Comments on the Consultative Document "Fundamental Review of the Trading Book" Released by Bank for International Settlement on May 3rd, 2012

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Elementary statistics teaches us that both mean and median measure the average size of a random quantity, but they have different properties. In particular, if we want to obtain a robust measurement, then median is a better choice than mean. Now what does this have to do with trading book capital requirements?

It is proposed in the consultative document that one of the major changes to the trading book capital rule is to "[move] from value-at-risk (VaR) to expected shortfall (ES), a risk measure that better captures tail risk." We have serious concerns about this proposal.

First of all, if we want to capture the tail risk, e.g., the size of the loss beyond VaR at 99% level, we can either use ES at 99% level, which is tail conditional mean at 99%, or, alternatively, tail conditional median (TCM) at 99% level, which is defined as the median of the conditional distribution of the loss given that the loss exceeds the 99% VaR. TCM at 99% level is simply equal to VaR at 99.5% level if the underlying loss distribution is continuous, and the two tend to be very close even if the distribution is not continuous. Hence, just like ES, TCM (equivalently, VaR at a higher level) also measures the riskiness of a position by taking into account both the size and likelihood of losses. However, TCM (equivalently VaR) is more robust than ES, because median is more robust than mean.

Secondly, TCM (equivalently VaR) is more suitable than ES for setting regulatory capital requirements, because robustness is indispensable for regulatory risk measurement. In the internal models-based approach for determining trading book capital requirements, regulators impose the risk measure and allow institutions to use their own internal risk models and private data in the calculation. There are two issues arising from the use of internal models and private data in external regulation: (i) the data can be noisy, flawed, or unreliable; and (ii) there can be several statistically indistinguishable models for the same instrument or portfolio due to limited availability of data. In particular, the heaviness of tail distributions cannot be identified in many cases. For example, Heyde and Kou (2004) show that it is very difficult to distinguish between exponential-type and power-type tails with 5,000 observations (about 20 years of daily observations) because the quantiles of the two types of distributions may overlap. Therefore, the tail behavior may be a subjective issue depending on people's modeling preferences.

To address the aforementioned two issues, regulatory risk measures should demonstrate robustness with respect to model misspecification and small changes in the data. From a regulator's viewpoint, a regulatory risk measure must be unambiguous, stable, and capable of being implemented consistently across all the relevant institutions, no matter what internal beliefs or internal models each may rely on. When the correct model cannot be identified, two institutions that have exactly the same portfolio can use

different internal models, both of which can obtain the approval of the regulator; however, the two institutions should be required to hold the same or at least almost the same amount of regulatory capital because they have the same portfolio. Therefore, the regulatory risk measure should be robust; otherwise, different institutions can be required to hold very different regulatory capital for the same risk exposure, which makes the risk measure unacceptable to both the institutions and the regulators. In addition, if the regulatory risk measure is not robust, institutions can take regulatory arbitrage by choosing a model that significantly reduces the capital requirements.

The requirement of robustness for regulatory risk measures is not anything new; in general, robustness is essential for law enforcement, as is implied by legal realism, one of the basic concepts of law; see Hart (1994). Legal realism is the viewpoint that a law is only a guideline for judges and enforcement officers (Hart, pp. 204–205) and is only intended to be the average of what judges and officers will decide. Hence, a law should be established in a robust way so that different judges will reach similar conclusions when they implement the law. In particular, the risk measures imposed in banking regulation should also be robust with respect to underlying models and data.

Thirdly, it seems to be more difficult to implement ES than VaR due to the limited amount of daily observations used for calculating regulatory capital. (i) The estimation error of ES can be much larger than that of VaR, especially when the loss distribution has a heavy tail. For example, with a sample size ranging from one year to 10 years of daily observations, the standard deviation of the estimator of ES at 99% level is around three to four times as high as that of TCM at 99% level (i.e., VaR at 99.5% level), if the underlying loss distribution is student t-distribution with degree of freedom two. (ii) The power of the backtest of ES model is expected to be smaller than that of TCM model at the same confidence level.

Although the consultative document mentions that "the recent literature suggests that many issues (complexity, computational burden, backtesting, etc.) associated with ES have been resolved or have been identified as less severe than originally expected", this statement seems to be arguable and needs further research and confirmation. For example, it is argued in the literature that "ES and VaR backtests have similar power, if compared on the basis that both risk measures have roughly the same value." (BIS 2011, p. 25) The conclusion is drawn based on the observation that the power of the backtest of ES at 97.5% level is higher than that of VaR at 99% level for some particular loss distributions. However, it is better to compare the power of the backtest of ES at 98% level with that of VaR at 99% level (i.e., TCM at 98% level), because ES and TCM should be compared at the same level. It is not clear whether the conclusion remains the same if this comparison is carried out.

Last but not least, the other comments in the consultative document that criticize VaR and favor ES do not seem to be convincing; in the following, we provide the counter-arguments to those comments one by one:

(i) "10-day 99th percentile VaR does not adequately capture banks' exposures to credit risk." This is not a problem of VaR itself but a problem of mis-specified time horizon, confidence level, and the model used for VaR calculation. In fact, the capital requirement for the banking book, which is essentially the 1-year 99.9% VaR, worked well even during the recent financial crisis; this provides the evidence that VaR is indeed able to adequately capture credit risk if the model is sufficiently well specified and the confidence level is appropriate.

(ii) “VaR’s inability to capture market liquidity risk”. This is a problem of the model used for calculating VaR instead of VaR itself; replacing VaR by ES does not help to solve the problem if the model does not capture liquidity risk.

(iii) “Incentive to take on tail risk: By not looking beyond the 99th percentile, VaR fails to capture so-called tail risks. This might provide perverse incentives to the banking system.” First, as we emphasized at the beginning, VaR is actually able to look beyond the 99th percentile because VaR at 99.5% level is equal to tail conditional median of the loss beyond 99th percentile. Second, to really capture tail events which occur with very small probability, the solution is to increase the confidence level instead of replacing VaR by ES. Without increasing the confidence level, ES is not able to capture the tail events either. At the same confidence level, TCM can be larger than ES, because median can be larger than mean; hence, at the same confidence level, TCM (equivalently VaR at a higher level) can better capture tail events than ES. Third, the 99.9% VaR for the banking book, which performed well during the recent financial crisis, provides evidence that VaR is able to capture the events related to default losses, which are tail events with small probability of occurrence.

(iv) “The inadequate capture of basis risk.” This is a problem of the model used for VaR calculation instead of VaR itself. Replacing VaR by ES does not solve the problem if the model does not capture basis risk.

(v) “A bank-specific notion of risk." This is the drawback of all micro-prudential capital rules no matter what risk measure is used; replacing VaR by ES does not solve the problem.

(vi) “Pro-cyclicality of market-implied measures of risk." This is not caused by VaR but by only using a short period of market data in the estimation of VaR. Replacing VaR by ES cannot solve this problem.

(vii) “Large VaR backtesting exceptions.” This is not caused by VaR but caused by the mis-specified model for VaR calculation. In addition, “qualitative analysis by the Trading Book Group shed some further light on the reasons for VaR not reflecting losses incurred. Specifically, many banks did not regularly update time series data and some key risk factors driving the observed losses were not incorporated into their VaR models."

Therefore, the proposed shift from VaR to ES does not make good sense. In fact, we have an academic paper, Kou, Peng, and Heyde (2012) discussing in great details why TCM or VaR is a more suitable measure for trading book capital requirements.

In the last decade financial institutions around the globe have spent considerable effort to develop capacities to compute VaR. Shifting from VaR to ES not only lacks sound justification, but also leads to huge implementation problems in financial institutions.

References

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