EBA REPORT

RESULTS FROM THE 2017 MARKET RISK BENCHMARKING EXERCISE

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EUROPEAN BANKING AUTHORITY

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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 01: with respect to credit default swaps, this refers to the credit exposure of the swap at a given point in time (it stands for 'credit spread value of one basis point')
CTP	correlation trading portfolio(s)
CV	coefficient of variation
EBA	European Banking Authority
ES	expected shortfall
EES	empirical estimate of expected shortfall
EQ	equity
EU	European Union
FRTB	Fundamental Review of the Trading Book
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
MAD	median absolute deviation
MC	Monte Carlo
MR	market risk
MRWA	market-risk-weighted asset(s)
NCA	national competent authority
P&L	profit and loss
PD	probability of default
RTS	regulatory technical standards
RWA	risk-weighted asset(s)
sVaR	stressed value at risk
VaR	value at risk

1. Executive summary

This report presents the results of the 2017 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).

The report summarises the conclusions drawn from a hypothetical portfolio exercise (HPE) that was conducted by the EBA during 2016/17. The main objective of this exercise was to assess the level of variability observed in risk-weighted exposure amounts for market risk (MRWA) produced by banks' internal models.

The exercise was performed on a sample of 51 European banks from 12 jurisdictions. The relevant institutions submitted data for 34 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 (CTP), for a total of 37 benchmark portfolios. As such, the exercise covers the entire population of EU banks with internal models on MR at the highest level of consolidation.

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

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.

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.

Main findings of the benchmarking analysis

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 MRWA variability, the IQD metric suggests significant dispersion for all the risk measures provided by banks.

From a risk factor perspective, interest rate portfolios exhibit a lower level of dispersion than the other asset classes. This is likely to be due to the use of more consistent practices and more homogeneous assumptions across the banks when modelling interest rate risk. This finding confirms the conclusions drawn in last year's analysis.

The analysis shows significant dispersion in the initial market valuation (IMV) results stemming 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.

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; respectively 24% and 30%).[3] More complex measures such as incremental risk charge (IRC) and all price risk (APR) show a much higher level of dispersion (respectively 47% and 48%).

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).

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

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[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.

banks only). In fact, for most risk types, 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.

Even so, within the subset of banks using an HS approach, modelling choices do make a noticeable difference. Scaled 1-day VaR, use of a lookback period greater than 1 year and use of unweighted returns tend to produce lower dispersion than other modelling configurations, as well as more conservative VaR results (i.e. higher average VaR figures).

The dispersion in sVaR figures is generally higher than the dispersion observed for regulatory VaR. The stressed period 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 an estimation of implied capital needs from the HPE. During some interviews with the banks, it was clear that the observed variability in sVaR could also be produced by differences in modelling.

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. The ratio generally varies significantly across the portfolios, especially for instruments subject to credit spread risk. However, on average, the ratio lies at around 2.4, very close to what was found in last year's exercise.

During the interviews with the banks, a lack of consistent practice for modelling some of the risk factors was found, especially with regard to the most sophisticated ones. In particular, this is the case for the basis risk between a credit default swap (CDS) and its equivalent bonds, the basis risk between an index and its components, the forward equity volatility surface, and, in general, the discounting and forwarding curves and the application of shocks in a low rates environment. Each of these practices and the assumptions they are based on are proper, and do not infringe legal requirements, but their results are difficult to compare consistently.

Banks note that negative or very low interest rates cause issues for VaR calculations, especially where still based on the log-normal volatility framework. A prudent risk-weighted assets (RWA) buffer might be considered for VaR and sVaR to ring-fence this issue.

The low rates environment issue was also observed in relation to the IRC risk, where the banks' modelling choices concerning the migration and transition matrices play a role in the variability of the results. Ensuring a conservative representation of the migration effects should be accounted for.

As expected, the larger banks, with significant trading activities, acknowledge the materiality of the benchmarking portfolios in their actual trading book. However, some trades, especially index options and quanto structures, need to be reviewed and simplified in the future. Smaller banks asked for a framework to be established for simple and ordinary plain vanilla trade.

