)
BASIA	Historical	G (0.42)	P (0.40)	P (0.82)	P (0.94)	P (0.23)	P (0.09)	F (0.03)	F (0.02)	P (0.41)	P (0.41)
(1464)	Student-t	G (0.98)	P (0.03)	F (0.04)	P (0.94)	P (0.07)	P (0.35)	P (0.11)	P (0.19)	P (0.50)	P (0.50)
	EWMA	G (0.75)	P (0.27)	P (0.54)	P (0.68)	P (0.38)	P (0.21)	P (0.23)	P (0.21)	F (0.02)	F (0.04)
	Normal	G (0.94)	P (0.07)	P (0.13)	P (0.83)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.16)	P (0.19)
BRAC	Historical	G (0.23)	P (0.21)	P (0.43)	P (0.83)	P (0.09)	F (0.04)	F (0.00)	F (0.00)	P (0.17)	P (0.19)
(1600)	Student-t	G (0.80)	P (0.21)	P (0.41)	P (0.83)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.44)	P (0.44)
	EWMA	G (0.95)	P (0.06)	P (0.09)	P (0.87)	F (0.01)	F (0.01)	F (0.00)	F (0.00)	P (0.06)	P (0.09)
	Normal	G (0.98)	F (0.02)	F (0.03)	P (0.54)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
CBL	Historical	G (0.20)	P (0.18)	P (0.38)	P (0.89)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.19)	P (0.21)
(1540)	Student-t	G (0.97)	F (0.03)	F (0.04)	P (0.54)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	EWMA	G (0.91)	P (0.11)	P (0.21)	P (0.85)	P (0.16)	P (0.15)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	Normal	G (0.99)	F (0.01)	F (0.01)	P (0.97)	F (0.03)	P (0.45)	F (0.00)	F (0.00)	P (0.23)	P (0.25)
DBBL	Historical	G (0.32)	P (0.31)	P (0.61)	P (0.97)	P (0.32)	P (0.15)	F (0.00)	F (0.00)	F (0.01)	F (0.03)
(1670)	Student-t	R (0.00)	F (0.00)	F (0.00)	P (0.97)	F (0.00)	P (0.41)	F (0.00)	F (0.00)	F (0.00)	F (0.00)
	EWMA	G (0.79)	P (0.23)	P (0.44)	P (0.94)	P (0.73)	P (0.84)	P (0.13)	P (0.12)	F (0.03)	P (0.06)
	Normal	G (0.92)	P (0.09)	P (0.17)	P (0.92)	F (0.03)	F (0.02)	F (0.00)	F (0.00)	P (0.29)	P (0.30)
EBL	Historical	G (0.22)	P (0.20)	P (0.41)	P (0.92)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.23)	P (0.25)
(1519)	Studen-t	Y (0.00)	F (0.00)	F (0.00)	P (0.92)	F (0.00)	P (0.06)	F (0.00)	F (0.00)	F (0.01)	F (0.03)
	EWMA	Y (0.05)	P (0.05)	P (0.08)	P (0.96)	F (0.00)	F (0.00)	P (0.13)	P (0.12)	F (0.03)	F (0.00)
	Normal	G (0.99)	F (0.00)	F (0.00)	P (0.35)	F (0.00)	P (0.21)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
EXIM	Historical	G (0.18)	P (0.15)	P (0.32)	P (0.48)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.15)	P (0.18)
(1294)	Student-t	G (0.99)	F (0.00)	F (0.01)	P (0.35)	F (0.02)	P (0.28)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	EWMA	G (0.96)	P (0.05)	P (0.07)	P (0.80)	F (0.03)	P (0.06)	F (0.01)	F (0.02)	P (0.34)	P (0.35)
	Normal	G (0.99)	F (0.01)	F (0.01)	P (0.99)	F (0.03)	P (0.45)	F (0.00)	F (0.01)	P (0.50)	P (0.50)
FSIBL	Historical	G (0.14)	P (0.13)	P (0.26)	P (0.99)	P (0.16)	P (0.12)	F (0.00)	F (0.00)	P (0.11)	P (0.14)
