Mr. Aldryn G. Consolacion is currently a Manager of the Capital Markets Specialist Group of the Supervision and Examination Sector of the Bangko Sentral ng Pilipinas (BSP). He conducts onsite examinations of universal and commercial banks where he assesses the effectiveness and appropriateness of market and liquidity risk management systems. Mr. Consolacion has post-graduate degrees in Applied Mathematics (Actuarial Science) and in Applied Finance from the University of the Philippines and University of Melbourne, respectively. He has also obtained the Professional Risk Manager (PRM) global designation in 2009. Due to his strong background in financial markets and his technical expertise, Mr. Consolacion has been tapped as a resource speaker in various supervision areas/topics including market risk, derivatives, and macroprudential supervision.
1. Introduction

In May 2012, the Basel Committee on Banking Supervision (BCBS) released a consultative document on trading book reforms which explicitly raised the possibility of completely phasing out the use of Value-at-Risk (VaR) and replacing it with a better tool, that is, Conditional VaR (C-VaR) also known as Expected Shortfall (ES).\(^1\) The implementation of such initiative has moved forward as the committee released in September 2014 the results of a quantitative impact study (QIS) on the trading book using a hypothetical portfolio. The QIS showed that the move to ES from using the sum of VaR and stressed VaR (SVaR) in measuring market risk increases the overall risk measure. Finally, the standards on the minimum capital requirements for market risk were released on 14 January 2016, which incorporate the shift from VaR to ES as the metric for measuring the market risk capital charge using the internal models approach (IMA).

Discussions on the use of ES as a measurement tool for market risk can easily be found in numerous literature, which were published after the decision of the BCBS to finally adopt the use of VaR as the underlying measure for the implementation of IMA in the 1996 amendment to Basel I (BCBS, 1996). There is a view that the use of VaR was initially preferred as the measure can be validated through backtesting (Chen, 2014). On the other hand, among the weaknesses of VaR is its non-compliance with the theory of coherence particularly on sub-additivity (Acerbi & Tasche, 2001) and the inability to measure tail risk (Yamai & Yoshida, 2001). The latter was further exemplified during the global financial crisis of 2008 (Chen, 2014).

With the revised standards already out, the shift from VaR to an ES measure is already required for IMA, which some argue should have been the case a decade ago (Yamai & Yoshida, 2002). An important question would be, “is there a possibility that the shift from VaR to ES could have provided a better measure of risk?”

Most universal and commercial banks in the Philippines use VaR as their market risk metric. However, the use of ES in place of VaR in international standards is expected to provide Philippine banks a good reason to also adopt the ES metric. It should be noted, however, that the use of the ES metric may still be limited to internal market risk measurement and will not necessarily result in a bank’s adoption of the IMA for capital charging. This is currently the case for most universal and commercial banks in the Philippines.\(^2\)

This discussion paper aims to compare VaR and ES and provide an empirical analysis.

---

1. VaR measures the maximum amount of loss that a trading portfolio could lose at a certain confidence level. ES, on the other hand, measures the expected loss conditional to VaR. Hull (2002) explains that in essence, VaR asks the question “How bad can things get?” whereas, C-VaR asks: “If things do get bad, how much can we expect to lose?”
2. To date, only two foreign bank branches calculate market risk capital charge using IMA.
using Philippine financial market data. This paper will also investigate the discrepancy between the market risk exposure measured using ES and that computed using VaR. For this purpose, historical prices were gathered for a period spanning 15 years, i.e., from March 2000 to March 2015, which encompasses both normal and stressed conditions. Specific price data were chosen to represent the primary sources of market risk affecting financial institutions in the Philippines, namely, (i) interest rates, (ii) foreign exchange rates and (iii) equity prices.

Please note that, to the knowledge of the author, no empirical paper exists which analyzes the impact of using ES against VaR for measuring market risk in the Philippines. The rest of the paper proceeds as follows. Section 2 describes the approaches for measuring market risk in the trading book. Section 3 describes the primary difference between VaR and ES in the context of coherence and elicitability. Section 4 provides an empirical analysis of market risk measures. The last section discusses the results and implications of the findings on Philippine banks.