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 (48%).

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 CTP, i.e. these portfolios are supposed to be in run-down mode.

A further metric considered as part of the analysis was the diversification benefits observed for VaR, sVaR and IRC in the aggregated portfolios. 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.

In light of the Fundamental Review of Trading Book (FRTB) proposed by the Basel Committee and integrated into the CRR/CRD IV, an assessment of the variability of the empirical estimates of 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 lower than that found for VaR and P&L VaR, especially for interest rate and equity trades. Except in a few cases, probably due to misunderstandings of the trades' specifications, EES tends to show a less accentuated level of variability than the other risk metrics.

These findings are in line with those of previous exercises, so they have the same implications.

Dispersion in capital outcome

Alongside the variability driver analysis, the EBA also conducted an assessment regarding possible underestimations of capital requirements. 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.

The average variability across the sample, measured by way of the IQD, is significant (around 26%), 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

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

interest rate products, the ranges of capital value dispersion are broadly consistent, irrespective of whether the banks' actual multiplication factors are used or not.

The implied capital needs proxy highlighted a few cases of underestimation with regard to the benchmarks. These were discussed in depth and further clarified during the interviews.

CAs' assessments based on supervisory benchmarks

CAs shared the outcomes of their assessments at bank level with the EBA. 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. When reviewing banks' models, supervisors should pay attention to the permitted modelling choices, and to the cumulative impact of the risks not captured in the model.

Furthermore, CAs plan to assess the materiality of risk factors not in VaR ('risk not captured by the model') and, where appropriate, to challenge the models to improve their coverage (e.g. through internal model authorisation extension).

For IRC models, supervisors plan to ensure that banks review the transition matrices in a prudent and adequate way, and to pay particular attention to any floor for the PDs imposed on both sovereign and highly rated counterparties. It also emerged during interviews with the banks that an IRC model enhancement, to simulate different spread shifts for different maturities, can better capture the migration dynamics of the different tenors of the credit spread curves. An additional model enhancement, ensuring the consistent representation of migration effects on low credit spread rates, leads to more conservative P&L impacts in case of rating migration.

2. Introduction and legal background

European legislators have acknowledged the need to ensure consistency in the calculation of RWA for equivalent portfolios, and the revised 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.

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, highlighting 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.

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 ongoing EBA work on benchmarking, supervisory consistency and transparency is fundamental to restore trust in internal models and the ways in which banks calculate asset risks.

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.

This MR benchmarking exercise is a MRWA variability assessment performed over a large sample of banks (51 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:

- general risk of equity instruments;
- specific risk of equity instruments;
- general risk of debt instruments;
- specific risk of debt instruments;
- foreign exchange risk;
- commodities risk; and
- correlation trading.

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.

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, thus the number of contributions for each hypothetical portfolio in this exercise varies across the sample.

Banks that have permission to use the internal model for calculating MR own funds requirements for only one or more 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.

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.

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 done to detect the pricing ability of the participating banks.

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 2017 market risk benchmarking exercise

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 so as to achieve a homogenous and comparable outcome across the sample; then, banks are asked to submit the data accordingly; and, finally, the EBA processes and analyses the data, providing feedback to national competent authorities (NCAs). During the process, the EBA supports NCAs' work by providing benchmarking tools to assess banks' results and detect anomalies in their submissions.

3.1 Definition of the market risk hypothetical portfolios

The MR portfolios have been defined as hypothetical portfolios composed of both non-CTP and CTP, as set out in Annex V of the Benchmarking ITS. The exercise includes 34 general portfolios (28 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 (7 individual portfolios), IR (5 individual portfolios), FX (4 individual portfolios), CO (2 individual portfolios) and CS (10 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 29) encompasses all products; the second (portfolio 30) is made up of all equity portfolios; the third (portfolio 31) is made up of all interest rate portfolios; the fourth (portfolio 32) is made up of all FX portfolios; the fifth (portfolio 33) is made up of all commodities portfolios; and the sixth (portfolio 34) is made up of all credit spread portfolios.