(1267)	Student-t	G (0.99)	F (0.01)	F (0.01)	P (0.99)	F (0.03)	P (0.45)	F (0.00)	F (0.01)	P (0.50)	P (0.50)
	EWMA	G (0.98)	F (0.02)	F (0.02)	P (0.80)	F (0.04)	P (0.30)	F (0.00)	F (0.01)	P (0.50)	P(0.50)
	Normal	G (0.96)	P (0.05)	P (0.07)	P (0.79)	P (0.05)	P (0.09)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
IBBL	Historical	Y (0.04)	P (0.05)	P (0.08)	P (0.93)	P (0.05)	P (0.08)	F (0.00)	F (0.00)	P (0.08)	P (0.11)
(1481)	Student-t	Y (0.01)	F (0.00)	F (0.00)	P (0.93)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F (0.02)	F (0.04)
	EWMA	G (0.39)	F (0.37)	P (0.74)	P (0.75)	F (0.01)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F (0.01)
	Normal	G (0.96)	P (0.05)	P (0.08)	P (0.78)	P (0.05)	P (0.08)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
IFIC	Historical	G (0.17)	P (0.15)	P (0.31)	P (0.81)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.18)	P (0.21)
(1475)	Student-t	G (0.92)	P (0.09)	P (0.17)	P (0.78)	P (0.11)	P (0.12)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	EWMA	G (0.58)	P (0.44)	P (0.88)	P (0.75)	P (0.56)	P (0.29)	F (0.00)	F (0.00)	P (0.05)	P (0.08)
	Normal	G (0.99)	F (0.01)	F (0.01)	P (0.87)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
JBL	Historical	G (0.23)	P (0.21)	P (0.43)	P (0.87)	P (0.06)	F (0.02)	F (0.00)	F (0.00)	P (0.17)	P (0.20)
(1412)	Student-t	G (0.97)	P (0.05)	P (0.06)	P (0.87)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	EWMA	G (0.87)	P (0.14)	P (0.26)	P (0.82)	P (0.18)	P (0.14)	P (0.05)	P (0.06)	P (0.08)	P (0.10)
	Normal	G (0.97)	P (0.05)	P (0.07)	P (0.84)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.50)	P (0.48)
MBL	Historical	G (0.18)	P (0.16)	P (0.33)	P (0.85)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.18)	P (0.20)
(1409)	Student-t	G (0.97)	P (0.05)	P (0.07)	P (0.84)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	EWMA	G (0.53)	P (0.48)	P (0.97)	P (0.80)	P (0.17)	P (0.06)	F (0.01)	F (0.01)	F (0.03)	P (0.06)
	Normal	G (0.94)	P (0.06)	P (0.11)	P (0.95)	F (0.01)	F (0.01)	F (0.00)	F (0.00)	P (0.17)	P (0.19)
MTB	Historical	G (0.33)	P (0.31)	P (0.63)	P (0.67)	F (0.01)	F (0.00)	F (0.00)	F (0.00)	P (0.27)	P (0.29)
(1483)	Student-t	G (0.86)	P (0.15)	P (0.29)	P (0.95)	P (0.05)	F (0.02)	F (0.00)	F (0.00)	P (0.47)	P (0.46)
	EWMA	G (0.65)	P (0.36)	P (0.73)	P (0.95)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F(0.00)
	Normal	G (0.99)	F (0.00)	F (0.00)	P (0.66)	F (0.00)	P (0.52)	F (0.00)	F (0.02)	P (0.50)	P (0.50)
NCC	Historical	G (0.52)	P (0.50)	P (0.99)	P (0.90)	P (0.50)	P (0.24)	F (0.00)	F (0.00)	P (0.45)	P (0.44)
(1280)	Student-t	G (0.99)	F (0.00)	F (0.01)	P (0.90)	F (0.03)	P (0.44)	F (0.01)	P (0.06)	P (0.50)	P (0.50)
