EBA REPORT

RESULTS FROM THE 2018 MARKET RISK BENCHMARKING EXERCISE

EUROPEAN
BANKING
AUTHORITY

Contents

List of figures and tables

Tables

Abbreviations

APR	all price risk
CA	competent authority
CDS	credit default swap
CO	commodities
CRD	Capital Requirements Directive
CRR	Capital Requirements Regulation
CS	credit spread
CS01	credit spread value of one basis point
CTP	correlation trading portfolio
CV	coefficient of variation
EBA	European Banking Authority
EES	empirical estimate of expected shortfall
EQ	equity
ES	expected shortfall
EU	European Union
FX	foreign exchange
HPE	hypothetical portfolio exercise
HS	historical simulation
IMV	initial market valuation
IQD	interquartile dispersion
IR	interest rates
IRC	incremental risk charge
ITS	implementing technical standards
LGD	loss given default
MC	Monte Carlo
MR	market risk
MRWA	market-risk-weighted asset
CA	competent authority
P&L	profit and loss
PD	probability of default
Q&A	question and answer
RTS	regulatory technical standards
RWA	risk-weighted asset(s)
sVaR	stressed value at risk
VaR	value at risk

1. Executive summary

1. This report presents the results of the 2018 supervisory benchmarking exercise pursuant to Article 78 of the Capital Requirements Directive (CRD) and the related regulatory and implementing technical standards (RTS and ITS) that define the scope, procedures and portfolios for benchmarking internal models for market risk (MR).

2. The report summarises the conclusions drawn from a hypothetical portfolio exercise (HPE) that was conducted by the EBA during 2017/18. The primary objective of this exercise was to assess the level of variability observed in risk-weighted assets (RWA) for market risk produced by banks' internal models.

3. The exercise was performed on a sample of 50 European banks from 12 jurisdictions. The relevant institutions submitted data for 27 market portfolios in all major asset classes, i.e. equity (EQ), interest rates (IR), foreign exchange (FX), commodities (CO) and credit spread (CS), as well as three correlation trading portfolios (CTPs), for a total of 30 benchmark portfolios. Thus, the exercise covers the entire population of EU banks with internal models for MR at the highest level of consolidation.

4. As well as assessing the overall level of variability in RWA produced by banks' internal MR models, the exercise also strove to examine and highlight the different drivers of the dispersion observed across the sample.

5. In addition to the analytical part of the exercise, the EBA, in cooperation with the competent authorities (CAs), conducted a set of interviews with a subsample of the participating banks to discuss the assumptions behind banks' models, the banks' results compared with the benchmarks, and how the banks approached and carried out the benchmarking exercise. The dialogue with banks was helpful in bringing to light any missing risk factors, provided information on how additional risk factors were modelled and taken into account, and provided feedback on how the EBA might improve forthcoming benchmarking exercises.

6. Finally, taking into consideration the results of the benchmarking exercise, CAs were asked to provide the EBA with responses to a questionnaire on the actions they plan to take with regard to each participating bank's internal model.

1.1 Main findings of the benchmarking analysis

7. The report measures variability in terms of the interquartile dispersion (IQD)[1] and the coefficient of variation (CV)[2] observed within each benchmark portfolio. The IQD is more robust than the CV when the sample is drawn from an unknown, fat-tailed distribution. As in the previous exercises on market-risk-weighted asset (MRWA) variability, the IQD metric suggests a level of dispersion for all the risk measures provided by banks that needs to be monitored.

8. The primary considerations are that the 2018 analysis shows a reduction in the dispersion in the initial market valuation (IMV) and risk measures, with respect to the 2017 exercise. This improvement was expected and is mainly due to the simplification in the market risk benchmark portfolios. Some variability in the results persists; this mainly stems from different interpretations and heterogeneous market practices adopted by the firms. Some of these issues have been addressed, and the quality of the data has improved thanks to successive resubmissions.

9. Nonetheless, data quality issues have proven to be still particularly challenging. Poor data quality stems from a wide variety of reasons. Some banks, for instance, submit data for instruments that they are not actively trading (e.g. EQ or FX) and for instruments where no internal model permission has been granted (e.g. CO). Other types of errors are more trivial (e.g. wrong currency, wrong unit, misunderstanding of the instruction, and so on). In order to improve data quality, the EBA notes that several rounds of iteration with submitters will be required, which can be difficult within the short time frame of the exercise.

10. The major part of the significant dispersions has been examined and justified by the banks and the CA. A minor part of the outlier observations remains unexplained and is expected to be part of the ongoing supervision activities of supervisors, who are expected to monitor and investigate the situation (see section 1.2 and Chapter 6 of this report).

11. From a risk factor perspective, interest rate portfolios exhibit a lower level of dispersion than the other asset classes. This lower level of variability is likely to be due to the use of more consistent practices and assumptions that are more homogeneous across the banks when modelling interest rate risk. This finding confirms the conclusions drawn in last year's analysis (see Table 4: Interquartile dispersion for IMV and risk metrics by risk factor).

12. Regarding the single risk measures, across all asset classes, as expected, the overall variability for value at risk (VaR) is lower than the observed variability for stressed VaR (sVaR) (20% and 30% respectively, compared with 24% and 30% in 2017).[3] More complex measures such as

[1] IQD is defined by the mid-interquartile range {(Q3 – Q1) ÷ 2} divided by the average of the quartiles {(Q3 + Q1) ÷ 2}, called the mid-hinge. The higher the IQD is, the higher the dispersion in the data.

[2] Coefficient of variation is computed as the ratio of the standard deviation to the mean.

[3] These values are derived as a simple average of the IQD across all non-CTP portfolios.

incremental risk charge (IRC) and all price risk (APR) show a higher level of dispersion (37% and 57% respectively, compared with 47% and 48% in 2017).

13. To deepen the analysis of VaR and further investigate the variability drivers, different VaR metrics were computed and compared with the banks' reported VaR. In particular:

- an alternative estimation of VaR, called profit and loss VaR (P&L VaR), computed by the EBA using the 1-year daily P&L series submitted by banks using a historical simulation (HS) approach; and

- a comparable VaR, called HS VaR, which corresponds to the regulatory VaR reported by those banks that use an HS approach (only).

14. When comparing the variability across the regulatory VaR and these 'alternative' risk measures, one finds a slight decrease in the IQD when considering a more homogeneous sample (i.e. HS banks only). In fact, for most risk types (IR, FX and CO), the dispersion observed for the P&L VaR tends to be lower. This finding suggests that the modelling approach is not the only driver of the observed VaR variability. Other drivers, such as risks not captured in the model or the choice of absolute versus relative returns, may be further explanations for the results' variability.

15. Even so, within the subset of banks using an HS approach, modelling choices (see Table 6: Coefficient of variation for regulatory VaR by modelling choice) seem to make a noticeable difference. Scaled 1-day VaR, use of a lookback period of 1 year and use of unweighted returns tend to produce lower dispersion than other modelling configurations. At the same time, the same modelling choices tend to produce less conservative VaR results, i.e. lower average VaR figures (see Table 7: Average regulatory VaR by modelling choice). This observation differs from the finding of the 2017 exercise. Overall, it has to be recalled that this analysis is quite sensitive to the different portfolio/institution used to produce the statistic, which is driven by the low number of observations available, so it cannot be easily generalised.

16. The dispersion in sVaR figures is generally higher than the dispersion observed for regulatory VaR (see Table 16: VaR statistics and Table 17: sVaR statistics). The stressed period used was the one applied by the bank for the capital purpose and it was not harmonised in the sample. Different choices for the stressed period are permitted by the Capital Requirements Regulation (CRR) and these choices are considered and challenged in the regulatory approval process. While allowing banks to use their individual stress period reduces the comparability of the sVaR results across the sample, doing so facilitates the estimation of implied capital needs from the HPE. The banks, during the interviews, confirmed that the observed variability in sVaR could also be produced by differences in the time window selected for the stress period. So far, the selection of the stress period has been assumed to be the primary driving force of the different variability levels. However, due to this observation more research was undertaken and now this finding needs to be reassessed in future exercises.

17. In addition to carrying out these analyses, the EBA compared across banks the ratio between sVaR and VaR for each of the hypothetical portfolios included in the benchmarking exercise (see

Table 5: sVaR–VaR ratio by range (number of banks as a percentage of the total) and Table 20: sVaR/VaR statistics). The ratio generally varies significantly between the portfolios, especially for instruments subject to credit spread risk (from 2.12 to 6.17). However, on average, the ratio lies at around 3.0 (2.4 in 2017).

18. As expected, for the larger banks with significant trading activities, the benchmarking portfolios are generally relevant to their actual trading book. For smaller banks, this is less the case, and, following requests for a framework to be established for simple and plain vanilla trades, the EBA has implemented this in the 2019 exercise. The challenge remains to design a benchmarking exercise that can fit banks that have a very specialised business model. Overall, the portfolios are, however, reflective of the risk factors experienced by most banks, especially taking into account the changes introduced in the 2019 exercise.

19. Regarding IRC, average variability (as measured by the average IQD for this category of portfolios) is relatively higher than that observed for all other metrics considered in the report (37%). Clearly, it is much improved with respect to the previous exercise (IQD was 50% on average for the 2017 exercise), due to the choice to drop out the most problematic CS portfolios. In general, the CV for the (remaining) 2018 portfolios is very close to the previous exercise (see Table 9: IRC statistics and cluster analysis and compare it with the previous exercise).

20. Regarding APR, average variability (as measured by the average IQD for this category of portfolios) is higher than that observed for all other metrics considered in the report (57%). Unfortunately, however, the APR assessment suffers from a lack of contributions – only a few banks are authorised to model this asset class internally and most banks are currently in the process of reducing their exposure to CTPs, i.e. these portfolios are supposed to be in run-down mode (see Table 10: APR statistics and cluster analysis).

21. A further metric considered as part of the analysis was the diversification benefits observed for VaR, sVaR and IRC in the aggregated portfolios (see Table 11: Diversification benefit statistics). As expected, there is evidence that larger aggregated portfolios exhibited greater diversification benefits than smaller ones. In general, the level of dispersion observed in diversification benefits tends to be lower than that in the corresponding metrics at the level of the individual portfolios.

22. As had been done for the previous exercise, an assessment of the variability of the empirical estimates of the expected shortfall (EES) at a 97.5% confidence level was also carried out. The results indicate that the dispersion in this metric across risk factors is similar to that found for VaR and P&L VaR (see Table 19: Empirical expected shortfall statistics).

Dispersion in capital outcome

23. Alongside the variability analysis, the EBA also conducted an assessment regarding possible underestimations of capital requirements (see Table 12: Interquartile dispersion for capital proxy). As the analysis is based on hypothetical portfolios and the capital requirements were defined using a proxy, the results should be interpreted as approximations of potential capital underestimations. The proxy for the implied capital requirements was defined as the sum of VaR

and sVaR across all portfolios. For purposes of comparison, the proxy was computed twice. In one case, the VaR and sVaR figures were multiplied by the banks' total multiplication factor and, in the other, by the regulatory minimum of 3 only, i.e. ignoring the banks' individual addend(s) set by the CAs.[4] This metric enables one to compare banks and assess their variability in this regard.

24. The average variability across the sample, measured by way of the IQD, is significant (around 27%), especially for the most complex portfolios in the credit spread asset class. The analysis of the capital proxy pattern across the HPE's trades, moreover, suggests that, with the exception of interest rate products, the ranges of capital value dispersion are broadly consistent, irrespective of whether the banks' actual multiplication factors are used or not.

1.2 CAs' assessments based on supervisory benchmarks

25. CAs shared the outcomes of their assessments at bank level with the EBA (see Figure 13: CAs' own assessments of the levels of MR own funds requirements). The CAs' assessments confirmed the existence of some areas that require follow-up actions on the part of specific institutions whose internal models were flagged as outliers in this benchmarking exercise.

26. Overall, CAs assessment of the over- and underestimation of RWA was encouraging, in the sense that CAs were aware of and able to explain the causes of the majority of the deviations. Although the majority of causes were identified and actions put in place in order to reduce the unwanted variability of the RWA, the effectiveness of these actions can be evaluated only with the future and via further analysis.

27. The CAs are expected to pay great attention to the minority of the cases in which the over- and underestimations were unexplained, to closely monitor these institutions, and to put in place additional effort in terms of reducing these cognitional gaps in the future exercises.

1.3 2019 exercise – expected changes

28. The 2019 exercise will represent a major change with respect to the 2018 exercise, in terms of simplification of the portfolios. This simplification should have a positive effect in terms of obtaining less dispersed results on existing portfolios, as it will solve the significant data quality issues related to some portfolios, while focusing on the model risk elements.

29. It should also be recalled that the 2019 exercise, which is already under way, will include, after 3 years, a new set of instruments. This raises concerns regarding the quality of the data that will be provided by the banks. The EBA is mindful of the risk that this can lead to unforeseen errors in the description of these new instruments, from a misunderstanding regarding the new

[4] Where information was not available, the addend was set to zero.

product itself by the bank, which was especially prevalent in 2016 when new portfolios were introduced. This factor is expected to have a negative impact on the statistic of the dispersion of the measures provided by the banks, but it is expected to be mitigated by submission of initial market valuations early in the process, which will allow a longer period to identify issues. Finally, the specific design of the hypothetical portfolio for 2019 will also allow for additional research in terms of testing the hypothesis on which the portfolio design is based.

30. Considerations on the differences generated by the modelling choices, such as HS versus Monte Carlo (MC) model, general versus full approval and stress period selection, will also be further reflected in the analysis to meet the expectation of the CAs and the credit institutions involved in the exercise.

2. Introduction and legal background

31. European legislators have acknowledged the need to ensure consistency in the calculation of RWA for equivalent portfolios, and the CRR and CRD include a number of mandates for the EBA to deliver technical standards, guidelines and reports aimed at reducing uncertainty and differences in the calculation of capital requirements.

32. In this regard, Article 78 of the CRD requires the EBA to produce a benchmarking study on both credit and market risk to assist CAs in the assessment of internal models. The study should highlight potential divergences among banks or areas in which internal approaches might have the potential to underestimate own funds requirements that are not attributable to differences in the underlying risk profiles. CAs are to share this evidence within colleges of supervisors as appropriate and take appropriate corrective actions to overcome these drawbacks when deemed necessary.

33. The EBA has devoted significant efforts to the analysis of the consistency of outcomes in RWA, to understand the causes of possible inconsistencies and to inform the regulatory repair process. The EBA's ongoing work on benchmarking, supervisory consistency and transparency is fundamental to restore trust in internal models and the ways in which banks calculate asset risks.

34. The use of internal models provides banks with the opportunity to model their risks according to their business models and the risks faced by the bank itself. The introduction of a benchmarking exercise does not change this objective; rather, it helps to identify the non-risk-based variability drivers observed across institutions.

35. This MR benchmarking exercise is an MRWA variability assessment performed over a large sample of banks (50 banks at the highest level of consolidation in 12 jurisdictions within the EU). The banks participating in this exercise are those that have been granted permission to calculate their own funds requirements using internal models for one or more of the following risk categories:

   a) general risk of equity instruments;

   b) specific risk of equity instruments;

   c) general risk of debt instruments;

   d) specific risk of debt instruments;

   e) foreign exchange risk;

   f) commodities risk; and

g) correlation trading.

36. According to Article 362 of the CRR, the general risk of debt instruments should refer to interest rate risk. Similarly, the general risk of equity instruments refers to the change in value of indexes.

37. Banks having approval only for general risk of equity or debt instruments (in accordance with Article 363 of the CRR) may use a different definition of general risk (for example, by including credit spread risk in the interest rate general risk) if they are able to demonstrate that it leads to higher RWA. A separate permission is required for each risk category. Many banks do not have permission for internal models for all risk categories, so the number of contributions for each hypothetical portfolio in this exercise varies across the sample.

38. Banks that have permission to use the internal model for calculating MR own funds requirements for one or more but not all of the risk categories, in accordance with Article 363(1) of the CRR ('partial use'), exclude certain risks or positions from the scope of the internal model approval. In this case, the own funds requirements for the risk categories outside the scope of the internal model are calculated according to the standardised approach.

39. In addition, as set out in Article 369(1)(c) of the CRR, banks should conduct validation exercises on hypothetical portfolios to test that the model is able to account for particular structural features. These portfolios should not be limited to the portfolios defined in this exercise; however, this exercise is a useful starting point for banks to meet this legislative requirement.

40. The assessed MR results, when provided and where applicable, are VaR, sVaR, IRC and APR figures for specific and aggregated trades. Moreover, a preliminary assessment of IMV was performed, primarily to ensure that the participating banks make uniform assumptions when entering the hypothetical trades.

41. In addition to these submissions, banks using an HS approach for VaR were requested to provide 1 year of P&L data for each of the individual and aggregated portfolios modelled. The objective of collecting this additional information was to employ the data vector to perform alternative calculations for VaR using, where possible, a consistent 1-year lookback period and controlling, as far as possible, for the different options that banks can apply within regulation.

3. Main features of the 2018 market risk benchmarking exercise

42.Based on the EBA Benchmarking ITS, the MR benchmarking exercise is carried out following three main steps. First, the EBA defines the hypothetical portfolios, which are the same for all banks in order to achieve a homogenous and comparable outcome across the sample. Second, banks are asked to submit the data accordingly. Third, and finally, the EBA processes and analyses the data, providing feedback to CAs. During the process, the EBA supports CAs' work by providing benchmarking tools to assess banks' results and detect anomalies in their submissions.

3.1 Definition of the market risk hypothetical portfolios

43.The MR portfolios have been defined as hypothetical portfolios composed of both non-CTPs and CTPs, as set out in Annex V of the Benchmarking ITS. The exercise includes 27 general portfolios (21 individual and 6 aggregated), capitalised under the VaR, sVaR and IRC models, comprising both plain vanilla and complex financial products in all major asset classes: EQ (6 individual portfolios), IR (3 individual portfolios), FX (3 individual portfolios), CO (2 individual portfolios) and CS (7 individual portfolios). The EBA also designed aggregated portfolios, obtained by combining individual ones, to take into account diversification effects. Each aggregated portfolio has a particular composition: the first (portfolio 22) encompasses all products; the second (portfolio 23) is made up of all EQ portfolios; the third (portfolio 24) is made up of all IR portfolios; the fourth (portfolio 25) is made up of all FX portfolios; the fifth (portfolio 26) is made up of all CO portfolios; and the sixth (portfolio 27) is made up of all CS portfolios.