2. Approaches in measuring market risk using the internal models

By definition, VaR is a statistically-derived estimate of the maximum amount by which a trading portfolio could decline during a specific period of time using a pre-defined degree of confidence. In formal terms, given a random Loss, \( L \), and a confidence level, \( \alpha \), \( \text{VaR}_\alpha(L) \) can be defined as the greatest lower bound (infimum) with a probability \( \alpha \) on the cumulative distribution function \( F \) of any financial position \( L \), expressed as a random variable (BCBS, 2011; Chen, 2014).

\[
\text{VaR}_\alpha(L) = \inf\{x \mid F_L(x) \geq \alpha\}
\]

As a matter of statistical modelling, parametric VaR is computed as a product of the statistical percentiles/quantiles of a standard normal distribution function \( z_\alpha \), standard deviation \( \sigma \), total value of the portfolio \( \nu \), and the square root of time, which can be expressed as follows:

\[
\text{VaR}_\alpha(L) = -z_\alpha \cdot \sigma \cdot \nu \cdot \sqrt{t}
\]

Under the amendment to the Capital Accord to incorporate market risk issued by BCBS (1996), banks opting to calculate capital charges using IMA should, at a minimum, adopt the VaR measure at the 99th percentile, using a one-tailed confidence interval and a minimum holding period of ten trading days. The historical observation period for calculating VaR is constrained to a minimum length of one year. No particular type of model was prescribed. The recommendation set out by BCBS in January 1996 was adopted in the Philippines under BSP Circular no. 360 dated 3 December 2002. However, most of the universal and commercial banks in the country opted not to adopt the IMA in measuring the capital charge for market risk but use the VaR methodology for internal risk measurement purposes. To date, only two foreign bank branches have been granted approval to calculate their market risk capital charge using IMA.

---

3 Banks are free to use models such as variance-covariance matrices (parametric approach), historical simulation, or Monte Carlo simulation.
VaR was put to a test during the global financial crisis of 2008 and was unfortunately proven incapable of capturing extreme losses particularly during a crisis (Chen, 2014). A revision to the Basel II market risk framework, commonly known as Basel 2.5, was published in response and introduced the concept of stressed VaR (BCBS, 2009). Stressed VaR extended the conventional VaR metric through the use of a one-year historical dataset that encompasses “a continuous 12-month period of significant financial stress relevant to the bank’s portfolio (BCBS, 2009).”

However, Basel 2.5 recognizes two particular cases where the stressed VaR might be inappropriate. First is when “a period of financial stress... corresponds to directional moves which would lead to the bank making money.” Second is when periods of stress may cause “some price factors” such as credit spreads “to have absolute values” that may distort the correspondence between large, volatile movements in those factors (Chen, 2012).

In the 2012 consultative document released by BCBS on trading book reforms, the prospect of phasing out VaR and replacing it with ES was explicitly raised (BCBS, 2013). The expected shortfall (ES) for any loss function \( L \) with confidence level \( 1-\alpha \) is defined formally as a transformation of VaR for \( L \).

\[
ES_\alpha(L) = \frac{1}{\alpha} \int_0^\alpha VaR_\tau(L) d\tau
\]

Intuitively, ES can be expressed as the expected loss conditional on the loss beyond the limit defined by \( \alpha \).

\[
ES_\alpha(L) = E(L|L \geq VaR_\alpha)
\]

For purposes of calculations using a historical simulation, ES can be computed by getting the expected (average) losses beyond VaR. On the other hand, the parametric approach for calculating ES assuming normally distributed profits and losses would use the formula:

\[
ES_\alpha(L) = E(L|L \geq VaR_\alpha) = \frac{q^2_{\alpha}}{\alpha \sqrt{2\pi} \sigma_L}
\]

where \( q^2 \) is the upper \( 100\alpha \) percentile of the standard normal distribution and \( \sigma_L \) is the standard deviation.

The formula above is based on the assumption that the distribution of profits and losses is normal, which implies that ES and VaR are scalar multiples of each other since both are also scalar multiples of the standard deviation, as provided by Yamai & Yoshiba (2002). Thus, at 99 percent confidence interval, standard deviation is multiplied by 2.33 for VaR; for ES, standard deviation is multiplied by 2.67 following the formula above.