	EWMA	G (0.97)	P (0.05)	P (0.06)	P (0.75)	P (0.11)	P (0.39)	F (0.04)	P (0.07)	P (0.50)	P (0.50)
	Normal	G (0.99)	F (0.00)	F (0.00)	P (0.64)	F (0.01)	P (0.44)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
ONE	Historical	G (0.18)	P (0.16)	P (0.33)	P (0.84)	P (0.06)	F (0.03)	F (0.00)	F (0.00)	P (0.18)	P (0.21)
(1410)	Student-t	G (0.99)	F (0.00)	F (0.00)	P (0.64)	F (0.02)	P (0.42)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	EWMA	G (0.91)	P (0.11)	P (0.19)	P (0.73)	P (0.13)	P (0.12)	F (0.00)	F (0.00)	F (0.00)	F (0.02)
	Normal	G (0.99)	F (0.00)	F (0.00)	P (0.90)	F (0.00)	P (0.17)	F (0.00)	F (0.01)	P (0.50)	P (0.50)
Premier	Historical	G (0.17)	P (0.15)	P (0.31)	P (0.80)	P (0.17)	P (0.11)	F (0.00)	F (0.00)	P (0.16)	P (0.19)
(1288)	Student-t	G (0.99)	F (0.00)	F (0.00)	P (0.90)	F (0.00)	P (0.17)	F (0.00)	F (0.01)	P (0.50)	P (0.50)
	EWMA	G (0.88)	P (0.13)	P (0.25)	P (0.75)	P (0.31)	P (0.31)	P (0.13)	P (0.14)	P (0.33)	P (0.34)
	Normal	G (0.26)	P (0.24)	P (0.50)	P (0.95)	P (0.25)	P (0.13)	P (0.07)	P (0.06)	P (0.06)	P (0.08)
PBL	Historical	Y (0.06)	P (0.05)	P (0.11)	P (0.95)	F (0.01)	F (0.02)	F (0.00)	F (0.00)	P (0.08)	P (0.11)
(1476)	Student-t	G (0.13)	P (0.12)	P (0.25)	P (0.95)	P (0.21)	P (0.19)	F (0.03)	F (0.03)	P (0.27)	P (0.29)
	EWMA	G (0.11)	P (0.09)	P (0.19)	P (0.82)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F (0.00)
	Normal	G (0.96)	P (0.05)	P (0.07)	P (0.96)	P (0.06)	P (0.12)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
RBL	Historical	G (0.27)	P (0.25)	P (0.50)	P (0.96)	P (0.09)	F (0.04)	F (0.00)	F (0.00)	P (0.26)	P (0.28)
(1631)	Student-t	G (0.95)	P (0.06)	P (0.11)	P (0.96)	P (0.08)	P (0.13)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	EWMA	G (0.57)	P (0.45)	P (0.90)	P (0.83)	P (0.06)	F (0.01)	F (0.00)	F (0.00)	F (0.06)	F (0.08)
	Normal	G (0.99)	F (0.00)	F (0.00)	P (0.94)	F (0.00)	P (0.16)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
SBL	Historical	G (0.25)	P (0.22)	P (0.46)	P (0.94)	P (0.19)	P (0.09)	F (0.00)	F (0.00)	P (0.22)	P (0.24)
(1274)	Student-t	G (0.99)	F (0.00)	F (0.00)	P (0.94)	F (0.00)	P (0.19)	F (0.00)	F (0.00)	P (0.50)	P (0.50)
	EWMA	G (0.98)	P (0.05)	F (0.03)	P (0.85)	P (0.07)	P (0.35)	F (0.01)	F (0.03)	P (0.29)	P (0.30)
	Normal	G (0.05)	P (0.05)	P (0.07)	P (0.87)	P (0.12)	P (0.31)	P (0.08)	P (0.12)	P (0.50)	P (0.50)
TBL	Historical	G (0.70)	P (0.32)	P (0.66)	P (0.87)	P (0.30)	P (0.13)	P (0.16)	P (0.14)	P (0.35)	P (0.36)
(1493)	Student-t	G (0.09)	P (0.08)	P (0.15)	P (0.87)	P (0.20)	P (0.28)	P (0.17)	P (0.20)	P (0.50)	P (0.50)
	EWMA	G (0.52)	P (0.47)	P (0.95)	P (0.82)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F (0.00)	F (0.02)