44.In addition, the set of portfolios includes three portfolios used for correlation trading activities, capitalised under the VaR, sVaR and APR models. These portfolios contain positions in index tranches referencing the iTraxx Europe index on-the-run series. The portfolios are constructed by hedging each index tranche with iTraxx Europe index on-the-run 5-year series to achieve zero credit spread value of one basis point (CS01) as of the initial valuation date (spread hedged). No further re-hedging is required.

45.A more detailed explanation of the portfolios can be found in the Benchmarking ITS on the EBA website.[5]

[5] https://www.eba.europa.eu/regulation-and-policy/other-topics/regulatory-and-implementing-technical-standards-on-benchmarking-portfolios. Please also refer to Commission Implementing Regulation EU 2016/2070 of 14.09.2016 and Commission Implementing Regulation 2018/688 of 23.03.2018, laying down ITS in accordance with Article 78(2) of Directive 2013/36/EU.

3.2 Data collection process

46.The data for the supervisory benchmarking exercise were submitted by banks to their respective CAs using the supervisory reporting infrastructure. Banks submitted the specified templates provided in the ITS, where applicable.

3.2.1 IMV

47.The reference date for IMV was 27 October 2017, 4.30 p.m. London time (5.30 p.m. CET). Banks entered all positions on 12 October 2017 ('reset or booking date'), and, once positions had been entered, each portfolio aged for the duration of the exercise. Furthermore, banks did not take any action to manage the portfolio in any way during the entire exercise period.

48.The IMV figure to be reported by the banks for each hypothetical portfolio was defined as the mark to market of the portfolio at the booking date plus the profit and loss from the booking until the valuation date and time. Therefore, it was the mark to market of the portfolio on 27 October 2017, 5:30 p.m. CET.

3.2.2 Risk measures

49.According to the common instructions provided, banks should calculate the risks of the positions without taking into account the funding costs associated with the portfolios (i.e. no assumptions are admitted with regard to the funding means of the portfolios). Banks should moreover exclude, to the extent possible, counterparty credit risk when valuing the risks of the portfolios.

50.Banks should calculate the regulatory 10-day 99% VaR on a daily basis. sVaR and IRC may be calculated on a weekly basis. sVaR and IRC should be based on end-of-day prices for each Friday in the time window of the exercise. For the three CTPs (28, 29, 30), APR was also requested.

51.For each portfolio, banks were asked to provide results in the base currency, as indicated in Annex V of the Benchmarking ITS. The choice of base currency for each trade was made to avoid polluting results with cross-dependencies on risk factors.

52.All collected data underwent a preliminary analysis to spot possible misinterpretations of the common instructions set out in the ITS/RTS on benchmarking and outliers, as defined hereafter.

3.3 Participating banks

53.A total of 50 banks representing 12 EU countries participated in the exercise (see Table 13 in the Annex). All EU banks with MR internal models approved by CAs were asked to submit data at all levels where own funds requirements are calculated. The EBA only collected the results at the highest level of consolidation.

54.CAs are in charge of conducting similar benchmarking investigations for results at a 'solo' level within their own jurisdictions for eligible banks.

3.4 Data quality issues

55. The data collection process aims to ensure the reliability and validity of the data obtained. In this regard, it is obvious that an unwanted driver of variability (which would pollute the results) could be misunderstandings vis-à-vis the portfolios and the specific instruments included in them.

56. IMV results reached the EBA in November/December 2017, whereupon the EBA carried out a preliminary IMV analysis and provided a tool to CAs to help them spot likely anomalies or misunderstandings regarding the interpretation of each portfolio. This was to guarantee that all risk measures were provided according to a correct interpretation of the portfolios. This step was done before the computation of the risk measures by the banks. Where the price of a portfolio fell outside a certain range,[6] more investigation had to be undertaken by the CA, which could – if necessary – ask the banks in its jurisdiction for a repricing and subsequent resubmission.

57. A significant data issue was related to the aggregated portfolio figures. In particular, some banks reported the IMVs and risk measures for the aggregated portfolios without including all relevant components.[7] The reason is that the 2018 ITS requires banks to report the value of aggregated portfolios even if not all individual portfolios are modelled for the benchmarking exercise. As a result, the submissions were not comparable with those valued in full. This issue will be addressed in the future (2019) exercise, since banks will have to report the results for the aggregated portfolios if, and only if, the results of all components have been submitted.[8]

58. In the data analysis, it was clear that errors in the interpretation of the instructions are still present after 3 years of the exercise. A complete list of the errors in the submitted data is not available, but the most common and easily avoided mistakes worth mentioning are:

- 1-day 99% VaR reported in place of 10-day 99% VaR, as stated in letter (e) of Annex 5;
- zero values reported only where the result of the calculation is actually zero (Annex 6 of the 2018 ITS);

[6] The range means the interval between the first and third quartiles. These quartiles were considered, and subsequently updated when resubmissions were received.

[7] Some banks reported values for aggregated portfolios, taking into account only those components for which they had permission to use an internal model. This is clearly not a data quality issue and it is correct that banks report results only where they have permission to do so for regulatory purposes.

[8] Annex 5 Market risk 2019 BM, Section 1 (Common instructions), letter (z)

- reporting the value in its own currency, instead of the currency of the trade, as required in Annex 5.

59. Although a large number of these mistakes were corrected by resubmission/cleansing of the data, unnoticed errors in data submission could still be present in the dataset analysed, and this can potentially drive and pollute the results.

60. Ensuring data quality is a fundamental step for this kind of exercise. However, reporting errors might still occur in the run of the future exercise, and the process will allow both regulators and participating banks to learn from it.

4. Market risk benchmarking framework

61. The benchmarking exercise aims to assess the variability in banks' MR models and to identify the drivers that account for it. Variability in banks' models can come from three types of drivers.

62. First, variability can stem from banks' modelling choices that are explicitly contemplated in the regulation. For example, when modelling VaR, institutions can choose to use a lookback period longer than the minimum (i.e. the previous year), use a weighting scheme for the data series, calculate the 10-day VaR directly or, alternatively, obtain a 1-day VaR and rescale it using the square root of time approximation, etc. Likewise, when modelling IRC, banks can choose from several sources of the probability of default (PD) and have a certain degree of freedom when choosing the transition matrices applied, or when deciding on the liquidity horizon applied to a particular instrument. It should be highlighted that all of these possibilities are, in principle, acceptable under the current regulatory framework (the CRR), provided that they have been agreed on with the CA during the approval process. Therefore, given the wide range of approaches, each institution using internal models can choose to implement, some degree of variability is expected.

63. Second, there are other modelling choices that are not explicitly contemplated in regulation, which may cause variability. Examples include differences in simulation engines, differences in pricing model assumptions, the modelling of returns, volatility, correlations and other indirect parameters estimates, additional risk factors considered in the models, different approaches to P&L computation and attribution, a stochastic framework for the simulated shocks, etc.

64. Finally, another source of potential variability originates from supervisory practices. In particular, the use of regulatory add-ons in the form of both VaR and sVaR multipliers and additional capital charges (e.g. to encompass risk not in VaR issues, any IT and organisational weaknesses, independent pricing valuations, detected flaws, etc.) and, quite significantly, the application of limits to the diversification benefits applied by banks (i.e. not allowing a single calculation at consolidated level and, instead, requesting an aggregation of the capital results at sub-consolidated and/or subsidiary levels) are likely to increase the observed variability in capital. In most cases, these supervisory actions have been established to address known flaws or model limitations, or to add an additional layer of prudence. Therefore, they typically result in higher capital requirements than would otherwise be the case. However, they can also increase the variation in market own funds requirements between banks, particularly across jurisdictions. Although the effects on capital levels of these supervisory actions can be substantial, a benchmarking portfolio exercise is not suitable for assessing some of these supervisory actions. In particular, any constraints on diversification benefits and direct capital add-ons cannot be properly assessed, since these effects are entirely portfolio dependent. To assess these effects, it would be necessary to use a much more realistic (hypothetical) portfolio,

comprising thousands of instruments and including partial model approval. Nevertheless, some supervisory actions can be assessed; namely, the effects of regulatory add-ons on the VaR and sVaR multipliers will be analysed as part of this assessment.

65. Possible additional drivers of variation include:

- misunderstandings regarding the positions or risk factors involved, which could not be resolved during the preliminary assessment (see section 3.2);
- non-uniform market conventions and practices adopted in the hypothetical portfolio booking;
- incompletely implemented models (for instance because a pricing module is under testing, or an additional risk factor is being taken into consideration);
- missing risk factors not incorporated in the model;
- differences in calibration or data series used in the modelling simulation;
- additional risk factors incorporated in the model;
- alternative model assumptions applied; and
- differences attributable to the methodology used (i.e. MC versus HS or parametric).

4.1 Outlier analysis

66. After the data quality assurance process, the EBA performed an 'extreme value' analysis aimed at excluding from the computation of the benchmarks those values for which the IMV was found to lie outside a certain tolerance range, due to misinterpretation of the trade or mistyping of bookings by the banks.

67. The presence of clear outliers in the data used to assess variability is deemed inappropriate, since these data points are likely to weigh heavily on the results, distorting the actual level of variability observed.

68. Extreme values are defined as values outside the range of two truncated standard deviations[9] from the median. Since some results exhibited empirical distributions that had fatter tails than expected, outliers were defined as values differing by twice the truncated standard deviation or more from the median.

[9] The truncated standard deviation is computed by excluding the values below the 5th and above the 95th percentile of the data series.

69. If a bank's IMV was found to be an extreme value for a particular portfolio, then all risk measures related to that particular portfolio were removed from the computation of the final benchmark statistics. This approach further increased the quality of the data, providing more consistency for the benchmarks of these metrics.

70. The dispersion across the contributions is summarised by the IQD coefficient, which is more robust when compared with the CV for data derived from fat-tailed distributions. The higher the IQD, the more dispersed the data. IQD is defined as:

$$IQD = abs[(Q_{75th} - Q_{25th})/(Q_{75th} + Q_{25th})],$$

where Q_{75th} and Q_{25th} denote the 75th and 25th percentiles respectively.

71. Another metric used in the variability studies is the CV, which is defined as the ratio between the standard deviation[10] and the mean (in absolute value):

$$CV = abs[StD/Mean].$$

72. The analysis reports both metrics, because they jointly allow a detection of the highest peaks of variability.

[10] The standard deviation was considered in order to get a feeling of the entire variability and a harmonised approach across the HPE. Obviously, a truncated standard deviation may appear more consistent for some highly dispersed trades.

Table 1: IMV statistics and extreme values

		Main statistics								Percentiles			
	Port. ID	Min	Max	Ave.	STDev	STDev_trunc[1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs.[3]	25th	50th	75th	Interquantile dispersion
Equity	1	53,515	76,456	67,164	5,522	4,925	2,858	8%	37	64,852	67,805	70,645	4%
	2	25,365	917,078	780,307	130,986	31,877	9,056	17%	38	794,096	804,646	813,475	1%
	3	-381,969	-18,286	-327,403	54,306	9,185	1,448	17%	36	-338,687	-337,624	-335,945	0%
	4	763,228	771,832	766,641	1,474	1,091	621	0%	38	765,906	766,521	767,176	0%
	5	827,470	835,785	832,238	1,202	719	379	0%	38	831,786	832,099	832,584	0%
	6	3,446	8,586	4,046	883	422	185	22%	36	3,664	3,792	4,122	6%
IR	7	3,670,060	6,155,026	3,984,943	334,660	54,548	2,998	8%	46	3,943,789	3,966,328	3,968,122	0%
	8	-31,430	22,348	15,537	7,697	3,302	3,065	50%	49	13,840	16,441	19,585	17%
	9	-59,750	-25,211	-44,370	6,267	4,150	2,005	14%	48	-46,916	-43,747	-42,052	5%
FX	10	-1,303,118	263,368	-792,953	254,923	129,133	56,031	32%	42	-915,221	-885,415	-743,730	10%
	11	57,351	423,556	355,516	56,558	26,711	19,519	16%	40	340,622	357,636	391,012	7%
	12	922,316	1,106,390	963,558	31,001	17,907	7,974	3%	35	947,637	954,112	987,577	2%
Comm	13	12,506	22,901	18,465	2,438	1,943	1,848	13%	23	16,643	18,491	20,692	11%
	14	-89,134	-64,617	-75,458	5,735	4,505	3,093	8%	22	-79,183	-76,326	-70,974	5%
Credit Spread	15	-26,902	547,319	142,840	101,597	68,742	60,596	71%	34	75,819	141,482	157,545	35%
	16	10,433,826	11,404,893	10,939,022	167,569	121,060	73,626	2%	34	10,880,450	10,978,484	11,033,809	1%
	17	166,215	176,410	173,315	2,474	2,136	1,288	1%	34	172,694	173,911	175,270	1%
	18	237,270	299,412	246,525	9,960	3,675	1,095	4%	35	243,864	245,518	246,613	1%
	19	254,003	289,914	262,837	6,031	3,377	1,769	2%	33	260,741	262,844	264,394	1%
	20	304,372	328,746	316,195	5,743	5,052	2,044	2%	34	314,217	317,098	319,067	1%
	21	6,822,437	7,309,202	6,990,453	95,640	74,338	39,129	1%	34	6,949,467	7,013,139	7,030,673	1%
All-in portfolio (1 to 21)**	22	25,035,841	25,875,802	25,355,883	216,819	216,819	131,737	1%	16	25,205,645	25,355,692	25,453,447	0%
Equity (1 to 6)**	23	1,816,339	2,317,574	1,983,107	71,825	28,574	9,330	4%	33	1,966,694	1,976,024	1,982,429	0%
Interest rate (7 to 9)**	24	3,661,124	6,129,523	3,962,113	337,712	55,286	9,410	9%	45	3,891,430	3,944,696	3,949,046	1%
FX (10 to 12)**	25	-11,767	931,408	481,177	160,583	116,054	93,826	33%	35	379,327	430,608	587,452	22%
Commodity (13 and 14)**	26	-63,326	-37,570	-48,836	7,324	6,392	4,183	15%	21	-53,358	-49,519	-41,380	13%
Credit spread (15 to 21)**	27	18,625,329	19,493,418	19,062,636	182,850	149,548	107,814	1%	31	18,978,270	19,119,033	19,148,223	0%
Correlation Trading	28	-4,204,421	4,966,360	3,213,267	3,291,356	3,291,356	105,436	102%	7	4,124,611	4,230,047	4,955,843	9%
	29	-395,251	1,396,896	363,500	528,544	528,544	73,961	145%	7	220,349	304,433	378,395	26%
	30	-98,822	245,352	38,668	110,973	110,973	56,961	287%	7	-41,754	10,074	89,742	274%

[1] *STDev trunc* is the standard deviation computed excluding values below the *5th* and above the *95th* percentile

[3] *Refers to the number of banks included in the computation of the statistics*

*** For the aggregated portfolios (22 to 27), banks that reported at least a missing portfolio IMV among the ones composing the aggregate are not included in the computation of the benchmarks for that particular aggregate portfolio.*

Table 2: Average interquartile dispersion by risk factor

	Interquartile range 2018 exercise	*Interquartile range 2017 exercise*
Equity	2%	16%
IR	8%	8%
FX	6%	7%
Commodity	8%	9%
Credit spreads	6%	17%
CTP	103%	24%

73.Table 2 depicts the results at the level of both each individual portfolio and each risk type. As shown, the highest dispersion at the level of the individual portfolios is detected for credit spread portfolio 15, as well as the CTP (portfolio 30). Comparing these portfolios with the same 2017 portfolios, it would appear that the quality of the data decreased. Nonetheless, it should be noted that the high IQD is mainly due to the low value of the trade, compared with a median absolute dispersion similar to the one of 2017. This means that the 'quality'/certainty of the data provided (IMV) has not decreased with respect to the previous exercise. The same argument is valid for portfolio 8, for FX. In addition, the apparent relative high values of CV and IQD for portfolios 6 and 8 are due to two extreme outliers reported in the sample. Such extreme values – such as an IMV two times higher than the median of the IMV, or the only negative value two times higher than the positive median value – are not justified by a difference in market practice, but are mostly linked to fat finger booking of the data/reported data or a deficiency in the pricing system.

74.From a more aggregated risk-type perspective, equity, FX and CS instruments show the lowest dispersion. CTP IMVs show significant dispersion, since there are proper differences in market practices and assumptions/conventions from banks (i.e. choice of on-the-run iTraxx Europe series, choice of coupons and tranching assumptions). These differences, along with the low number of contributions, do not allow a well-founded analysis.

75.A cluster analysis was performed to strengthen and deepen the aforementioned descriptive insights. It shows the dispersion of the IMVs by portfolio and helps in identifying clusters in the portfolios' pricing that could explain the scattering of IMVs for some trades. Despite all data quality assurance efforts, the results of this analysis suggest that the clusters observable for some portfolios are brought about by different feasible interpretations of the portfolios.