### 3. VaR and ES in the context of coherence and elicitability

There is a continuing discussion on the viability of using VaR as a risk measure as it is not able to satisfy one of the four accepted properties of a “coherent” risk measure. The theory of coherence requires that a measure of risk satisfy four mathematical criteria, namely:
A risk measure \( \rho \) is coherent if it satisfies the following axioms:

(i) Translation invariance for all \( X \) and real number \( c \): \( \rho(X+c) = \rho(X) + c \)

(ii) Positively homogeneous for all \( X \) and all \( \lambda > 0 \): \( \rho(\lambda X) = \lambda \rho(X) \)

(iii) Monotonic for all \( X_1, X_2 \): \( X_1 > X_2 \rightarrow \rho(X_1) > \rho(X_2) \)

(iv) Sub-additive for all \( X_1, X_2 \): \( \rho(X_1+X_2) < \rho(X_1) + \rho(X_2) \)

Acerbi & Tasche (2001) point out that the first three conditions are neither difficult to satisfy nor controversial among experts in quantitative finance. However, VaR fails to satisfy sub-additivity. Although ES for any confidence interval is derived directly from VaR for that interval, ES has been proven to be sub-additive. The reason for this apparent anomaly stems from the mathematical properties of the two measures (Chen, 2014). A risk measure can be characterized by the weights it assigns to percentiles of the loss distribution. VaR gives 100 percent weighting to the \( X^{th} \) quantile and zero to other quantiles. ES gives equal weight to all quantiles greater than the \( X^{th} \) quantile and zero risk weight to all quantiles below the \( X^{th} \) quantile (Hull, 2012).

On the other hand, ES fails in the context of elicitability. The value of an elicitable risk measure is that it can be subjected to a consistent scoring function that properly reports the measure’s reliability in forecasting future losses. ES cannot be reliably backtested; that is, forecasts of ES cannot be verified through comparison with historical observations. This is the primary respect in which VaR holds a regulatory advantage vis-a-vis ES as a measure of risk. VaR is modelled such that the quantile at which it is measured not only identifies the frequency with which it is expected to encounter legally significant losses, but also sets the level of the loss that triggers regulatory attention (Chen, 2014).

4 Empirical analysis on the use of models – VaR, Stressed VaR, and ES

a. Data description

With the clear BCBS direction of replacing VaR with ES for the purpose of determining capital requirements for trading book exposures, it is befitting to conduct a study on the value of shifting from VaR to ES in the Philippine context. The empirical study is based on a dummy trading portfolio involving three risk factors: (a) interest rates, (b) foreign exchange rates and (c) equity prices. The data set comprises prices of a long-term RoP bond (ROP19), USD/PhP rates, and the Philippine stock index for 15 years (i.e., March 2000 to March 2015). The historical data set is intended to be simple and practical to better illustrate the impact of shifting from a VaR to an ES model.

b. Methodology

The calculation of VaR and ES is based on a single factor approach using a one-tail loss distribution with a 99 percent confidence interval. Both historical and parametric approaches were employed. Historical VaR is computed by taking the 99th percentile of profit and loss (P&L) using 250 days of rolling data while the parametric VaR is calculated by getting the product of the notional amount of the exposure, volatility, and the standard normal parameter at 99 percent confidence interval, 2.33. Historical ES, on the other hand, is calculated by getting the expected (average) loss conditional to the initially computed VaR while parametric ES is computed similarly as VaR but using the ES standard normal multiplier, 2.67. The empirical study
also includes the computation of stressed VaR, which is derived by determining a 12-month period of stress that occurred within the 15-year sample period and subsequently generating the VaR during the stressed period. The inclusion of the stressed VaR will provide a holistic appreciation of the evolution of market risk models.

c. Results

The results of the empirical analysis are provided in Figure 1, where the disparity of results between the risk models is quite evident. The resulting VaR, ES, and Stressed VaR under both business-as-usual and stressed scenarios are also compared against the largest daily loss experienced during the period covered by the analysis. This can provide an insight on the capability of risk models to predict daily losses. Risk metrics using the historical and parametric approaches are both shown.

![Figure 1: Risk Metrics for Republic of the Philippines Bond (ROP 19)](image)

<table>
<thead>
<tr>
<th>Table 1</th>
<th>ROP 19 Bond - VaR and ES Historical Simulation Results (Notional: $100 thousand)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value at Risk</td>
<td>$247.80</td>
</tr>
<tr>
<td>Expected Shortfall</td>
<td>$298.67</td>
</tr>
<tr>
<td>Maximum Loss</td>
<td>$323.00</td>
</tr>
</tbody>
</table>