Note: P-values are mentioned in parentheses. G: Green, Y: Yellow, R: Red, P: Pass, F: Fail; Source: authors' contribution based on Matlab (2020a) Output. Altogether ten backtests are considered, eight for VaR and two for ES, for each of the twenty banks under investigation. For each bank, four user-friendly models are backtested under a particularly user-friendly design. For the TL test, the pass/fail need to be read from p-values in the parenthesis (the tests are all conducted at 95% level which should not be confused with the 97.5% coverage level of VaR and ES);

whereas G, Y, and R represent the traffic zones of Green, Yellow, and Red, respectively, based on excess ration ranges as defined by eq.16. The excess ratio ranges remain same for all banks as well as for all models, and should not be confused with p-values in the parenthesis which varies from bank to bank as well as from model to model.

Table 5. Descriptive Statistics of variables included in the model

Variables	Observations	mean	Standard deviation	minimum	Maximum
MarketCap	25,500	13.297	11.902	3.228	29.402
Normal-VaR	25,500	3.982	1.245	2.390	8.711
HS-VaR	25,500	3.306	0.670	1.905	6.941
StuT-VaR	25,500	3.720	1.179	1.342	6.227
EWMA-VaR	25,500	3.598	1.904	1.068	9.029
Normal-ES	25,500	5.730	2.173	3.728	11.711
HS-ES	25,500	6.216	2.057	3.015	12.743
StuT-ES	25,500	6.923	2.815	3.730	10.394
EWMA-ES	25,500	5.829	2.629	3.881	13.592

Source: Authors' estimations based on output generated from STATA 16.00

Table 6. Parameter estimations of Econometric Models

Dependent variable: ln(MarketCap)		Estimation methods of Models			
		Pooled OLS	Fixed Effect	Random Effect	GLS
Explanatory Variables	Normal-VaR	6.129***	-4.107**	-4.101**	6.129***
		(0.278)	(0.113)	(0.113)	(0.278)
	HS-VaR	-10.785***	2.723**	2.715***	-10.785***
		(0.493)	(0.201)	(0.200)	(0.493)
	StuT-Var	5.147***	3.295***	3.275***	5.147***
		(0.196)	(0.168)	(.166)	(0.196)
	EWMA-VaR	1.485***	1.099**	1.099**	1.485***
		(0.155)	(0.059)	(0.059)	(0.155)
	Constant	19.331***	26.830***	26.834***	19.331***
		(1.344)	(0.535)	(4.552)	(1.344)
N (sample size)		25,500	25,500	25,500	25,500
R^2		0.6140	0.9958		
F		278.1213***	469.8478***		
Rho			0.8831	0.6098	
σ_u			31.3817	14.2763	
σ_e			11.4177	11.4176	
χ^2				1402.4108***	834.6257***

Note: *, ** and *** indicate the level of significance at 5%, 1% and 0.1% level respectively.
Standard errors of coefficient are in parenthesis.
Source: Authors' estimations based on the output generated from STATA 16.00

Table 7. Parameter estimations of Econometric Models

Explained variable: ln(MarketCap)		Estimation methods of Models			
		Pooled OLS	Fixed Effect	Random Effect	GLS
Explanatory Variables	Normal-ES	15.7130***	-4.4821**	-4.4821**	15.7130***
		(0.6517)	(0.2394)	(0.2395)	(0.6517)
	HS-ES	-15.7241***	10.5173***	10.5171***	-15.7241***
		(0.1162)	(0.4261)	(0.4262)	(0.1162)
	StuT-ES	19.2835***	6.7283***	6.7284***	19.2835***
		(0.4207)	(0.3902)	(0.3901)	(0.4207)
	EWMA-ES	1.8209***	9.9741***	9.9740***	1.8209***
		(0.3620)	(0.1205)	(0.1205)	(0.3620)
	Constant	30.3501***	30.0175***	30.0174***	30.3501***
		(3.1721)	(1.1124)	(1.1124)	(3.1721)
N		25,500	25,500	25,500	25,500
R^2		0.5571	0.6127		
F		250.950***	247.45***		
Rho			0.9056	0.8466	
σ_u			0.7396	0.5610	
σ_e			0.2387	0.2387	
χ^2				741.42***	753.10***

Note: *, ** and *** indicate the level of significance at 5%, 1% and 0.1% level respectively.

Standard errors of coefficient are in parenthesis.

Source: Authors' estimations based on the output generated from STATA 16.00