Table 3: IMV cluster analysis – number of banks by range

2018 IMV cluster analysis: number of banks by range

(X = ratio with the median)

100 *Range containing more than 15% of the total obs for that particular portfolio*

	Port. ID	300% < X	300% ≥ X >200%	200% ≥ X >150%	150% ≥ X >100%	100% ≥ X >50%	50% ≥ X >0	0 ≥ X >-100%	-100% ≥ X > -200%	X ≤ -200%	Num obs. [3]
Equity	1				17	20					37
	2				19	18	1				38
	3				18	17	1				36
	4				19	19					38
	5				19	19					38
	6		1		17	18					36
IR	7			1	22	23					46
	8				24	24			1		49
	9				24	24					48
FX	10				21	18	2	1			42
	11				20	19	1				40
	12				16	19					35
Comm	13				11	12					23
	14				11	11					22
Credit Spread	15	1	2	2	12	12	3	2			34
	16				16	18					34
	17				17	17					34
	18				17	18					35
	19				16	17					33
	20				17	17					34
	21				17	17					34
All-in portfolio (1 to 21)**	22				13	16	8	1			38
Equity (1 to 6)**	23				18	19	2				39
Interest rate (7 to 9)**	24			1	22	23					46
FX (10 to 12)**	25	1	1	3	13	17	1	2	1	1	40
Commodity (13 and 14)**	26				10	11		2			23
Credit spread (15 to 21)**	27				15	17	2				34
Correlation Trading	28				3	3		1			7
	29	1			2	3			1		7
	30	3				1		1		2	7

76.In particular, as shown in Table 3:

- Portfolio 6 (EQ): only one extreme outlier observation, which is being followed up by the CA.
- Portfolio 8 (IR): only one observation is an extreme outlier (IMV close to -200% of the median value), which can be explained by the portfolio not being within the business remit of the firm.
- Portfolio 10 (FX): only three outliers, which can be explained by issues in the pricing module and limitations of IT systems.
- Portfolio 15 (CS): similarly to last year's exercise, in this sovereign credit default swap (CDS) short position, there was a high dispersion for this portfolio – 10 banks reported IMV outside the +/-50% of the median IMV; the clusters derive from different assumptions on the running spreads among the participants. It was found that some outliers are due to the trade being outside of the current activity of some banks, which increases the likelihood of booking errors.

77.Some of these extreme outlier banks were classified as a high priority for the CAs (see also Chapter 6), so that they were followed with greater attention during the whole exercise, in order to specifically define the reason for the extreme result.

78.Other kinds of difficulties were found for CTPs, principally because of the scarcity of contributions and the complex nature of these trades, along with their spread hedging. However, from the observed IMV results, there is slightly more pricing consistency for the first CTP, portfolio 28, which refers to a long-hedged position on an equity tranche of iTraxx EU index (attachment 0%; detachment 3%). This is due to the more standard market tranching points.

79.One source of variability for these instruments is related to the index hedge practice. Commonly, the index hedge seems to be made at the point of inception of the trade when a CS01 spread hedge tranche is traded. However, a couple of banks did not comply with this market practice. Moreover, variability in the IMV and risk measures results could also occur if the banks calculated different hedge ratios (i.e. the ratio of the change in the mark to market of the tranche to the change in the mark to market of the index for a shift in the credit curve for all underlying names) based on their proprietary pricing models.

80.In the past, some banks erroneously computed the IMV results as a P&L from the booking date to the valuation date. In order to achieve a uniform interpretation, the EBA issued a question and answer (Q&A) tool that defined the IMV as the mark to market at the valuation date and time for each trade.[11] This has helped in the 2018 exercise, and this error seems not to be present.

81.Some minor misalignments in the IMV have been detected due to the reporting of the ‘clean price’ (i.e. the price of a trade excluding the accrued interest) instead of the ‘dirty price’ (i.e. the price of a trade including any interest), which is what was intended for the mark to market valuation.

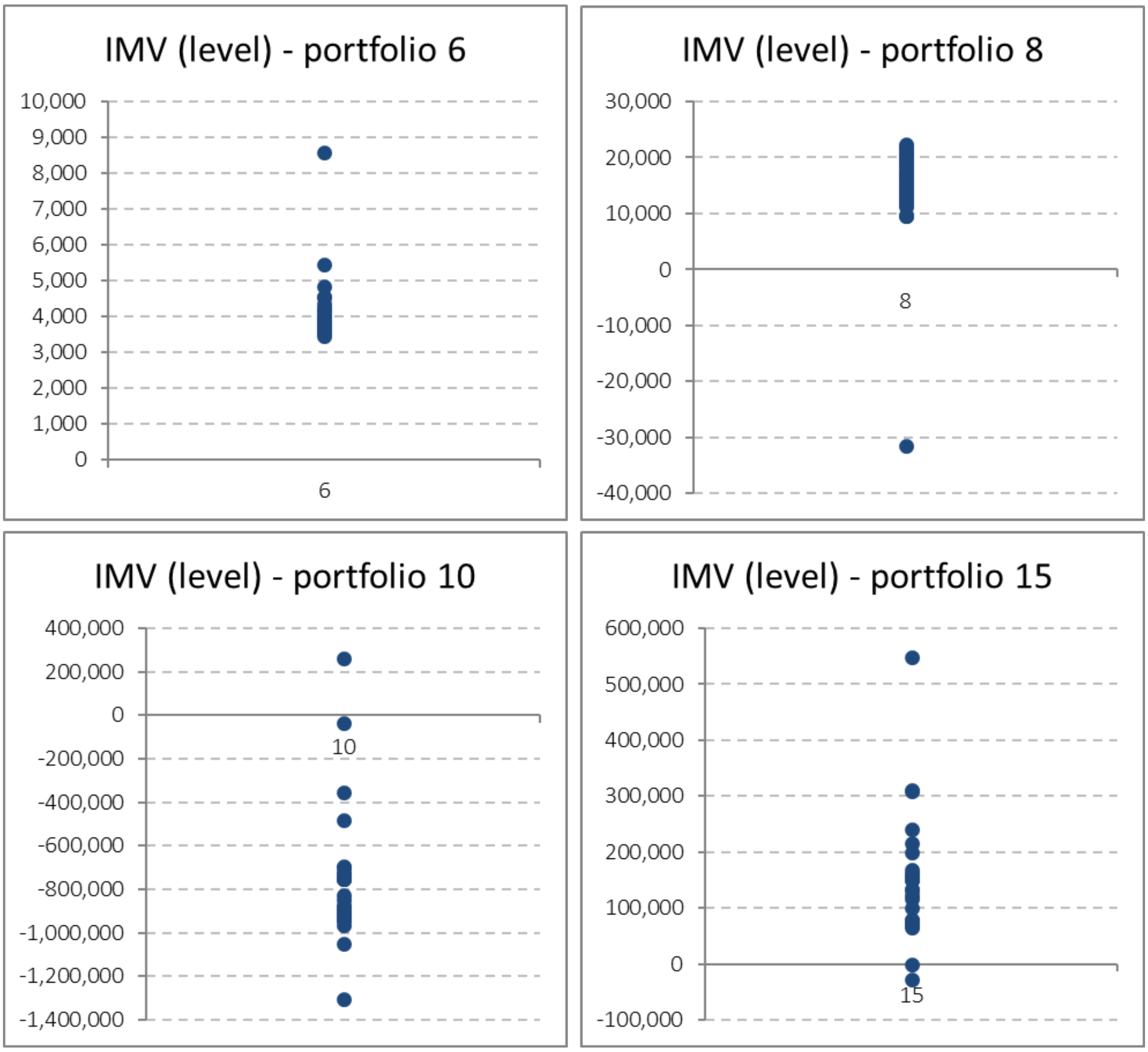
82.In addition, during the interviews with the banks, the EBA recommended that banks make better use of the Q&A tool, by submitting questions before the starting of the exercise, to avoid misinterpretations in the future. Banks are kindly invited to provide, using the Q&A tool, their best practice and market standard conventions when further specifications of the hypothetical trades are needed.

83.Evidence from the large majority of the banks is that IMV comes from front office systems. This is acknowledged as the best practice for alignment with real market trading activities.

84.Figure 1 reports the visible clusters found in the IMV results for the most affected portfolios.

[11] See Q&A 2016/2993 published on the EBA website on 2 December 2016.

Figure 1: IMV scatter plot – clustered portfolios



85.The 'concentration index', given by the percentage of values between 50% and 150% of the median value in Table 3, shows that, overall, 95% of the observations lie between those ranges.

86.This result is a substantial improvement on that reported following last year's MR benchmarking exercise.

87.Given the EBA's experience with past benchmarking exercises, values lying in this range might be considered acceptable, on the basis of fine tuning as successive benchmarking exercises are run. Nevertheless, the aim will be to increase this IMV empirical range coverage in the next exercises.

88.For many hypothetical portfolios, the IMV variability is explained by the divergence in terms of both fixings and market practice assumptions by the participating banks. Therefore, the interpretation of the deals and market practices substantially explain the observed variability.

4.2 Risk and stressed measures assessment

89. For VaR and sVaR, variability was assessed by using the banks' reported VaR and sVaR over a 2-week period (from 5 February 2018 to 16 February 2018). Banks submitted weekly or daily observations, depending on their models, and the final risk measures by portfolio were obtained by averaging the observations over the 2 weeks.

90. In the sample, 16 out of 50 banks (i.e. one third of the sample) calculated weekly sVaR measures. The remaining two thirds of the participating banks computed daily sVaR measures.

91. In addition, a P&L VaR measure produced by the EBA using the P&L data provided by banks using an HS approach was analysed. The relevant banks delivered a yearly 1-day P&L vector for each of the individual and aggregated portfolios modelled. These were used to compute the P&L VaR.

92. The additional P&L information for non-APR portfolios allowed the EBA to compute the alternative measure for VaR previously defined, and to check the variability of the results across banks by calculating VaR using a 1-year lookback period.

93. Additional checks were carried out for the available P&L vectors. For instance, the EBA checked the sign of reported gains and losses by computing the correlation between movements in banks' daily P&L values. Additional checks regarding the 1-day P&L versus the 10-day P&L (either overlapped or not) were performed where applicable. A final consistency check across the HS banks consisted of the computation of the ratio between P&L VaR and the provided regulatory VaR, which can be expected to be close to 1.[12]

94. Clearly, the P&L VaR assessment is possible only for banks applying an HS approach, and with at least 185 days of results submission. Accordingly, banks applying an MC or parametric approach, or another approach other than HS, cannot be subject to this assessment.

95. The P&L VaR was computed as the absolute value of the empirical 1st percentile of the P&L vector rescaled to 10 days by applying the square root of time approximation, without applying any data-weighting scheme:[13]

$$VaR_{99\%}^{10day} = \sqrt{10} \ * VaR_{99\%}^{1day}$$

96. The P&L vector is used to assess the degree of P&L correlation across banks, as well as the level of volatility shown in each bank's vector. This analysis should provide useful insights into the degree of market consensus on the relevant risk factors, in terms of both market dynamics and

[12] It should be noted that this expectation depends on the lookback period for VaR.

[13] Some banks apply data weighting at a risk factor level and these will be present in the P&L vectors. This is an implicit source of variability that cannot be controlled.

volatility levels. Obviously, this analysis, like most of those discussed here, relies on sufficient data points and portfolios modelled by banks to ensure robustness and consistency.

97. The IRC analysis cannot be deepened like that for VaR because of the higher level of confidence (99.9%) and longer capital horizon (1 year) applied in these metrics. Nevertheless, a variability analysis was performed. In the paragraph concerning IRC, particular emphasis is reserved for missing, zero or unrealistically low results, which suggest that key underlying risk factors are not efficiently captured by the IRC internal model.

98. In the sample, 15 out of 33 banks (i.e. 45%) computed weekly IRC measures.

99. It is apparent that more complex risk measures are computed on a weekly basis only.

100. For APR, only a small number of contributions were submitted because of the scarcity of approved internal models on CTPs, and because, as a result of the recent financial crisis, most institutions deem the CTP business to be in considerable attenuation. Therefore, the sample is quite limited.

101. In the sample, 5 out of 7 banks (i.e. 71%) computed weekly APR measures.

102. The expected shortfall (ES), as an alternative to VaR as risk metrics, has been estimated from the daily P&L series by averaging the P&L observations below the 2.5th percentile converted by the square root of time approximation and taking the absolute value:

$$ES_{97.5\%}^{10day} = \sqrt{10} * ES_{97.5\%}^{1day} = \sqrt{10}\,\frac{1}{n}\sum_{i=1}^{n} P\&L_{t_i}$$

n = number of days describing the 2.5th quantile rounded to the highest decimal

103. For the aggregated portfolios, diversification effects were checked with regard to the VaR, sVaR and IRC metrics both provided and, where applicable, alternatively estimated. Diversification effects were also assessed by comparing larger and smaller market portfolios.

104. For the most inclusive portfolios, the aggregate portfolios, the implied capital charges were also computed and their variability analysed. Where possible, the idiosyncratic factors that drive variability and the impact of regulatory add-ons (e.g. multipliers) were analysed.

105. It is worth noting that, although the effects on capital levels of these supervisory actions can be substantial, an HPE is not suitable for assessing such differences. This is particularly the case for diversification benefits, since these effects are entirely portfolio dependent. More on this is included in the following subsection, ‘Limitations’.

106. Finally, to make the analysis more comprehensive, CAs were asked to complete a questionnaire about the takeaways from this benchmarking analysis and the actions they plan to take to overcome potential weaknesses in the banks’ MR models. With the banks invited for an interview, the EBA had the opportunity to discuss directly some issues raised by CAs when challenging the models in the ongoing assessment process.

4.2.1 Limitations

107. The design of the benchmarking portfolio exercise described in the ITS aims to ensure the quality of the data used in the report to be produced by the EBA and, more importantly, to identify the banks and portfolios that need specific attention from the responsible CAs. Nevertheless, any conclusions on the total levels of capital derived from the hypothetical data should be treated with due caution. The hypothetical portfolios are very different from real portfolios (in terms of size and structure). What is more, the data cannot reflect all actions taken by supervisors.

108. From a methodological perspective, the sVaR metric variability observed could originate either from differences in modelling or from the different data periods used for sVaR computation. Further variability might stem from different stress periods of banks because there is no common benchmarking stress period. To allow more specific analyses on this aspect, in the 2019 benchmarking exercise, more information about the stressed VaR window time will be requested from banks, by expanding the relative template envisaged in Annex VI of the Benchmarking ITS.

109. Another limitation is that there is no segregated analysis for institutions with partial model approval (e.g. general risk only); therefore, portfolios with specific risk may show the further unwarranted dispersion of VaR figures. For future benchmark analysis, the sample of banks will be split among banks with full and partial approval for equity and IR, in order to filter out the variability of the risk measure introduced by the partially approved banks.

110. Banks with partial model approval provided insights on how they approach the benchmarking exercise. It has been found that, when considering the internal measure of risk, not approved for the capital purpose, but more complete in terms of risk factor coverage, the differences reported by the banks with respect to the EBA benchmark measure of the EBA are almost entirely explained.

111. In summary, the reporting of partial use approval results should be continued for the purpose of the exercise, but be treated within the specific sample, in order not to skew the results of the rest of the sample observed. Moreover, the additional information on the stress period will be used to assess the materiality of the impact of the timing selection within the overall benchmarking exercise.

5. Overview of the results obtained

5.1 Analysis of VaR and sVaR metrics

112. The dataset used to perform the assessment of risk measures was determined based on the outcome of the IMV extreme value analysis. As explained in section 4.1, banks' data were taken into account only for portfolios for which an IMV was submitted and the IMV was not classified as an outlier.

113. To check if submissions (by portfolio) were at least approximately symmetrically distributed around the mean and/or the median, the EBA checked for any significant differences between the mean and median values for the truncated sample. Table 15 in the Annex reports the banks' VaR results in relation to the median, aggregated into six buckets, to enable detection of unexpected clusters. As can be seen, some clusters that were evident for IMV (see Figure 3) were not reflected in VaR.

114. Unexpected excess variability has been found in portfolios 5 and 6 within the equity asset class. The analysis also identifies clusters for portfolios 17 to 21 (credit spread).

115. As they did in the previous exercise, the VaR values for CTPs (portfolios 28 to 30) show substantial dispersion. Regrettably, the small sample size and scattering of results did not allow a deeper analysis. However, the variability analysis concerning CTPs and the results found are reported, since internal models, for this risk category, are formally authorised and envisaged by the CRR.

116. The cluster analysis presented above is superior to a simple outlier analysis that flags submissions more than a designated number of standard deviations from the mean, as this method cannot easily be used for clustered or strongly asymmetric portfolios.

Interquartile dispersion

117. Figure 2 and Table 4 summarise the variability of the results, measured via the IQD and coefficient of variation, for the IMV as well as all three VaR measures (i.e. VaR, VaR for HS banks only, and VaR calculated from the 1-year P&L series submitted by HS banks). Table 4 also includes the VaR results for MC simulation banks.

118. In terms of risk type, the IQDs for VaR for IR, FX and CS portfolios are lower than for the other risk types. Overall, the IQD is lower than in the 2017 exercise, due to the simplification of the portfolios in the 2018 exercise.

119. As expected, the IQD for sVaR is higher than for VaR (see the bottom panels of Figure 2). One of the reasons for this is likely to be the difference in the 1-year stress period used between banks, which is chosen based on each participating bank's actual portfolio. It might therefore be

the case that the sVaR is not calculated with respect to the 1-year period that maximises VaR for the given hypothetical portfolio.