* Stressed VaR

Clearly, a significant disparity can be observed between the estimate of potential loss in a business-as-usual (BAU) scenario and the estimate for a stressed scenario as provided in Table 1 above. In a BAU scenario, VaR was able to capture 76.7 percent of the maximum loss while ES was able to cover 92.5 percent. During a stressed scenario, the coverage of both VaR and ES went down to 16.7 percent and 49.9 percent, respectively. Meanwhile, stressed VaR overestimated the risk by 661.4 percent during the normal scenario but only estimated 16.7 percent of losses during stressed conditions.
Similar to the observation above, the risk metrics for USD/PHP rates as provided in Figure 2 and Table 2 also prove inadequate when faced with a stressed scenario. In a BAU scenario, VaR was able to capture 58.0 percent of the maximum loss while ES was able to cover 88.4 percent. During a stressed scenario, however, the coverage of both VaR and ES significantly went down to 13.4 percent and 44.1 percent, respectively. Consistent with the measurement results for the ROP, stressed VaR overestimates the measurement of risk during a normal scenario and underestimates the same during a stressed scenario.
Equity price data yielded a different result as provided in Figure 3 and Table 3. In a BAU scenario, VaR was able to capture 58.9 percent of the maximum incurred loss while ES was able to cover 85.9 percent. During a stressed scenario, the coverage of VaR and ES slightly went up to 66.1 percent and 86.7 percent, respectively. This reflects the prevalence of volatility in equity prices, which is easily captured by both VaR and ES measures.

Overall, from the charts above, it can easily be observed that the gap between the computed VaR and ES is wider when highly volatile market conditions are present particularly when a crisis (financial and/or political) is affecting the economy. For Philippine equities, absent a crisis scenario, the gap between VaR and ES was also prevalent in 2013 mainly due to the unexpected move by the Federal Reserve to taper its quantitative easing measures following the perceived improvement in the US economy.

Figure 1 shows that during the US subprime crisis / global financial crisis of 2008, the price of ROP19 substantially declined and on 23 October 2008, registered a one-day decline of 12.2 percent. It was noted that the actual historical VaR computed on that
day is only 26.1 percent of the actual loss while ES estimated 53.4 percent of the actual loss. Similarly, for the overbought foreign currency exposure (USD/PHP, Figure 2), it was observed that during a political crisis in the Philippines, specifically the impeachment of President Estrada, the USD abruptly depreciated by 10.5 percent from USD/PHP 54.75 to PHP 49 in a single day (i.e., from 18 to 19 January 2001). Historical VaR calculated on this day was just 13.4 percent of the actual loss while ES was able to estimate 44.1 percent of the total loss. When applied to the Philippine Stock Exchange Index data, the results are similar. For instance, on 13 June 2013, when the index suddenly dropped by 6.75 percent from 6,556.65 to 6,114.08, VaR was able to capture 59.9 percent of the actual loss while the computed ES estimated 78.1 percent of the total loss.

5. Discussion

The examples provided above clearly indicate that VaR, stressed VaR, and ES are not particularly good estimators of market risk during a stressed or crisis scenario. However, it can easily be concluded that among the three tools, ES is the best estimator of risk during stressful scenarios as it considers tail risk. During a normal market scenario, the VaR result is not too far from ES as both metrics estimated at least 58.0 percent and 85.0 percent of the maximum loss, respectively. Meanwhile, stressed VaR overestimates the risk of loss during a normal market scenario yet underestimates losses during a stressful scenario. The measure is seen as highly dependent on a specific stress scenario that already occurred and could only provide a static estimation of risk. In addition, it can be empirically observed that VaR and ES are practicable when used on equity prices as both models are sensitive to the frequently swinging prices of equities.

With the unending arguments and discussions in several literature on the appropriate model for measuring market risk, practitioners and users should be aware of the limitations and weaknesses of the models they are adopting. The paper finds that the prevalent weakness of VaR of being unable to capture tail risk particularly during stressful scenarios persists, and this was likewise true when volatile market conditions were observed in the Philippines. The shift to ES can be considered a reasonable and practical move by BCBS, but given the results of this study, practitioners and supervisors alike may need to reconsider their reliance on ES measures particularly when there is unusual volatility in the market. Moving forward, additional buffers can be considered as ES is still deficient in considering cases of less frequent but high impact losses. In addition, greater supervisory focus is needed in assessing the strength of a bank’s model risk management framework which includes (i) governance, (ii) model development/acquisition and implementation, and (iii) model validation mechanisms by implementing initial and periodic independent model review and back-testing.

5 Using the parametric approach, ES was able to capture the entire loss. This is, however, a one-off case since there is only one loss amount higher than the VaR figure.
References: