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Internal Models: to contributate at the quality of risk's control

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Dominique GUEGAN[1], Bertrand K. HASSANI[2].

The ECB-SSM[3], the EBA [4] and the Basel Committee have been constantly reviewing the methodological framework of risk modelling for the past 20 years. We analyse some of the issues observed when measuring the risks that would be worth addressing in future regulatory documents.

During the 2007/08' crisis[5], the failure of models and the lack of capture of extreme exposures have led regulators to change the way risks were measured, either by requiring financial institutions to use particular families of distributions (Gaussian (BCBS (2005)), sub-exponential (EBA (2014*b*))), or by changing the way dependencies are captured (EBA (2014*b*)) or by suggesting a shift from the Value-at-Risk (VaR) to sub-additive risk measures like the Expected Shortfall (ES) (BCBS (2013)). Indeed, inappropriate risk modelling had played a major role during the crisis which began in 2008 either as a catalyst or trigger. The latest changes proposed by the authorities have been motivated by the will to come closer to the reality of financial markets.

In recent papers we have discussed the importance of the choice of the distributions in measuring

1 Université Paris 1 Panthéon-Sorbonne, LabEx ReFi, 106 boulevard de l'Hopital 75647 Paris Cedex 13, France, e-mail: dguegan@univ-paris1.fr

2Grupo Santander and Université Paris 1 Panthéon-Sorbonne CES UMR 8174, 106 boulevard de l'Hopital 75647 Paris Cedex 13, France, phone: +44 (0)2070860973, e-mail: bertrand.hassani@malix.univ-paris1.fr. Disclaimer:
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3 European Central Bank - Single Supervisor Mechanism

4 European Banking Authority

5 Known as the subprime crisis.

the risks (Guégan and Hassani (2016)), and the impact of the notion of sub-additivity, which interested many researchers in the past 20 years (Guégan and Hassani (2015*a*), Guégan and Hassani (2015*b*) and Bensoussan et al. (2015)), complying with regulatory requirements (BCBS (2011*a*), BCBS (2011*b*), BCBS (2013), EBA (2014*a*)). Considering that the classical approach in terms of risk measure are insufficient to correctly control the risks inside the institution, we open the debate proposing new routes for measuring the risks: the spectral approach, the spectrum representation of a risk measure (i.e. the value of the risk measure for each and every percentile of a given distribution), and also the spatial approach.

We argue that approaches proposed by the regulator focusing on the use of : (i) specific distributions to characterise the risks, (ii) specific risk measures, (iii) specific associated confidence level, (iv) and these strategies independently from each other, engender a bias (positive or negative) in the assessment of the risks, and consequently a distortion in both the corresponding capital requirements and the management decision taken since the problem of the measurement is not dealt with in its entirety, and as such we question the motivation of the regulator.

We point specific questions: (i) Is the choice of a particular risk measure ensuring conservativeness? (ii) When moving from a VaR_p to sub-additive risk measures such as the ES_p, for which distributions is the sub-additivity property fulfilled given that we consider several risk factors? (iii) Given that each risk type is modelled based on different distributions and using different p-s, how can the sub-additivity criterion be fulfilled? Is that really important in practice? (iv) Should we combine risk measures? (v) Should we focus on ranges of risk values rather than unique value? These different points are linked to the choice of a particular distribution, to the choice of the confidence level p and to the risk measure itself.

The regulatory documents state with respect to market risk - since 1995 (BCBS for instance) that "the VaR risk measure is inadequate for measuring the risks because it does not take into account the extreme events" and also "one of the problems of recognising banks"' value-at-risk measures as an appropriate capital charge is that the assessments are based on historical data and that, even under a 99% confidence interval, extreme market conditions are excluded"[1]. To confirm this fact, in the Consultative Document concerning the Fundamental review of the trading book (BCBS (2013)), the

[1] There is no mean to know for sure that the most extreme market conditions have been met.

Basel Committee proposes "to move from Value-at-Risk (VaR) to Expected Shortfall (ES) as a number of weaknesses have been identified using VaR for determining regulatory capital requirements, including its inability to capture tail risk". The Committee has agreed "to use a 97.5th ES for the internal models-based approach and to use it to calibrate capital requirements under the revised market risk standardised approach". We may argue that this modification has been decided with the Gaussian distribution in mind as the values of the 97.5th ES and the 99th VaR are very close to each other.

In these documents the regulator states that the choice of the VaR as a risk measure does not take into account extreme values. This statement is not correct as the choice of the VaR is not the issue; it is the choice of the underlying distribution with which the associated quantile is evaluated that determines if the extreme events are captured or not. This point actually implies a second question about what an extreme event is and answering it would suppose a complete information set. Then in 2013, it seems that the regulator thought that the use of the ES instead of the VaR would be more effective to capture the most relevant information to measure the risks. This is not necessarily true as once again, it depends on the choice of the distributions used for the computation of this ES. Nevertheless, we know that this last measure is more interesting than the VaR when considering the same distribution because it provides better information concerning the amplitude of the risk, but if the fitted distribution is inappropriate[2] the problem of capturing extreme events remains the same. Besides, the choice of the level of confidence, for instance 97.5 is also arbitrary (this point will be illustrated in the next section). Indeed, why did the regulator move from 99% (in 1995) to 97.5 % (in 2013)? - Why did they not suggest 95% or another value *p*?

Another point is considered by regulators for modelling operational risk (EBA (2014*b*)[3]). Indeed, they consider that a "risk measure means a single statistic extracted from the aggregated loss distribution at the desired confidence level, such as Value-at-Risk (VaR), or shortfall measures (e.g. Expected Shortfall, Median Shortfall)". This definition is particularly, reductive, limiting and dangerous. How can the risk measures computed for different factors with different levels be aggregated? If we use the ES measure, it loses its sub-additivity property in that latter case. Thus, other approaches could be more

[2] Goodness-of-fit test are only relevant with respect to the information considered. Besides, though a distribution might be appropriate given a data set, if the underlying information evolves (in other words if the sample changes), the distribution might not be valid anymore according to that test.

[3] The discussed philosophy is also implied in the final version of the document.

robust and realistic, for instance the use of spectral measure, or a spectrum of the previous risk measures.

Our recommendations are the following:

We have analysed several guidelines issued by the EBA and the Basel Committee, we pointed out the fact that the regulators impose specific distributions, risk measures and confidence levels to analyse the risk factors in order to evaluate capital requirements of financial institutions. It appears that their approach is non holistic and their analysis of the risks relies on a disconnection between the components outlined in the previous sentence, i.e. the tools necessary to assess the risks.

We show that risk measurement in financial institutions depends intrinsically on how the tools are chosen, i.e. the distribution, the combinations of these distributions, the type of risk measure and the level of confidence. Therefore, the existence of a risk measure as discussed in the regulation is questionable, as for example modifying the level of confidence by a few percent would result in completely different interpretations. The regulators fail to propose an appropriate approach to measure these risks in financial institutions as soon as they do not take into account the problem of risk modelling in its globality.

Regulators are far too prescriptive and their choices questionable:

- Imposing distributions does not really make sense whatever the risks to be modelled as these may change quite quickly. We may wonder where these *a priori* are coming from (Guégan and Hassani (2013*b*)).
- The regulation reflects some misunderstanding regarding distribution properties (probabilistic approach) and of the particular properties surrounding their fittings (statistical approach) (Guégan et al. (2011)).
- The levels of confidence *p* seem rather arbitrary. They neither take into account the flexibility of risk measures nor the impact of the underlying distribution, misleading risk managers.

While these fundamental problems are not addressed, others are completely ignored such as the concept of spectral analysis, spectrum or distortion risk measures (Guégan and Hassani (2015*a*), Hassani and Yang (2016)). Despite the cosmetic changes included in Basel II and III, the propositions do not enable a better risk management, and the response of banks to regulatory points is not appropriate

as they do not correspond to the reality. It is therefore not surprising that capital calculations and stress testing are still unclear, and that these are not able to capture asymmetric shocks corresponding to extreme incidents.

We came up to the conclusion that the debate related to the selection of a risk measure over another is not really relevant, and considering issues raised in the previous sections our main recommendation would be to leave as much flexibility as possible to the modellers to build the most appropriate models for risk management purposes initially and then extend with conservative buffers for capital purposes (Guégan et al. (2016*c*), Guégan et al. (2016*a*) and Guégan et al. (2016*b*)). The objective would be to suggest that good risk management would mechanically limit the exposures and the losses and therefore ultimately reduce the regulatory capital burden. Models should only be a reflection of the underlying risk framework and not a tool to justify a reduced capital charge. We would like to see the supervisory face of the authorities more and their regulatory face less; in other words we would like them to stop focusing so much on a bank's risk measurement comparability and more on financial institutions risk understanding. It would probably be wise if both regulators and risk managers worked together (e.g., academic formation open to both corpus, regular workshops, etc., (Guégan (2009))) rather than as opponents, in order to reach their objective of stability of the financial system first and profitability second.

Finally, we believe that the implementation of combinations of risk measures such as the spectral risk measures, spatial VaR, risk measure spectrum or the distortion of the risk measure may help addressing the limitations, the inefficiencies or blind spots of the more traditional risk measures for instance the VaR or the ES. Indeed, the combinations help capturing a more diffuse risk, and not a specific value in a spot, providing a better representation of the exposure, incorporating the uncertainty related to the selection of the distribution used to assess the risks and the fittings. Furthermore, they allow capturing the multi-modality of some distributions. Besides, the combination also smooths the risk measurement reducing the volatility of these over time. Consequently, we would suggest financial institutions to start implementing the methodology to measure their risk more accurately, and regulators to start considering them for regulatory capital calculations. As presented in the previous section, it is really important to understand that capturing the exposure more accurately does not necessarily lead to larger regulatory capital, but mechanically to better risk management[4].

[4] A similar exercise has been done in a multivariate manner in Guégan and Hassani (2013*a*)

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