Figure 2: Interquartile dispersion for IMV and risk metrics by portfolio

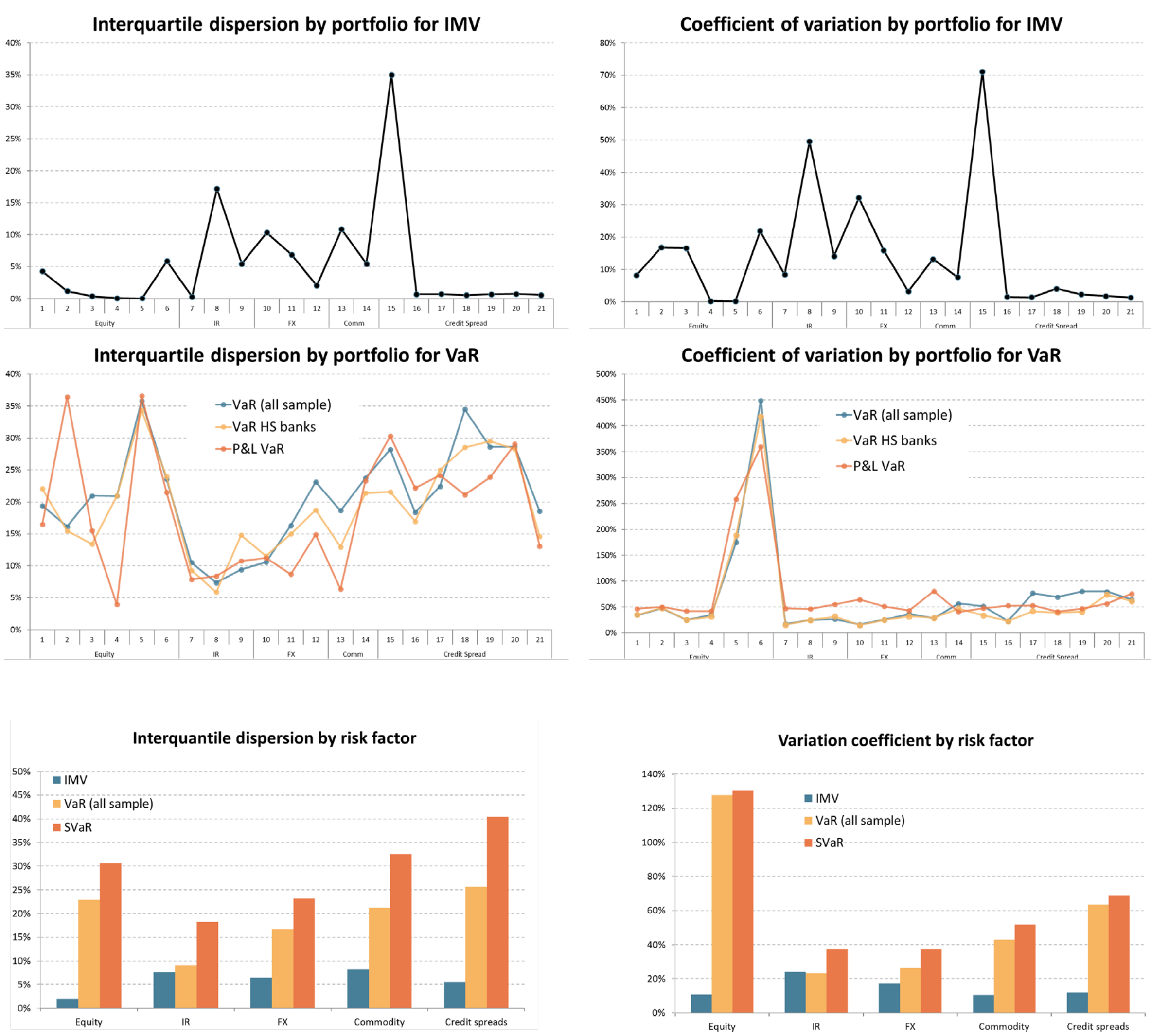


Table 4: Interquartile dispersion for IMV and risk metrics by risk factor

	IMV	VaR (all sample)	SVaR	P&L VaR	VaR HS banks	VaR MC banks	Exp shortfall
Equity	2%	23%	31%	22%	22%	15%	22%
IR	8%	9%	18%	9%	10%	7%	8%
FX	6%	17%	23%	12%	15%	16%	10%
Commodity	8%	21%	33%	15%	17%	22%	12%
Credit spr.	6%	26%	40%	23%	24%	18%	23%

120. Table 4 suggests that there is evidence that when a homogeneous subset of banks is considered (i.e. HS banks) the VaR results show less dispersion than the total sample. With regard to the P&L VaR, it is observed that the dispersion is slightly decreased with respect to both HS VaR and all-sample VaR for all asset classes.

121. When comparing variability for HS VaR and MC VaR, a clear conclusion could not be drawn, as the sample of MC banks is quite small compared with HS banks (i.e. 8 MC banks versus 34 HS banks). Regarding parametric banks, a similar analysis is not informative, as the total number of parametric banks is very small (i.e. 3 banks in the sample) and, furthermore, most of them could not provide results for many trades.

122. The ratio between sVaR and VaR was also analysed across the sample (see Table 20 in the Annex). Some banks have ratios below 1 for many portfolios, while other banks have extremely high ratios for some portfolios. To better understand the basis for these results, the EBA used the sVaR–VaR ratio as one criterion for the ranking that determined if a bank should be invited for interview.

123. As indicated in Table 5, which reports the distribution of the sVaR–VaR ratio classified in three buckets (i.e. below 1, between 1 and 3, above 3) for each portfolio, there is higher dispersion of this ratio for the credit spread positions (see Table 20 in the Annex). It is worth noting that one equity trade (portfolios 5 and 6) and two interest rate trades (portfolios 7 and 8) have a significant proportion of ratios below 1. This indicates that the (bank-level) stress period was not appropriate for these particular hypothetical trades.

Table 5: sVaR–VaR ratio by range (number of banks as a percentage of the total)

	Port. ID	X > 3	1 < X ≤ 3	X ≤ 1
Equity	1	8.1%	89.2%	2.7%
	2	71.1%	26.3%	2.6%
	3	27.8%	69.4%	2.8%
	4	10.5%	84.2%	5.3%
	5	5.3%	71.1%	23.7%
	6	22.2%	63.9%	13.9%
IR	7	8.7%	76.1%	15.2%
	8	2.0%	85.7%	12.2%
	9	16.7%	81.3%	2.1%
FX	10	32.6%	65.1%	2.3%
	11	9.8%	85.4%	4.9%
	12	42.9%	51.4%	5.7%
Comm	13	78.3%	17.4%	4.3%
	14	68.2%	31.8%	0.0%
Credit Spread	15	55.9%	44.1%	0.0%
	16	2.9%	91.2%	5.9%
	17	70.6%	29.4%	0.0%
	18	54.3%	45.7%	0.0%
	19	66.7%	33.3%	0.0%
	20	55.9%	44.1%	0.0%
	21	38.2%	55.9%	5.9%
All-in portfolio (1 to 21)**	22	15.8%	84.2%	0.0%
Equity (1 to 6)**	23	56.4%	35.9%	7.7%
Interest rate (7 to 9)**	24	2.2%	87.0%	10.9%
FX (10 to 12)**	25	51.2%	46.3%	2.4%
Commodity (13 and 14)**	26	78.3%	17.4%	4.3%
Credit spread (15 to 21)**	27	50.0%	50.0%	0.0%
Correlation Trading	28	71.4%	28.6%	0.0%
	29	71.4%	28.6%	0.0%
	30	57.1%	42.9%	0.0%

5.2 A closer look at the VaR and sVaR results

124. Figure 3 and Figure 4 give an overview of the VaR and sVaR results for portfolios 1 to 21, i.e. they do not include the aggregated portfolios, where fewer observations were available for the reasons explained above (see section 3.4).

125. Distinguished by portfolio, the figures show the average VaR and sVaR over the 10-day submission period for each bank, normalised by the median[14] of the given portfolio.[15]

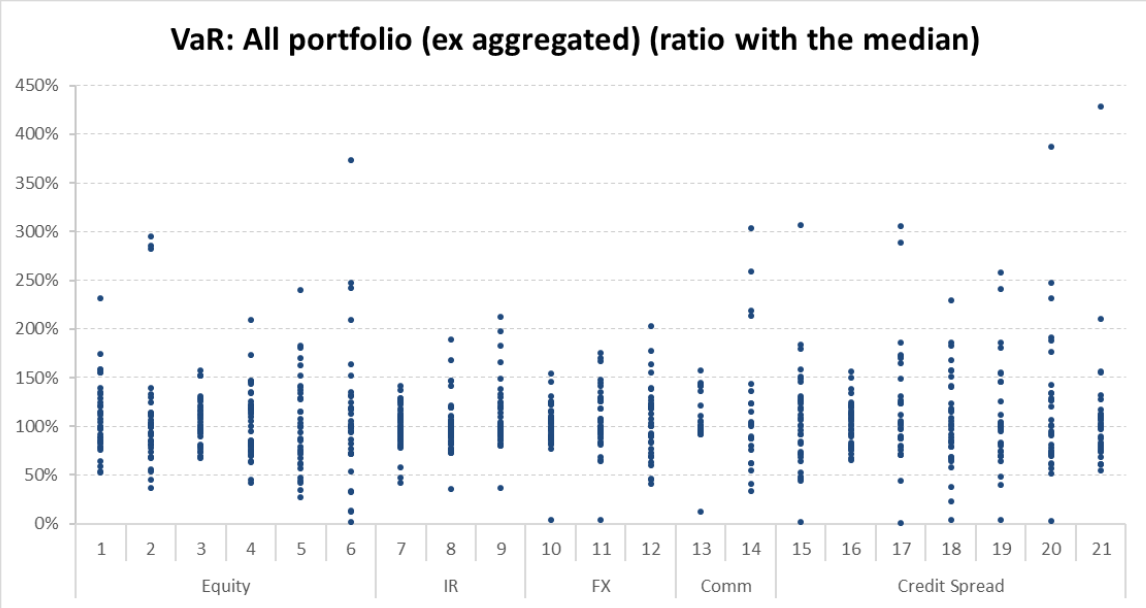
126. Comparing Figure 3 and 4, it looks clear that the dispersion is higher for sVaR than for the VaR (31% IQD versus 23% IQD on average). Differences in dispersion between VaR and sVaR seem steady, but more marked for the credit spread portfolios, in which sVaR shows a higher level of dispersion than the other asset classes (approximately 40%). This is due to the higher complexity of some of these products than other asset classes and to the different banks' choices regarding the stress period.

127. The IR is the asset class with the lowest level in dispersion for VaR (9%) and sVaR (18%). This could be seen as a positive factor due to the prevalence of the IR asset class among the banks with IMA approval.

[14] The portfolio median is the median of the average VaR and sVaR over the submission period.

[15] Note that the figures are restricted to VaR–median and sVaR–median ratios below 450%.

Figure 3: VaR submissions normalised by the median of each portfolio



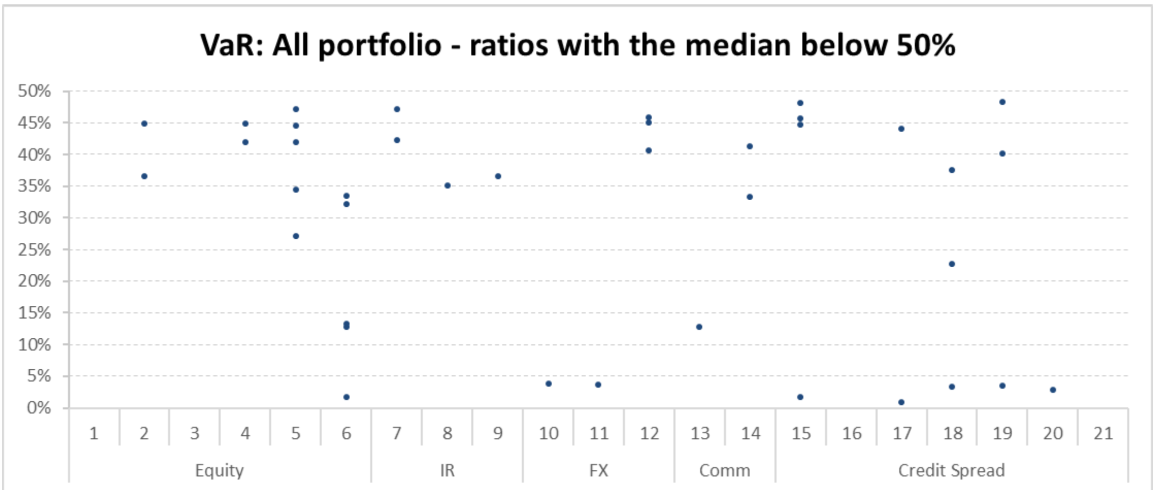
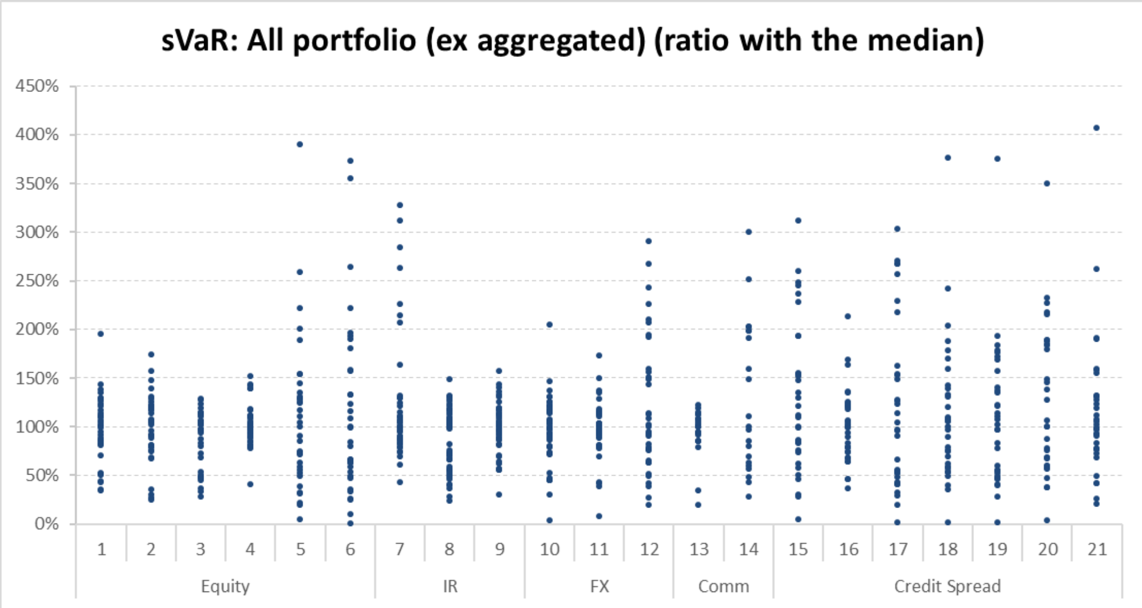
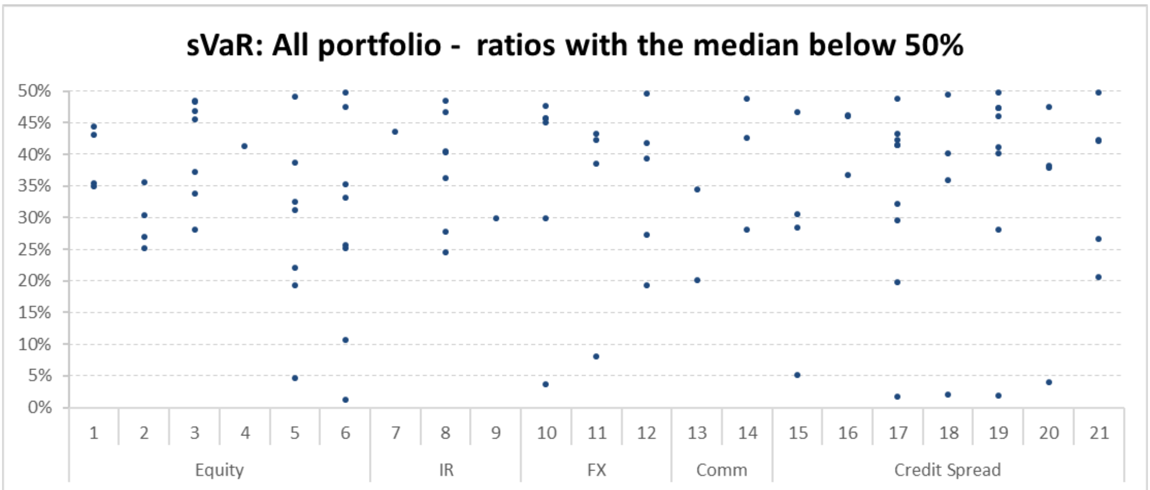


Figure 4: sVaR submissions normalised by the median of each portfolio





128. Table 16 and Table 17 in the Annex report VaR and sVaR statistics along with EU benchmarks for all HPE trades.

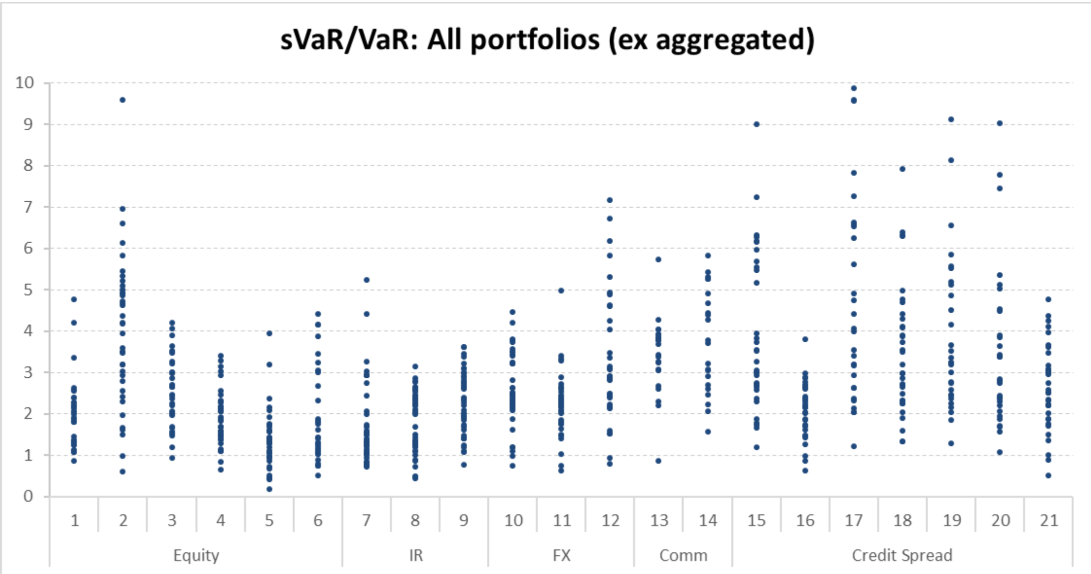
5.2.1 Comparison of sVaR to VaR ratios

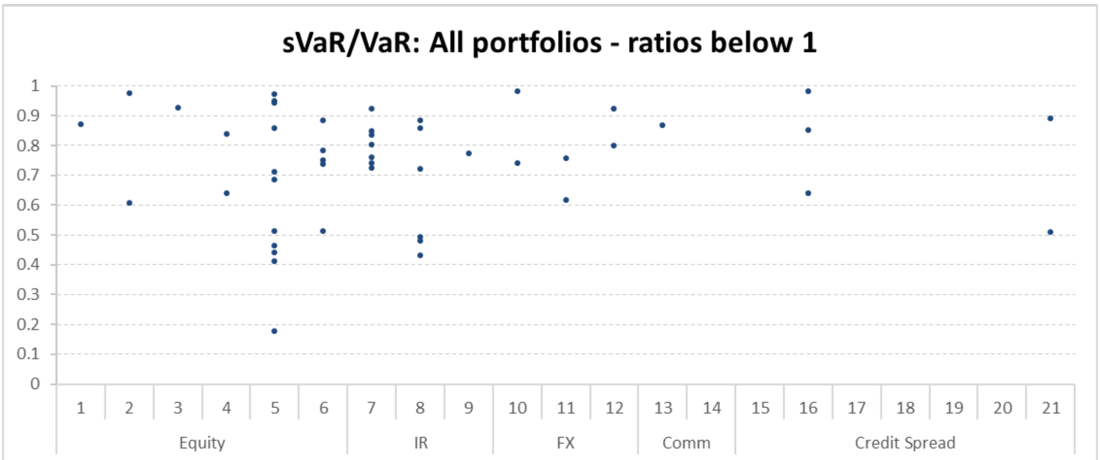
129. Banks were ranked in relation to the full sample not only by their VaR and sVaR values but also by their sVaR–VaR ratios. In general, it should be expected that sVaR would be at least as high as VaR, as sVaR is calibrated to a 1-year period of significant stress. This is verified in 94% of cases. However, since the stress period is calibrated on a bank-by-bank basis using the banks'

actual portfolios, for the hypothetical portfolios underlying the HPE, the sVaR–VaR ratio could in some instances conceivably be smaller than 1.

130. Figure 5 shows the ratio of the average sVaR to the average VaR for each bank. The sVaR–VaR ratio varies significantly across the portfolios. Excluding outliers, the average sVaR–VaR ratio per portfolio varies between 0.96 and 7.10.[16] The portfolios with the lowest levels of dispersion for the sVaR–VaR ratio (excluding outliers) are portfolios 13 (commodity trade gold forward) and 11 (FX – knock-out currency option).

Figure 5: sVaR–VaR ratio for the average VaR and sVaR by portfolio





[16] 0.96 is the minimum among the single asset class portfolios (1-21) among the 25th and 75th percentile; see Table 20.

131. A few banks have a high sVaR–VaR ratio for portfolios in certain asset classes only. This suggests that this asset class dominates the banks' real trading portfolios and, for that reason, drives the calibration of the sVaR window.

132. In line with the higher dispersion observed for the sVaR for this asset class, for the ratio, the dispersion for credit spread portfolios (on average) also seems to be higher than the dispersion for the other asset classes.

5.2.2 Drivers of variation

133. Based on the qualitative information provided by banks (Figure 6 to Figure 10), the most common methodological approach used by banks to model MR is HS (68%). Although the majority of banks use the same methodological approach (i.e. HS), the dispersion of VaR remains significant, probably because other modelling choices play a key role in producing variability on the risk measures (e.g. differences in time scaling and/or weighting scheme choices, absolute versus relative returns for different asset classes, etc.).

Figure 6: Qualitative data: VaR methodological approaches

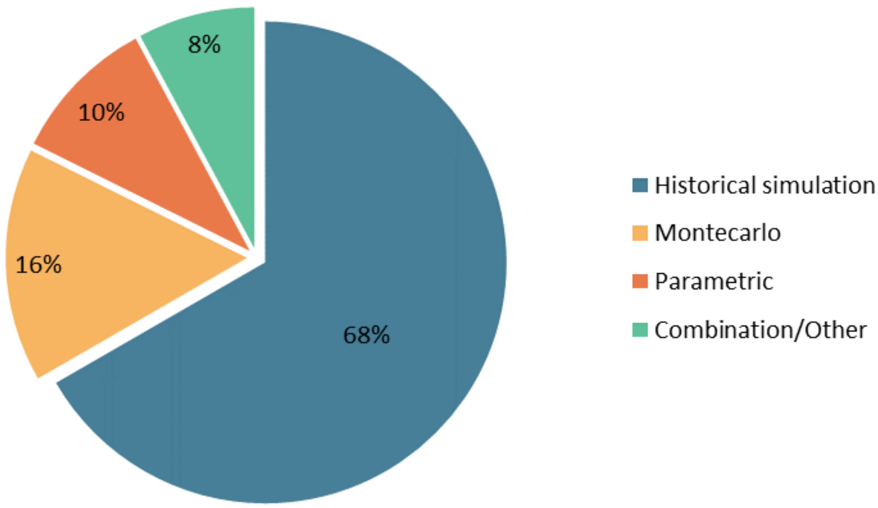
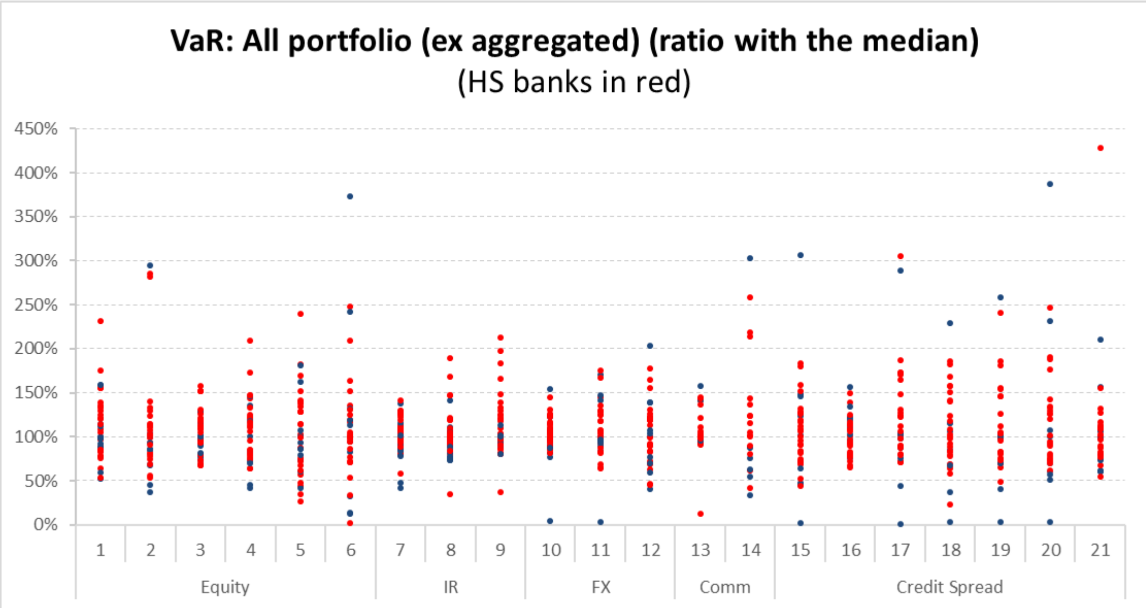
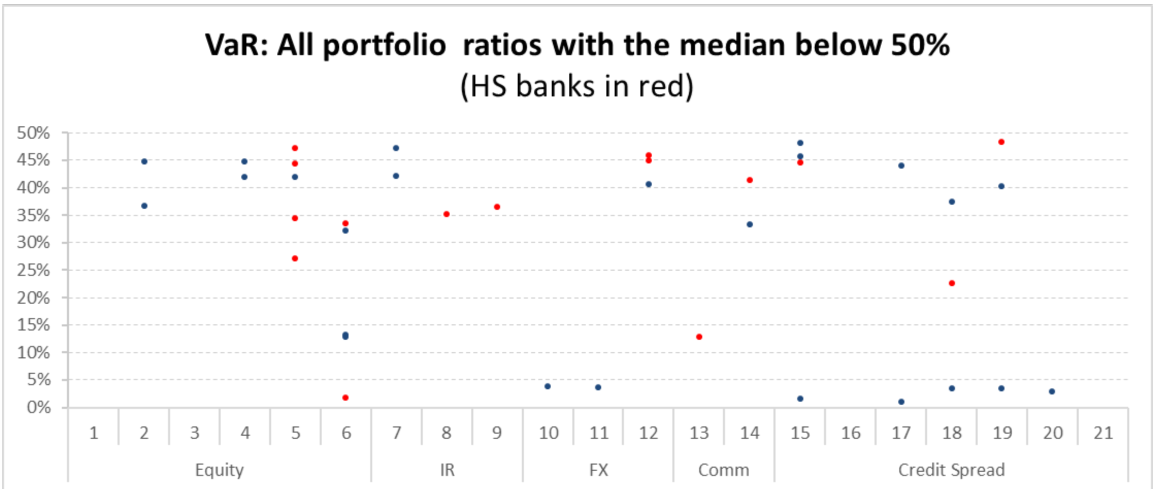


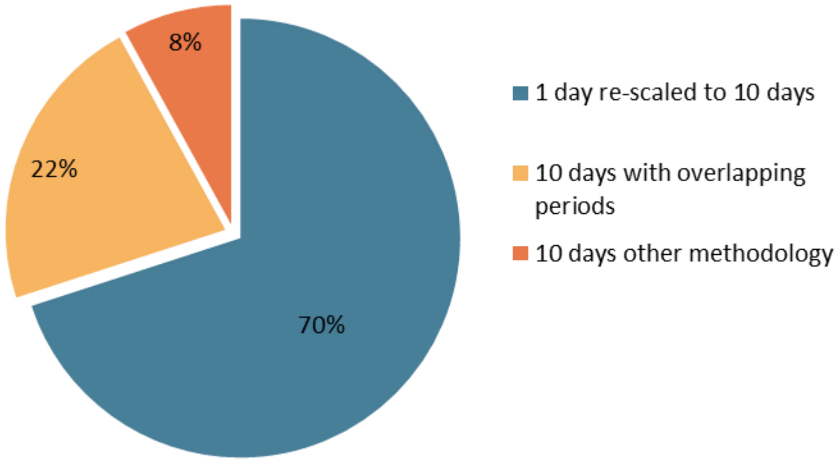
Figure 7: VaR submissions normalised by the median of each portfolio (by methodological approach)





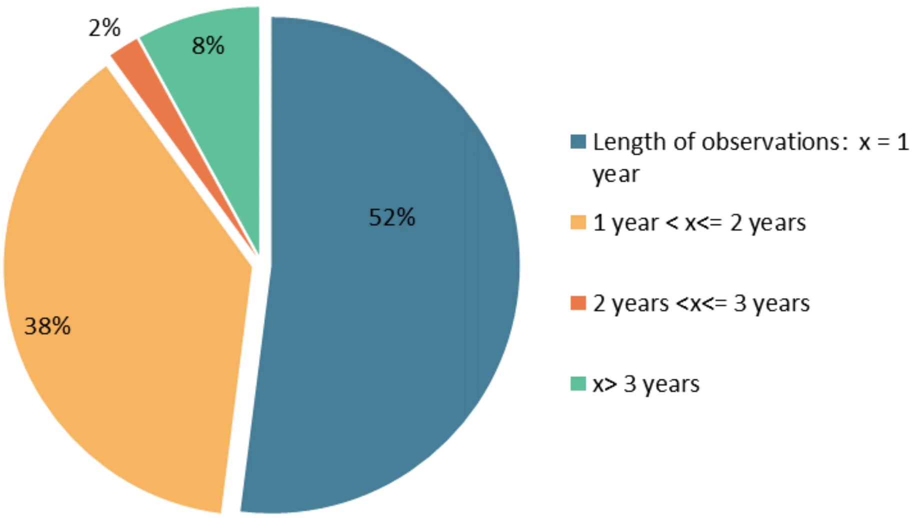
134. With regard to the regulatory 10-day VaR computation, by far, the preferred method is rescaling the 1-day VaR to the 10-day VaR using the square-root-of-time approximation.

Figure 8: Qualitative data: VaR time scaling techniques



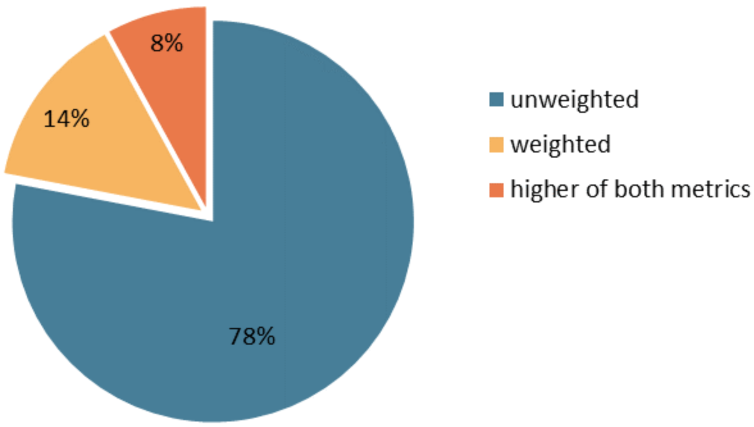
135. Concerning the historical lookback period used to calibrate banks' VaR models, more than half of the banks use the minimum period of 1 year. Only a minority (5 out of 50) of the banks use a period greater than 2 years.

Figure 9: Qualitative data: VaR lookback period length



136. As for the possible use of a data weighting scheme, the great majority of banks' models use unweighted data in the regulatory VaR computation (36 out of 50 respondents, or 72%).

Figure 10: Qualitative data: VaR weighting choices



137. Finally, with regard to supervisory actions on regulatory add-ons, 66% of the banks in the sample have a total multiplication factor greater than the minimum of three, which includes the addend resulting from the number of over-shootings (Table 1 in Article 366 of the CRR) and any supervisory extra charge(s). The average total multiplication factor in this sample is equal to 3.4, with a maximum of 5. Hence, quite a number of banks either have to correct for excessive over-shootings or are subject to supervisory measures. In addition, some banks have been assigned other kinds of added penalties that encompass risk 'not in VaR' and additional charges for IRC and APR. This was apparent from the additional and related information provided by some CAs for their supervised banks, and from discussions with some banks during the interviews.

138. These responses suggest that the observed variation may be due to a number of different drivers. The EBA choose to present the analysis using the following broad headings:

1. supervisory actions;
2. modelling differences; and
3. other drivers of variation.

5.2.3 Supervisory actions

139. Supervisory actions can take different forms and are therefore difficult to capture fully in the analysis. However, the effect of some types of supervisory charges can be approximated.

The effect of a higher VaR or sVaR multiplier imposed by an CA because of model weaknesses, for example, can be studied using the following proxy:

$$\text{Capital proxy} = m_{vaR} * VaR + m_{sVaR} * sVaR$$

where m_{vaR} and m_{sVaR} are the total regulatory multipliers given by 3 plus any add-on resulting from excessive back-testing exceptions and other prudential extra charges imposed by the regulator (where appropriate).

140. Including the multipliers in the analysis did not significantly change the results in terms of variability across the sample; that is, the positioning across the sample changed, but, on average, the extent of the dispersion did not.

141. Other supervisory measures, such as capital add-ons, cannot be easily captured. They are normally calculated at an aggregate level on the basis of the banks' actual portfolios and, therefore, cannot readily be computed for the hypothetical portfolios used for benchmarking. Moreover, it tends to be the case that these add-ons are intended to capture difficulties in modelling risks associated with more exotic trades not represented well in the HPE.

5.2.4 Modelling differences

142. As explained in Chapter 4, the CRR permits banks to tailor their VaR models to their specific requirements by making different modelling choices. To test the impact of different modelling choices in a controlled manner, four sample portfolios were selected. Obviously, the average sample size in this analysis is limited,[17] since controlling for the subsequent modelling choices, and picking up banks with all completed results, drastically reduces the sample size.

143. The portfolios – portfolios 2, 8, 10 and 16 – cover the main asset classes (i.e. EQ, IR, FX and CS) and were chosen due to the low variability of the submissions received for them. Six subsets of banks were defined, within (and hence controlling for) the sample of banks using historical simulation, distinguishing the following modelling choices:

- 1-day scaled versus 10-day overlapping returns;
- the length of the historical lookback period (1 year versus > 1 year); and
- the use of weighting (yes or no).

144. As shown in Table 6 and Table 7, there seems to be evidence that the modelling choices matter. For instance, for the subsamples of banks using the HS methodological approach, the

[17] They were 16 banks for the 1-day scaled versus 10-day overlapping returns (2 samples of 8 banks); 12 banks for the length of the historical lookback period (1 year versus > 1 year) (2 samples of 6 banks); and 8 banks for the use of weighting (2 samples of 4 banks).

choice of regulatory VaR stemming from a scaled 1-day VaR, a lookback of 1 year and use of unweighted returns seems to produce lower dispersion VaR results. On the other hand, in terms of the magnitude of the VaR, it seems that 10-day overlapping and weighted returns and a lookback period of more than 1 year produce results that are more conservative. This seems to dispute the finding of the 2017 exercise. It is also likely that these results depend on the portfolios' selection for this analysis and on the small sample size. Therefore, from this analysis, it is difficult to support the idea that one specific model choice will lead to consistently low-risk measures.

Table 6: Coefficient of variation for regulatory VaR by modelling choice

	Coefficient of Variation for regulatory VaR (controlling for HS)					
Port.	*1-day*	*10-day*	*1y*	*>1y*	*unweighted*	*weighted*
EQ 2	10%	34%	13%	49%	74%	79%
IR 8	6%	24%	12%	17%	8%	25%
FX 10	15%	16%	10%	14%	16%	9%
CS 16	23%	20%	14%	47%	5%	30%
mean	13%	24%	12%	32%	26%	36%

Table 7: Average regulatory VaR by modelling choice

	Average VaR subsamples					
	1-day	*10-day*	*1y*	*>1y*	*unweighted*	*weighted*
EQ 2	135,581	137,499	151,852	144,864	215,975	190,509
IR 8	99,405	127,348	101,485	112,497	99,214	119,891
FX 10	482,157	499,770	448,989	500,647	482,630	545,786
CS 16	109,921	135,956	104,020	131,855	100,769	119,177

5.2.5 Other drivers of variation

145. In addition to the drivers of variation discussed in the preceding two subsections, there may be other drivers of variation.

146. In the subsection 'Modelling differences', for instance, only results obtained with HS VaR were discussed, although the methodological aspects considered are expected to be important for other model types (e.g. MC simulation) as well.

147. Another driver of variation may be that certain risks are not captured in a model. Due to the simplification of the portfolios between the exercises in 2017 and 2018, the majority of the most exotic instruments were deleted, so most of the possible risk factors not in the models are no longer present in the exercise. This resulted in a reduction of the dispersion for IMV and risk measure of the exercise.

148. Moreover, the use of proxies leads to spurious variability in some of the hypothetical portfolios characterised by less liquid risk factors, for example some credit spreads. This consideration also applies to the sVaR.

5.2.6 Portfolio comparison

149. Selective comparison of VaR results across portfolios can be informative in instances where the riskiness of those portfolios may be ranked in a model-independent way. For example, all else being equal, it is expected that a more diversified portfolio would lead to a lower VaR than a more concentrated portfolio.

150. This hypothesis can be analysed using portfolios 17 and 20 (Table 8). Both of these portfolios involve corporate instruments, yet portfolio 17 is more concentrated than portfolio 20. Against this background and in view of the specific portfolio definitions, one would expect the following result:

$$60\% \times VaR_{Portfolio\ 20} < VaR_{Portfolio\ 17};$$

the rescaling by 60% is necessary to align the notional amounts.

Table 8: Portfolio comparison for VaR, sVaR and IRC

	60% VaR(port.20) < VaR(port.17)*	*60%* sVaR(port.20) < sVaR(port.17)*	*60%* IRC(port.20) < IRC(port.17)*
Num of banks	**2 out of 34**	**1 out of 34**	**2 out of 32**

151. The comparison between the two portfolios with respect to regulatory VaR shows that only 2 out of 34 banks are not fulfilling the initial expectation. The same comparison based on sVaR yields only one bank not in line with this expectation. Concerning the IRC model, two banks do not fulfil the a priori expectation. These findings are consistent with last year's results.

5.3 Analysis of IRC

152. Banks with an approved IRC model constitute a subsample of those with an approved VaR model; only banks using internal models for specific risk of debt instruments are permitted to use IRC models (Article 372 of the CRR).

153. The total number of submissions for IRC results for each trade, after the data cleansing process run as previously described, is reported in Table 9.

154. In the context of the HP exercise, only a few banks made submissions for IRC, and, among those banks, a number submitted very low results. This suggests that important risk factors (in the context of the HPE) have not been modelled. While the submission of low results may be linked to 'risk factors not modelled', this should not be taken to mean that banks with higher IRC results included all risk factors from a given portfolio in their model.

155. The number of submissions is particularly small for some of the all-in portfolios. Statistical inferences for these portfolios are thus not appropriate. A prerequisite for consideration of banks' submissions for the all-in portfolios is that a bank needs to be able to model all corresponding underlying portfolios.

156. As it is for VaR, a selective comparison of IRC results across portfolios can be informative in instances where the riskiness of those portfolios may be ranked in a model-independent way. As shown in subsection 5.2.6, the expected diversification relationship holds for all but two of the submitted banks.

157. It is recommended that CAs assess the extent to which these missing risk factors are important in the context of banks' overall risk, and whether or not they need to be added to the model.

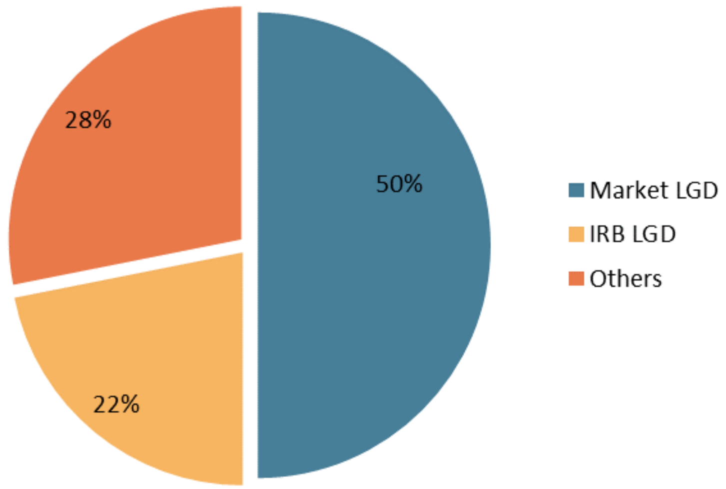
158. Particular attention from CAs should be devoted to portfolios 7 and 16. IRC shows a higher level of dispersion for portfolios 7 and 16 than the dispersion observed in other credit spread portfolios, especially the simplest ones.

159. As is the case for VaR and sVaR, banks can choose from a range of permitted modelling approaches for IRC. For example, banks need to choose:

- a source of credit risk estimates such as PD and loss given default (LGD);
- the number of systemic factors used to model the co-movement among obligors in their portfolios;
- the size and granularity of credit spread shocks to apply to positions with an obligor following a rating transition; and
- the liquidity horizons to assign to positions with a particular obligor.

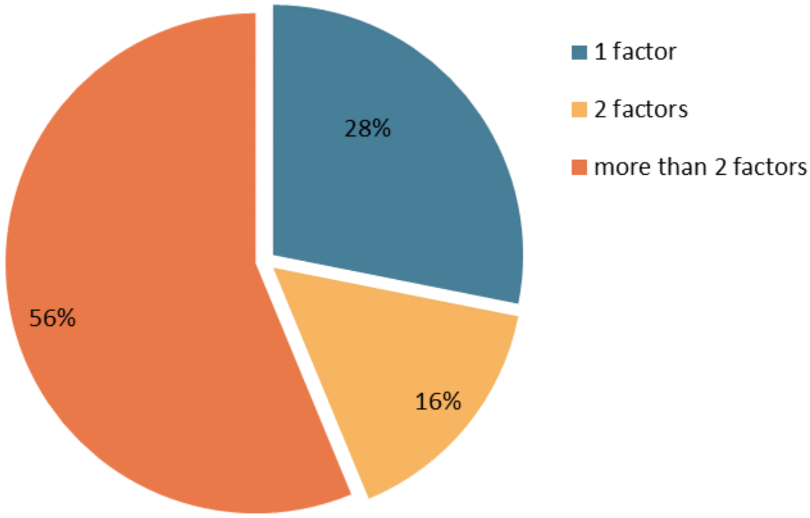
160. The responses to the qualitative questionnaire relating to the IRC methodological aspects suggest that the use of market LGD predominates across respondents (Figure 11). Both PD (18 respondents out of 32, or 56%) and transition matrices are mostly taken from rating agencies (25 respondents out of 32, or 78%).

Figure 11: Qualitative data: source of LGD for IRC modelling



161. A majority of respondents stated, moreover, that they use more than two systemic modelling factors at the overall IRC model level (Figure 12). The liquidity horizon applied at the portfolio level for the IRC model is predominantly between 9 and 12 months (23 respondents out of 30, or 76%).

Figure 12: Qualitative data: number of modelling factors for IRC



162. Hence, in the context of IRC, the modelling practices across the sample of banks participating in the benchmarking exercise seem to be consistent.

Table 9: IRC statistics and cluster analysis

		Main statistics								Percentiles		
	Port. ID	Min	Max	Ave.	STDev	STDev_trunc[1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs.[3]	25th	50th	75th
IR	7	235,679	5,697,658	2,886,279	1,790,466	1,744,180	1,362,064	62%	27	1,428,508	2,707,736	4,348,491
Credit Spread	15	90,928	1,625,993	852,982	475,419	459,284	380,705	56%	27	504,412	952,313	1,225,000
	16	3,693	1,793,600	411,401	407,577	303,069	205,444	99%	27	118,955	265,596	588,293
	17	475,061	1,224,700	845,401	210,965	191,064	164,783	25%	27	658,504	840,606	977,528
	18	262,415	6,101,000	1,136,666	1,328,278	965,306	225,281	117%	30	536,101	655,953	1,279,436
	19	604,847	3,052,500	1,235,017	576,865	462,647	221,352	47%	29	849,679	1,061,212	1,487,672
	20	399,379	1,872,820	970,169	331,535	267,146	202,382	34%	27	775,170	981,846	1,133,066
	21	6,289	3,948,843	734,177	805,722	507,004	130,700	110%	28	355,006	455,750	699,198
All-in portfolio (1 to 21)**	22	2,098,892	8,885,354	5,298,965	2,229,378	2,229,378	1,456,721	42%	15	3,646,318	5,103,039	7,298,979
Credit spread (15 to 21)**	27	1,900,763	10,180,500	3,874,851	2,293,843	1,908,732	766,886	59%	24	2,214,397	2,700,086	4,881,023

163. Table 9 shows that the IRC average variability is higher than that observed for VaR. This table presents a summary of the descriptive statistics concerning the IRC submitted values, along with the median, the first and the third quartiles used to select out-of-range values to be discussed with the banks during the interviews. On average, 28 banks provided results for IRC in relation to the IR and CS hypothetical trades, net of the aggregated portfolios where missing values were predominant.

5.4 Analysis of APR

164. In their responses to the qualitative questionnaire relating to the APR methodological aspects, 5 out of 7 respondents, i.e. all 7 banks with an authorisation for CTP, stated that they use more than 2 modelling factors at the overall CTP model level.

165. With regard to the source of LGD estimates at the overall CTP model level, most respondents use market LGD while a minority of banks use the LGD underlying their internal ratings-based approach for credit risk or other sources. As in the case of IRC, the source for PD estimates (6 respondents out of 7) and transition matrices (6 respondents out of 7) are mostly rating agencies. The liquidity horizon applied at the portfolio level for the CTP model is predominantly between 9 and 12 months (6 respondents out of 7).

166. It should be highlighted that all of these options are, in principle, acceptable under the current regulatory framework and that it is up to banks and CAs to agree on the most appropriate ones to be applied by each bank during the validation process, with particular reference to the banks' individual trading portfolios and trading activities. Thus, given the wide range of approaches that institutions using an internal model can choose to implement, some degree of variability among the resulting capital requirements is expected.

167. At the same time, these differences in implementation are clearly not the only factors behind variability. There are other modelling choices that are not explicitly contemplated in regulation, such as differences in simulation engines and data sources, differences in the methods used to compute risk factors when data are not directly observable (e.g. all indirect parameters such as volatilities and correlations), the absence of some of the risk factors considered, differences in approximations when repricing positions, etc.

168. The majority of banks with an approved APR model used a one-factor Gaussian copula model, where the potential loss is estimated by averaging a number of worst scenarios corresponding to a 1-year development in the market along with market parameter simulations (i.e. credit spreads, recovery rates, default correlations, CDS/Index basis) and transition matrices for rating migrations.

169. The average variability for the APR charge is 57% when computed by averaging the IQD of each CTP. This variability is due to the assumptions and modelling choices made by banks, but it is difficult to arrive at any takeaway because of the very small number of contributions (Table 10). This is also the reason why no further meaningful analysis, for example with respect to VaR, is possible. Table 10 should therefore be used for reference only, since the sample size cannot be considered statistically robust.

Table 10: APR statistics and cluster analysis

		Main statistics								Percentiles		
	Port. ID	Min	Max	Ave.	STDev	STDev_trunc[1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs.[3]	25th	50th	75th
Correlation Trading	28	967,566	7,876,503	4,074,605	2,411,398	2,411,398	1,361,501	59%	6	2,636,898	3,803,381	5,359,900
	29	234,714	1,837,543	749,578	645,952	645,952	205,399	86%	6	271,708	458,610	1,236,281
	30	27,488	298,935	125,549	109,456	109,456	63,851	87%	6	32,063	93,627	207,556

5.5 P&L analysis

170. The P&L analysis is complementary to the outcome of the assessment of variability based on VaR modelling. For each individual portfolio, the P&L vectors provided by banks using HS were compared and, for all portfolios, used to construct correlation matrices between banks. In other words, for each portfolio, the standard correlation coefficient between the P&L vectors across banks was derived.[18] Because of the high dimensionality of this exercise, for each portfolio, all banks with a high correlation (greater than 80%) and all banks with a low correlation (less than 40%) were grouped and counted.

171. This analysis allows the detection of banks that systematically exhibit a high or a low correlation level in their P&L. The EBA computed the percentage of banks for each correlation bucket (high, medium and low) by risk category and also examined the top 10 most correlated and top 10 least correlated banks. The EBA found evidence that, for many portfolios, banks with highly correlated P&L time series also tend to be aligned in their risk measures. This result is even more evident for the least correlated banks. That is to say, for many portfolios, highly correlated P&L vectors tend to be associated with a homogeneous method for the actual P&L computation. This confirms the results derived from last year's exercise.

172. Across the 21 non-CTPs, there are HS banks for which the level of variability observed in the P&L is least harmonised in the sample of all remaining HS banks. This is an important point because it reflects the differences in how the actual P&L is computed across the banks.

173. Another useful check for the submitted P&L results was a comparison of the ratio between the P&L VaR computed by the EBA (see section 4.2) and the regulatory VaR submitted by the participating banks. A significant deviation of this ratio from 1 indicates an incoherent submission from the bank (see Table 18 and Table 21 in the Annex). Moreover, it allows the tightness or the width of the realised P&L distribution for each bank to be checked by each hypothetical trade position. This can be done by referring to the standard deviation of the P&L series.

[18] Obvious limitations to this exercise were data availability and consistency in the reported dates across banks.

174. Another metric computed by the EBA from the P&L series provided by HS banks is the empirical ES (see Table 19 in the Annex). The empirical ES results have more or less the same level of dispersion as the P&L VaR, but the level of dispersion is significantly lower for interest rate products (see Table 4 in section 5.1). This implies that harmonisation increases when simple interest rate products are tested.

5.6 Diversification benefit

175. An additional metric considered as part of the analysis was the diversification benefit observed for VaR, sVaR and IRC in the aggregated portfolios.

176. The diversification benefit of a given metric (e.g. VaR) is computed as the absolute benefit, i.e. the difference of the sum of the single results for each individual position and the result for the aggregated portfolio, divided by the sum of the single results from each individual portfolio. Table 11 summarises the results of the analysis.

177. As expected, there is evidence that larger aggregated portfolios exhibited greater diversification benefits than smaller ones. The diversification benefit for all-in portfolios 22 (all portfolios), for instance, clearly exceeds the benefit for the other risk types, whose all-in portfolios are based on fewer individual instruments. With regard to the dispersion shown by the diversification benefits, it is possible to observe a significantly higher IQD for some portfolios than for others, and – in some cases – a quite comparable dispersion across VaR, sVaR and IRC (e.g. interest rate and commodity risk categories).

Table 11: Diversification benefit statistics

Diversification benefit = (Sum of single portfolios VaR - Aggregated Port. VaR)/Sum of single portfolios VaR

VaR

		Other statistics			Percentiles			
	Port.	Ave.	STDev	Num obs. [3]	25th	50th	75th	Interquartile dispersion
All-in portfolio (1 to 21)**	22	67%	4%	16	64%	67%	69%	**4%**
Equity (1 to 6)**	23	48%	10%	33	42%	49%	56%	**14%**
Interest rate (7 to 9)**	24	21%	9%	45	14%	23%	26%	**31%**
FX (10 to 12)**	25	56%	11%	35	49%	56%	63%	**12%**
Commodity (13 and 14)**	26	41%	7%	21	39%	41%	42%	**5%**
Credit spread (15 to 21)**	27	43%	10%	31	39%	46%	49%	**12%**

sVaR

		Other statistics			Percentiles			
	Port.	Ave.	STDev	Num obs. [3]	25th	50th	75th	Interquartile dispersion
All-in portfolio (1 to 21)**	22	89%	16%	16	79%	85%	94%	**9%**
Equity (1 to 6)**	23	70%	26%	30	56%	63%	70%	**12%**
Interest rate (7 to 9)**	24	39%	10%	33	33%	38%	45%	**15%**
FX (10 to 12)**	25	80%	29%	29	58%	70%	86%	**19%**
Commodity (13 and 14)**	26	18%	9%	18	13%	15%	22%	**23%**
Credit spread (15 to 21)**	27	89%	51%	32	55%	77%	112%	**34%**

IRC

		Other statistics			Percentiles			
	Port.	Ave.	STDev	Num obs. [3]	25th	50th	75th	Interquartile dispersion
Credit spread (15 to 21)**	27	41%	13%	29	33%	41%	49%	**20%**

5.7 Dispersion in capital outcome

178. As a final means of comparison, for each individual position, a variable given by the sum of the regulatory VaR and sVaR was computed. This variable was used in two ways: using the banks' total multiplication factor; and using the regulatory multiplication factor only, i.e. ignoring the banks' individual addend(s) set by the CAs. The results were averaged across a given risk type, thus arriving at a proxy for the implied capital outcome.

Table 12: Interquartile dispersion for capital proxy

	Capital proxy (banks own mult)	*Capital proxy (fixed mult, =3)*
Equity	26%	23%
IR	16%	13%
FX	24%	21%
Commodity	30%	29%
Credit spreads	38%	35%
CTP	38%	31%

179. Table 12 suggests that variability is slightly exacerbated by regulatory add-ons. In any case, the ranges of capital value dispersion remain broadly aligned whether or not the banks' actual multiplication factors are used.

180. The EBA used the implied capital outcome as another criterion for identifying banks to invite for interview. Looking at this capital outcome proxy by risk category, it is possible to rank the banks on the basis of how they are distributed below the first quartile or above the third quartile.

181. A few banks were identified as aggressive, and their approaches and results were challenged during the interviews. Other banks also contributed to the observed dispersion because of their submission of high values. The analysis of this capital proxy variable across the HPE trades shows that a few banks are underestimating the implied requirements with respect to the average implied own funds requirement. The interviews focused on these cases, aiming to understand the reasons. When banks' own regulatory multipliers are taken into account, the number of cases reduces.

6. Competent authorities' assessment

183. The CAs provided individual assessments for each participating institution of any potential underestimation of the capital requirement as required by Article 78(4) of the CRD and Articles 9 and 10 of the draft RTS on supervisory benchmarking. This chapter highlights some key information derived from these assessments.

184. The EBA designed a questionnaire regarding this assessment, which asked CAs to provide detailed information concerning the level of priority, based on both judgemental and qualitative/quantitative examination results, the overall assessment concerning the MR capital requirements of the internal models, and, finally, the CAs' ongoing monitoring activities.

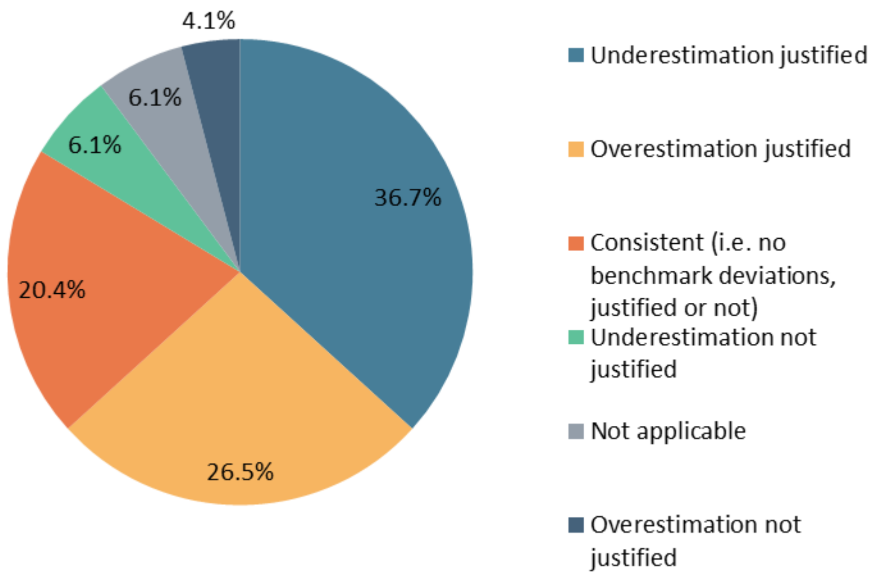
185. A total of 49 questionnaires, provided by the CAs, from 12 jurisdictions, have been considered in this assessment of the MR benchmarking exercise.

186. Regarding the level of priority of the assessments, 8 banks (around 17%) are reported to be 'high priority' for intervention by CAs. CAs gave high priority to those banks that were either an outlier in the analysis or identified as a candidate for the interview process. The criteria for selecting banks were substantially based on firms' results in terms of the capital requirement proxy (below the 25th percentile or above the 75th percentile) and other thresholds relating, for instance, to the ratio of sVaR to VaR across all portfolios, low results for IRC and other issues that came to light during the interviews when challenging the banks.

187. Figure 13 reports the CAs' own overall assessments of the levels of own funds requirements. When it comes to benchmark deviations, justified or not, 36 banks were reported by CAs as under- or overestimating MR own funds requirements, of which 31 provided justifications for this. Obviously, 'not justified' implies that further and targeted CA investigation is required. Finally, 10 banks had consistent results (i.e. no benchmark deviations) and 3 banks were assessed as 'not applicable' by CAs.

188. Briefly, CAs' assessments acknowledge 5 cases out of 48 of non-justified under- or overestimation of internal models market capital requirements that require further in-depth analysis. Obviously, CAs, and the joint supervisory team where applicable, pay more attention to the potential underestimation cases, both across the portfolio and across the risk categories.

Figure 13: CAs' own assessments of the levels of MR own funds requirements



189. The main factors and reasons that may explain possible underestimations are that the benchmarking portfolios do not represent the actual composition of the real trading portfolios of the institutions, missing risk factors not incorporated in the models, weaknesses in pricing model assumptions or modelling choices that are not particularly accurate, misunderstandings regarding the positions or risk factors involved, and differences in calibration or data used in modelling estimation and/or simulation. These explanations were offered by the large majority of the applicable respondents.

190. Three banks were identified for possible underestimation, not justified, during the banks' internal assessment process run by the CAs. CAs are currently undertaking some monitoring activities (both ongoing and on site) of the internal models, to check all the issues related to challenging the banks. To be more specific, for one of these subjects the benchmark portfolio is not very representative, the bank has limited exposure to the market risk, and the CA has identified itself as the source of underestimation and required a specific action (linked to the modelling of the returns), with a due date for completion. For the second subject, which is currently under inspection, only generic explanations for the underestimation are provided (such as calibration or data used in modelling estimation, use of proxies, differences attributable to the way of calculating indirect risk parameters, etc.). The CA, with a formal recommendation to the bank, will address weaknesses discovered, not only those related to the benchmark. The third subject of 'unexplained underestimation', the only one classified as high priority by the CA, was also subject to a specific interview by the CA in order to increase the CA's understanding of the possible source of misalignment.

191. Two banks were identified for possible overestimation, not justified. In both cases, the overestimation was deemed not of concern, and low priority, since the observations were not far from the 75th percentile of the sample.

192. Overall, CAs planned some actions for 13 banks, such as:

a. reviewing the banks' internal VaR and IRC models, alongside the European Central Bank TRIM (Targeted Review of Internal Models) in-depth assessment, where applicable within the Single Supervisory Mechanism countries;

b. supervisory extra charge;

c. stringent conditions on any extension of the internal model approach;

d. further internal model investigation at a peer level.

193. Currently, 10 banks have a due date for making the improvements to their MR internal models already requested by CAs.

7. Conclusion

194. This report has presented an analysis of the observed variability across results provided by EU banks that have been granted permission to adopt internal models for MR own funds requirements.

195. It must be recalled and emphasised that, as the quantitative analysis is based on hypothetical portfolios, this report focuses solely on potential variations and not on actual variations. The analysis shows the extent of the variability in these hypothetical portfolios, but that cannot mechanically lead to conclusions regarding real under- or overestimations for the MR capital charge.

196. However, the analysis might help in determining possible supervisory activities to address uniformity and harmonisation across the Member States, and in promoting in-depth future cross investigations on this matter.

197. The objective of the benchmarking exercise was not to reach a final judgement on the key drivers of variation and the calculation of the implied capital charges, but to provide supervisors with insights into how to increase comparability and reduce the variability effects attributable to non-risk-driven behaviours between the banks.

198. In particular, the report provides inputs for CAs on areas that may require their further investigation, such as IMV variability for some credit spread products. Supervisors should pay attention to the materiality of risk factors not in VaR and, in particular, not encompassed in the IRC models.

199. Moreover, the conclusions reached in regular supervisory model monitoring activities will take into account the outcome of the supervisory benchmarking exercises to achieve greater alignment between CAs' targeted internal model reviews and EU benchmarking analysis.

200. Finally, this report provides a framework that can be considered useful for the purpose of future benchmarking exercises under Article 78 of the CRD. Therefore, the type of analysis conducted (i.e. the statistical tools provided to CAs, the graphs and tables created, the methodology defined, the discussions held during the interviews with the selected subgroup of participating banks, etc.) offers a clear direction for future investigations and activities on these issues.

8. Annex

Table 13: Banks participating in the 2018 EBA MR benchmarking exercise

Country	Bank name
AT	Erste Group Bank AG
AT	Raiffeisen Zentralbank Österreich AG
BE	Belfius Banque SA
BE	KBC Group NV
DE	Commerzbank AG
DE	DekaBank Deutsche Girozentrale
DE	Deutsche Bank AG
DE	Deutsche Zentral-Genossenschaftsbank AG
DE	LandesbankBaden-Württemberg
DE	LandesbankHessen-ThüringenGirozentrale
DE	NORD/LB Norddeutsche Landesbank Girozentrale
DK	Danske Bank A/S
DK	Nykredit Realkredit A/S
ES	BFA Tenedora De Acciones, S.A.
ES	Banco Bilbao Vizcaya Argentaria, SA
ES	Banco Santander SA
ES	Criteria Caixa Holding, S.A.
FR	BNP Paribas SA
FR	Groupe BPCE
FR	Groupe Credit Agricole
FR	Société Générale SA
GB	Barclays Plc
GB	Citigroup Global Markets Europe Limited
GB	Credit Suisse International
GB	Credit Suisse Investments (UK)
GB	Goldman Sachs Group UK Limited
GB	HSBC Holdings Plc
GB	ICBC Standard Bank Plc (was Standard Bank Plc)
GB	J P Morgan Capital Holdings Limited
GB	Lloyds Banking Group Plc
GB	Merrill Lynch UK Holdings Ltd
GB	Mitsubishi UFJ Securities International PLC
GB	Morgan Stanley International Ltd
GB	Nomura Europe Holdings PLC
GB	Standard Chartered Plc
GB	The Royal Bank of Scotland Group Public Limited Company
GR	Alpha Bank S.A.
GR	Eurobank Ergasias S.A.
GR	National Bank of Greece SA
IT	Banco BPM SpA
IT	Intesa Sanpaolo SpA
IT	UniCredit SpA
NL	ABN AMRO Groep N.V.
NL	Coöperatieve Rabobank U.A.
NL	ING Groep N.V.
NL	NIBC Holding N.V.
PT	Banco Comercial Português SA
SE	Nordea Bank - group
SE	Skandinaviska Enskilda Banken - group
SE	Swedbank - group

Country	AT	BE	DE	DK	ES	FR	GB	GR	IT	NL	PT	SE
N.banks	2	2	7	2	4	4	15	3	3	4	1	3

Table 14: Portfolios underlying the HPE

Risk factor	Port.ID	Portfolio description
EQUITY	1	Bullish leveraged trade
	2	Volatility trade on S&P 500
	3	Volatility trade on FTSE 100
	4	Covered call on Generali
	5	Collar strategy on Sanofi
	6	long strangle 12-m maturity on Aviva
IR	7	Curve sovereign trade
	8	Interest rate swap
	9	IRS USD 10y vs 3m
FX	10	Covered FX call on EUR/USD
	11	Knock-out currency option
	12	Double no touch binary currency option
COMMODITIES	13	Long short-term ATM OTC Ldn Gold fwd & Short long-term ATM OTC Ldn Gold fwd
	14	Short oil put options
CREDIT SPREAD	15	Sovereign CDS portfolio
	16	Sovereign bond/CDS portfolio
	17	Sector concentration portfolio
	18	Diversified index portfolio
	19	Diversified index portfolio with higher concentration
	20	Diversified corporate portfolio
	21	CDS bond basis
ALL IN	22	All-in portfolio
ALL EQ	23	All Equity portfolios
ALL IR	24	All IR portfolios
ALL FX	25	All FX portfolios
ALL COM	26	All commodity portfolios
ALL CS	27	All credit spread portfolios
CTP 1	28	Long position in spread hedged equity tranche of CDX.NA.IG index
CTP 2	29	Long position in spread hedged mezzanine tranche of CDX.NA.IG index
CTP 3	30	Short position in spread hedged super senior tranche of CDX.NA.IG index

For a detailed description of the portfolios, please refer to the EBA website: https://www.eba.europa.eu/regulation-and-policy/other-topics/regulatory-and-implementing-technical-standards-on-benchmarking-portfolios.

Refer also to Commission Implementing Regulation (EU) 2016/2070 of 14 September 2016, and Commission Implementing Regulation (EU) 2017/1486 of 10 July 2017 laying down ITS in accordance with Article 78(2) of Directive 2013/36/EU.

Table 15: VaR cluster analysis – number of banks by range

VaR cluster analysis: number of banks by range

(X = ratio with the median)

100	*Range containing more than 15% of the total obs for that particular portfolio*

	Port. ID	300% < X	300% ≥ X >200%	200% ≥ X >150%	150% ≥ X >100%	100% ≥ X >50%	50% ≥ X >0	Num obs. [3]
Equity	1		1	5	13	18		37
	2	1	3		15	17	2	38
	3			5	14	17		36
	4			2	16	18	2	38
	5	2	2	4	12	13	5	38
	6	3	3	3	10	13	5	37
IR	7				23	21	2	46
	8			2	21	25	1	49
	9		1	3	20	23	1	48
FX	10			1	20	21	1	43
	11			3	15	22	1	41
	12			3	14	16	3	36
Comm	13			1	10	11	1	23
	14	1	3		7	9	2	22
Credit Spread	15	1		5	12	12	4	34
	16			2	17	15		34
	17	3		6	10	13	2	34
	18	1	1	6	9	15	3	35
	19	2	1	4	9	14	3	33
	20	2	2	3	10	16	1	34
	21	1	1	2	12	18		34
All-in portfolio (1 to 21)**	22		1	1	12	19	5	38
Equity (1 to 6)**	23	1	1	5	10	20	2	39
Interest rate (7 to 9)**	24			2	18	26		46
FX (10 to 12)**	25			4	16	18	3	41
Commodity (13 and 14)**	26		1	1	9	11	1	23
Credit spread (15 to 21)**	27	1		3	13	16	1	34
Correlation Trading	28				3	3	1	7
	29	1	1		2	1	2	7
	30		1	1	2	1	2	7

Table 16: VaR statistics

	Port. ID	Min	Max	Ave.	STDev	STDev_trunc[1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs.[3]	25th	50th	75th
Equity	1	22,068	97,600	45,188	15,577	12,312	8,845	34%	34	35,491	42,177	52,583
	2	71,394	453,302	167,856	80,179	62,280	22,642	48%	34	128,294	159,050	177,793
	3	73,742	172,757	114,418	28,730	26,520	20,836	25%	31	88,048	108,318	132,741
	4	33,179	165,534	82,870	28,651	24,093	20,277	35%	35	62,868	83,690	98,941
	5	506	32,002	3,137	5,557	2,252	700	177%	34	1,250	1,852	2,617
	6	16	116,800	4,301	19,585	623	255	455%	35	665	920	1,207
IR	7	107,520	260,869	187,593	32,873	28,091	18,821	18%	36	164,339	184,952	203,057
	8	36,032	194,131	104,396	26,001	17,182	8,143	25%	46	93,287	102,381	108,112
	9	45,226	243,531	130,836	34,657	21,711	9,412	26%	40	114,382	123,521	138,133
FX	10	381,324	721,288	486,080	79,797	69,123	50,083	16%	37	419,619	468,917	519,000
	11	163,222	443,483	278,225	71,246	64,655	42,445	26%	37	235,008	253,369	326,804
	12	33,617	167,433	87,228	30,869	26,560	16,983	35%	33	68,408	85,390	101,295
Comm	13	6,643	81,716	55,984	16,067	10,638	4,363	29%	21	48,535	51,807	70,798
	14	8,956	81,393	29,549	16,770	16,770	6,300	57%	19	20,426	26,839	33,139
Credit Spread	15	484	89,400	31,635	16,514	11,271	8,256	52%	29	20,952	29,170	37,426
	16	83,198	191,075	126,718	27,398	24,127	22,540	22%	30	102,377	125,178	145,780
	17	298	163,900	37,736	29,326	15,774	7,069	78%	29	24,840	30,410	38,336
	18	2,116	278,800	69,249	46,104	25,130	19,526	67%	33	48,452	61,671	86,521
	19	1,894	288,400	64,072	48,708	23,963	14,528	76%	31	39,638	54,165	78,766
	20	17,083	180,030	43,114	35,387	23,592	9,270	82%	28	24,427	32,019	43,706
	21	37,956	295,761	73,380	45,048	15,978	11,728	61%	30	53,147	69,550	76,407
All-in portfolio (1 to 21)**	22	517,959	1,135,252	742,963	144,652	144,652	82,250	19%	16	659,213	723,429	824,098
Equity (1 to 6)**	23	126,140	925,000	241,540	156,767	93,677	36,375	65%	31	156,176	199,607	235,982
Interest rate (7 to 9)**	24	252,551	532,311	343,612	71,477	63,620	46,225	21%	35	282,168	341,732	387,957
FX (10 to 12)**	25	123,434	643,405	368,943	107,930	88,907	63,443	29%	33	292,827	356,267	420,059
Commodity (13 and 14)**	26	10,659	86,069	48,017	14,489	14,489	6,513	30%	19	40,811	47,324	56,408
Credit spread (15 to 21)**	27	125,136	868,700	250,718	139,376	58,185	39,284	56%	26	180,398	214,299	283,029
Correlation Trading	28	213,520	312,742	254,840	36,772	36,772	25,385	14%	6	222,111	253,894	272,881
	29	5,556	85,789	34,837	27,644	27,644	9,218	79%	6	15,730	33,893	34,165
	30	378	17,045	7,418	6,046	6,046	4,287	81%	6	1,789	7,466	10,363

[1] *STDev trunc* is the standard deviation computed excluding values below the *5th* and above the *95th* percentile

[3] *Refers to the number of banks included in the computation of the statistics*

*** For the aggregated portfolios (22 to 27), banks that reported at least a missing portfolio IMV among the ones composing the aggregate are not included in the computation of the benchmarks for that particular aggregate portfolio.*

Table 17: sVaR statistics

	Port. ID	Min	Max	Ave.	STDev	STDev_trunc[1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs.[3]	25th	50th	75th
Equity	1	30,559	171,185	83,495	31,907	27,277	19,481	38%	34	61,778	87,562	105,887
	2	159,887	1,104,361	631,171	214,627	186,142	132,864	34%	34	505,099	633,670	770,900
	3	110,068	419,429	287,575	94,917	88,904	54,321	33%	31	174,038	318,290	361,922
	4	58,036	213,250	144,251	30,874	25,129	15,710	21%	35	125,707	139,900	156,278
	5	115	28,582	3,799	5,790	3,871	984	152%	34	1,372	2,363	3,339
	6	17	486,400	15,713	81,920	1,820	738	521%	35	766	1,416	2,580
IR	7	105,095	790,860	271,485	134,117	99,766	34,829	49%	36	206,603	241,497	273,069
	8	50,445	306,558	182,892	63,971	56,686	54,332	35%	46	137,293	205,923	233,277
	9	87,637	459,368	290,747	79,110	66,033	44,544	27%	40	254,502	292,618	343,711
FX	10	377,418	1,860,580	1,235,824	342,332	301,474	231,724	28%	37	1,018,590	1,264,907	1,480,832
	11	221,912	997,943	576,187	154,097	127,341	63,605	27%	37	531,102	575,300	649,342
	12	45,539	628,525	275,834	153,850	138,987	102,975	56%	33	178,178	234,802	366,745
Comm	13	38,028	231,583	177,128	47,462	35,247	23,573	27%	21	161,974	189,491	203,071
	14	24,200	400,185	119,993	91,960	91,960	44,080	77%	19	51,374	86,109	171,378
Credit Spread	15	4,360	462,500	119,150	92,419	63,898	40,676	78%	29	65,184	85,731	133,435
	16	124,363	443,500	265,945	75,065	64,345	57,222	28%	30	213,676	269,962	328,120
	17	2,939	1,023,000	223,667	214,170	149,906	91,654	96%	29	73,052	161,595	273,973
	18	4,891	890,500	255,197	170,829	124,204	91,399	67%	33	137,866	229,265	309,652
	19	4,894	968,000	272,248	185,685	129,903	114,066	68%	31	128,301	250,637	361,181
	20	46,170	584,500	168,561	125,245	96,381	57,965	74%	28	73,306	121,679	229,584
	21	34,944	690,250	183,534	117,597	66,003	42,963	64%	30	131,007	165,339	222,029
All-in portfolio (1 to 21)**	22	1,066,879	2,743,923	1,739,064	577,497	577,497	208,922	33%	16	1,319,408	1,492,072	2,316,371
Equity (1 to 6)**	23	150,790	1,020,721	0	211,866	198,692	142,169	36%	31	482,922	628,775	717,844
Interest rate (7 to 9)**	24	306,087	776,000	498,380	117,508	105,357	79,947	24%	35	417,269	492,152	598,805
FX (10 to 12)**	25	279,725	3,061,263	1,204,592	689,778	602,627	193,755	57%	33	765,050	935,876	1,604,797
Commodity (13 and 14)**	26	49,626	222,913	153,610	34,815	34,815	12,717	23%	19	140,281	152,998	169,731
Credit spread (15 to 21)**	27	321,529	2,534,500	800,135	477,161	322,307	288,030	60%	26	435,798	709,243	1,074,667
Correlation Trading	28	541,224	1,038,681	767,137	205,902	205,902	180,137	27%	6	583,948	742,723	953,523
	29	20,036	321,604	146,068	114,876	114,876	94,505	79%	6	36,037	136,843	225,046
	30	484	55,282	24,593	18,166	18,166	7,443	74%	6	14,681	23,772	29,567

[1] *STDev trunc* is the standard deviation computed excluding values below the *5th* and above the *95th* percentile

[3] *Refers to the number of banks included in the computation of the statistics*

*** For the aggregated portfolios (22 to 27), banks that reported at least a missing portfolio IMV among the ones composing the aggregate are not included in the computation of the benchmarks for that particular aggregate portfolio.*

Table 18: P&L VaR statistics

	Port. ID	Min	Max	Ave.	STDev	STDev_trunc[1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs.[3]	25th	50th	75th
Equity	1	59,897	244,289	95,250	44,673	33,551	12,432	47%	26	67,916	79,364	94,701
	2	77,210	427,992	185,498	92,962	79,958	50,644	50%	27	110,784	161,428	237,898
	3	88,187	360,342	141,194	59,841	34,781	17,380	42%	22	108,102	124,133	147,863
	4	51,055	197,560	74,515	30,354	18,107	2,562	41%	27	61,358	64,876	66,408
	5	104	50,442	4,459	10,942	5,077	690	245%	24	790	1,262	2,803
	6	39	79,057	4,366	15,922	633	209	365%	24	762	970	1,281
IR	7	106,411	565,730	206,131	97,851	66,767	12,582	47%	27	164,438	177,021	192,474
	8	60,630	323,778	112,289	52,151	35,969	10,498	46%	33	90,232	101,303	106,748
	9	78,576	371,563	126,802	69,946	52,297	11,857	55%	28	98,192	106,901	121,888
FX	10	146,966	2,037,458	592,693	380,683	258,305	55,838	64%	29	442,747	470,428	554,947
	11	153,794	823,625	277,781	142,410	97,655	21,045	51%	29	222,711	241,762	265,183
	12	37,947	245,416	94,477	40,762	24,782	18,809	43%	25	77,555	85,381	104,730
Comm	13	5,755	238,828	63,468	48,883	48,883	3,902	77%	16	50,184	54,198	56,921
	14	5,418	34,858	21,632	8,095	8,095	5,545	37%	14	18,787	19,327	28,078
Credit Spread	15	9,487	69,570	30,487	16,224	14,132	11,548	53%	23	18,367	28,569	40,332
	16	73,395	380,082	142,093	74,639	55,836	28,113	53%	24	97,604	123,677	153,992
	17	13,560	87,645	37,391	20,008	16,667	6,905	54%	22	22,951	32,507	37,577
	18	33,292	163,502	69,420	32,065	25,882	14,234	46%	26	46,236	58,973	82,219
	19	29,389	138,341	59,327	29,895	25,172	13,759	50%	24	37,370	48,544	73,709
	20	18,974	124,987	45,641	25,734	19,502	9,519	56%	23	26,433	40,091	49,611
	21	37,558	290,034	86,679	65,907	51,984	10,938	76%	25	57,247	64,956	75,895
All-in portfolio (1 to 21)**	22	596,798	777,920	703,982	66,104	66,104	61,523	9%	11	645,105	716,397	764,353
Equity (1 to 6)**	23	136,408	664,400	252,193	120,802	84,043	75,121	48%	24	155,298	227,658	331,954
Interest rate (7 to 9)**	24	256,144	1,113,694	375,948	190,685	124,413	34,251	51%	27	299,319	324,228	365,924
FX (10 to 12)**	25	256,012	4,315,337	568,693	793,944	147,789	59,134	140%	25	334,552	393,686	445,305
Commodity (13 and 14)**	26	6,823	55,131	42,548	11,387	11,387	2,853	27%	14	41,056	43,785	49,246
Credit spread (15 to 21)**	27	170,956	575,090	251,247	112,755	88,138	24,985	45%	21	192,440	217,426	237,821
Correlation Trading	28	120,486	236,345	177,950	63,017	63,017	53,997	35%	4	123,488	177,485	232,412
	29	4,643	31,623	20,565	10,391	10,391	5,884	51%	5	17,646	21,514	27,398
	30	1,828	12,137	6,673	4,224	4,224	2,287	63%	4	4,076	6,363	9,269

[1] *STDev trunc* is the standard deviation computed excluding values below the *5th* and above the *95th* percentile

[3] *Refers to the number of banks included in the computation of the statistics*

*** For the aggregated portfolios (22 to 27), banks that reported at least a missing portfolio IMV among the ones composing the aggregate are not included in the computation of the benchmarks for that particular aggregate portfolio.*

Table 19: Empirical expected shortfall statistics

	Port. ID	Min	Max	Ave.	STDev	STDev_trunc[1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs.[3]	25th	50th	75th
Equity	1	56,261	238,312	91,831	43,093	31,754	12,997	47%	26	66,567	80,178	92,562
	2	88,447	573,281	199,330	113,174	86,148	53,995	57%	27	122,112	160,133	237,682
	3	87,151	396,110	143,392	68,339	39,146	13,023	48%	22	110,017	119,693	143,349
	4	51,861	171,199	67,926	25,293	15,007	2,131	37%	27	57,116	58,538	62,614
	5	-3,162	43,384	3,409	9,258	4,449	771	272%	26	384	1,008	1,804
	6	0	90,125	4,338	17,163	806	218	396%	27	710	908	1,294
IR	7	98,892	524,399	194,897	88,887	59,670	8,500	46%	27	160,824	168,623	183,359
	8	64,187	316,950	108,170	51,172	35,306	8,808	47%	33	85,649	95,842	100,797
	9	86,146	384,505	125,255	68,809	47,847	8,476	55%	28	99,592	107,882	116,607
FX	10	147,419	2,058,707	595,696	379,466	252,095	47,386	64%	29	448,458	482,002	535,707
	11	149,818	792,938	270,341	137,260	94,849	23,471	51%	29	222,531	233,824	261,114
	12	39,133	231,912	91,109	38,042	23,221	14,712	42%	25	77,017	83,784	101,996
Comm	13	5,268	430,060	74,603	95,761	95,761	3,062	128%	16	50,019	53,759	56,145
	14	5,270	35,024	21,517	8,148	8,148	4,591	38%	14	19,026	20,808	27,399
Credit Spread	15	10,277	60,083	28,335	14,747	13,329	9,830	52%	23	16,765	24,899	37,695
	16	74,179	361,950	137,757	71,078	53,773	30,094	52%	24	94,597	113,777	156,726
	17	13,909	81,975	36,098	18,810	15,902	10,749	52%	22	20,983	32,690	42,481
	18	27,810	160,071	68,050	31,740	25,527	12,236	47%	26	52,487	61,529	75,706
	19	29,987	143,298	58,597	29,793	24,182	11,180	51%	24	41,092	50,436	65,371
	20	14,823	113,681	42,026	24,498	19,316	9,674	58%	23	23,018	37,305	45,032
	21	32,809	280,815	85,716	63,875	50,534	9,148	75%	25	57,810	67,311	74,088
All-in portfolio (1 to 21)**	22	612,561	814,246	717,756	66,498	66,498	51,400	9%	11	650,419	716,130	767,530
Equity (1 to 6)**	23	139,977	528,991	240,763	105,102	87,079	41,826	44%	24	159,061	195,728	327,073
Interest rate (7 to 9)**	24	252,052	1,040,739	354,997	177,764	116,758	22,987	50%	27	280,592	303,579	332,663
FX (10 to 12)**	25	250,835	4,206,806	555,631	772,746	138,241	47,330	139%	25	349,392	386,988	434,318
Commodity (13 and 14)**	26	6,977	53,883	41,575	10,921	10,921	2,581	26%	14	40,449	41,898	45,519
Credit spread (15 to 21)**	27	163,526	616,916	247,305	119,582	87,580	33,932	48%	21	181,103	215,035	241,217
Correlation Trading	28	142,754	239,596	199,438	43,322	43,322	25,086	22%	4	166,089	207,701	232,788
	29	4,262	34,082	21,147	11,580	11,580	8,801	55%	5	17,299	20,647	29,447
	30	1,524	11,714	6,443	4,167	4,167	2,448	65%	4	3,819	6,266	9,066

[1] *STDev trunc* is the standard deviation computed excluding values below the *5th* and above the *95th* percentile

[3] *Refers to the number of banks included in the computation of the statistics*

*** For the aggregated portfolios (22 to 27), banks that reported at least a missing portfolio IMV among the ones composing the aggregate are not included in the computation of the benchmarks for that particular aggregate portfolio.*

Table 20: sVaR/VaR statistics

	Port. ID	Min	Max	Ave.	STDev	STDev_trunc [1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs. [3]	25th	50th	75th
Equity	1	0.87	4.77	1.93	0.83			43%	37	1.30	1.89	2.28
	2	0.61	9.60	3.99	1.79			45%	38	2.82	4.06	4.99
	3	0.93	4.21	2.54	0.82			32%	36	1.99	2.56	3.06
	4	0.64	3.41	1.94	0.65			34%	38	1.47	2.00	2.24
	5	0.18	3.94	1.37	0.72			53%	38	0.96	1.31	1.60
	6	0.51	4.41	1.87	1.09			58%	37	1.08	1.41	2.68
IR	7	0.72	5.25	1.70	0.96			57%	46	1.07	1.33	1.93
	8	0.43	3.15	1.82	0.72			39%	49	1.26	2.05	2.44
	9	0.77	3.62	2.28	0.71			31%	48	1.82	2.35	2.79
FX	10	0.74	4.45	2.59	0.85			33%	43	2.19	2.47	3.24
	11	0.62	4.99	2.23	0.74			33%	41	1.82	2.20	2.53
	12	0.80	7.16	3.31	1.55			47%	36	2.35	2.88	4.34
Comm	13	0.87	5.72	3.42	0.91			26%	23	3.06	3.69	3.88
	14	1.57	5.83	3.78	1.23			33%	22	2.76	3.75	4.86
Credit Spread	15	1.20	9.01	3.88	1.85			48%	34	2.66	3.15	5.52
	16	0.64	3.80	2.12	0.67			31%	34	1.72	2.18	2.64
	17	1.21	20.29	6.17	4.97			81%	34	2.70	4.25	7.10
	18	1.34	40.91	4.86	6.53			134%	35	2.41	3.50	4.56
	19	1.29	16.97	5.02	3.63			72%	33	2.58	3.52	5.57
	20	1.08	12.83	4.71	3.37			72%	34	2.32	3.40	5.29
	21	0.51	4.78	2.64	1.02			39%	34	1.92	2.55	3.15
All-in portfolio (1 to 21)**	22	1.23	4.15	2.30	0.71			31%	38	1.80	2.07	2.73
Equity (1 to 6)**	23	0.53	4.68	2.85	1.10			38%	39	2.21	3.16	3.50
Interest rate (7 to 9)**	24	0.61	3.51	1.63	0.57			35%	46	1.20	1.64	1.97
FX (10 to 12)**	25	0.92	7.88	3.33	1.49			45%	41	2.32	3.02	3.63
Commodity (13 and 14)**	26	0.87	4.66	3.26	0.76			23%	23	3.09	3.37	3.62
Credit spread (15 to 21)**	27	1.45	7.29	3.35	1.74			52%	34	1.87	2.96	4.20
Correlation Trading	28	2.19	4.55	3.23	0.78			24%	7	2.64	3.32	3.63
	29	1.27	9.42	4.44	2.53			57%	7	2.92	3.43	5.57
	30	1.28	8.20	3.46	2.11			61%	7	2.11	3.24	3.64

[1] *STDev trunc* is the standard deviation computed excluding values below the *5th* and above the *95th* percentile

[3] *Refers to the number of banks included in the computation of the statistics*

*** For the aggregated portfolios (22 to 27), banks that reported at least a missing portfolio IMV among the ones composing the aggregate are not included in the computation of the benchmarks for that particular aggregate portfolio.*

Table 21: P&L VaR/VaR statistics

	Port. ID	Min	Max	Ave.	STDev	STDev_trunc[1]	MAD (median absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs.[3]	25th	50th	75th
Equity	1	0.18	1.01	0.56	0.20			36%	28	0.45	0.54	0.64
	2	0.32	2.78	1.13	0.52			46%	29	0.87	0.98	1.22
	3	0.34	1.43	0.95	0.23			24%	26	0.78	0.92	1.12
	4	0.31	2.50	1.25	0.42			34%	28	0.97	1.14	1.48
	5	-1.08	15.60	2.06	2.82			137%	26	1.08	1.55	2.03
	6	0.30	1.60	0.97	0.34			35%	25	0.84	1.01	1.09
IR	7	0.32	1.59	1.05	0.25			24%	32	1.00	1.05	1.21
	8	0.32	1.64	1.04	0.26			25%	35	1.00	1.05	1.16
	9	0.34	2.29	1.25	0.44			35%	35	1.06	1.16	1.58
FX	10	0.28	3.29	1.02	0.47			46%	32	0.89	1.03	1.11
	11	0.33	1.98	1.09	0.35			32%	30	0.95	1.08	1.25
	12	0.31	1.76	0.99	0.27			27%	27	0.83	0.91	1.15
Comm	13	0.26	1.50	1.00	0.27			27%	17	0.87	0.98	1.15
	14	0.93	7.86	1.85	1.60			86%	16	1.13	1.54	1.75
Credit Spread	15	0.34	5.14	1.43	0.94			66%	27	1.01	1.17	1.50
	16	0.32	2.15	1.05	0.34			32%	27	0.94	1.00	1.15
	17	0.29	3.17	1.37	0.66			49%	27	0.98	1.16	1.67
	18	0.28	2.71	1.19	0.57			48%	28	0.85	1.13	1.42
	19	0.29	2.92	1.34	0.65			49%	26	0.97	1.13	1.61
	20	0.30	2.84	1.18	0.57			48%	27	0.79	1.14	1.45
	21	0.32	2.32	1.04	0.34			33%	27	0.93	1.03	1.10
All-in portfolio (1 to 21)**	22	0.28	2.85	1.08	0.42			39%	28	0.95	1.04	1.13
Equity (1 to 6)**	23	0.26	3.84	1.19	0.67			57%	28	0.89	1.12	1.31
Interest rate (7 to 9)**	24	0.32	1.73	1.08	0.28			26%	32	1.00	1.07	1.21
FX (10 to 12)**	25	0.14	3.29	0.98	0.51			52%	30	0.83	0.90	1.17
Commodity (13 and 14)**	26	0.27	2.16	1.16	0.38			33%	17	1.00	1.07	1.42
Credit spread (15 to 21)**	27	0.30	2.80	1.11	0.45			40%	27	0.92	1.03	1.29
Correlation Trading	28	0.90	1.91	1.36	0.43			31%	5	1.00	1.17	1.84
	29	0.89	1.56	1.20	0.22			18%	5	1.08	1.20	1.25
	30	0.85	1.22	1.06	0.13			12%	5	0.98	1.11	1.12

[1] *STDev trunc* is the standard deviation computed excluding values below the *5th* and above the *95th* percentile

[3] *Refers to the number of banks included in the computation of the statistics*

*** For the aggregated portfolios (22 to 27), banks that reported at least a missing portfolio IMV among the ones composing the aggregate are not included in the computation of the benchmarks for that particular aggregate portfolio.*

EUROPEAN BANKING AUTHORITY

Floor 46 One Canada Square, London E14 5AA

Tel. +44 (0)207 382 1776
Fax: +44 (0)207 382 1771
E-mail: info@eba.europa.eu

http://www.eba.europa.eu