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 CS01 as of the initial valuation date (spread hedged). No further re-hedging is required.

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

3.2 Data collection process

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.

IMV

The reference date for IMV was 27 October 2016, 4.30 p.m. London time (5.30 p.m. CET). Banks entered all positions on 13 October 2016 ('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.

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 2016, 5:30 pm CET.

Risk measures

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.

[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 2017/1486 of 10.07.2017, laying down ITS in accordance with Art. 78(2) of Directive 2013/36/EU.

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 CTP (35, 36, 37), APR was also requested.

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. During the interviews, a few banks, especially those with limited trading activities, claimed some difficulties in dealing with this, and a couple of them admitted repeated FX conversions with their accounting currencies, bringing operational risks.

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

A total of 51 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 the highest level of consolidation.

NCAs 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

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.

IMV results reached the EBA in November/December 2016, 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.

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] As a result, the submissions were not comparable with those valued in full.

During the interviews with the banks, just a couple of firms stated that they had manually recalculated the figures denominated in the foreign (base) currency using the historical FX market data vectors. This is not perceived as best practice and it should be avoided for related operational reasons. In addition, during the discussion concerning the submitted results, two banks were excluded from the final benchmarks computation due to flaws and operational issues.

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

[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.

4. Market risk benchmarking framework

The aim of the benchmarking exercise is 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.

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 immediate 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 (sqrt(10)), etc. Likewise, when modelling IRC, banks can choose from several sources of 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.

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, absolute versus relative returns, volatility, correlations and other indirect parameters estimates, additional risk factors considered in the models, different approaches to P&L computation and attribution, stochastic framework for the simulated shocks, etc.

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.

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. Monte Carlo (MC) versus HS or parametric).

4.1 Outlier analysis

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.

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.

Extreme values are defined as values outside the range of two truncated standard deviations[8] 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.

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

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.

The dispersion across the contributions is summarised by the IQD coefficient, which is more robust when compared with the coefficient of variation 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 percentile respectively.

Another metric used in the variability studies is the coefficient of variation (CV), which is defined as the ratio between the standard deviation[9] and the mean (in absolute value):

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

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

[9] 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	-26,322	2,101,445	1,367,616	985,251	976,711	14,799	71%	36	4,344	2,068,050	2,069,156	100%
	2	4,823	30,268	19,544	3,501	1,790	873	18%	37	18,488	19,068	20,788	6%
	3	457,649	744,750	703,381	47,003	21,859	7,897	7%	37	700,298	712,387	717,871	1%
	4	-309,447	-223,529	-275,300	14,196	9,677	1,605	5%	35	-279,371	-277,766	-276,080	1%
	5	559,255	622,922	567,123	9,624	2,316	960	2%	38	564,353	565,449	566,395	0%
	6	681,322	692,204	689,074	1,770	1,139	718	0%	38	688,479	689,453	690,118	0%
	7	3,406	500,935	25,220	90,877	43,605	137	360%	37	4,724	4,861	4,966	2%
IR	8	-15,397,530	-15,133,342	-15,210,064	30,566	3,530	2,090	0%	46	-15,209,558	-15,207,107	-15,205,450	0%
	9	-64,303	20,357	-54,054	11,538	3,053	1,245	21%	48	-56,726	-55,910	-53,757	3%
	10	-197,764	21,596	-52,344	40,328	31,886	4,500	77%	48	-70,930	-67,254	-47,469	20%
	11	-104,599	-6,937	-47,181	17,356	11,352	6,506	37%	45	-52,880	-43,835	-37,422	17%
	12	-1,119,801	-727,892	-904,575	48,848	13,406	6,013	5%	36	-911,248	-907,481	-897,162	1%
FX	13	-1,186,793	-487,383	-941,751	110,971	73,550	48,550	12%	42	-1,010,392	-976,270	-858,271	8%
	14	-111,130	379,821	136,776	86,057	47,613	17,251	63%	40	123,658	139,551	157,417	12%
	15	382,545	504,464	455,269	20,621	12,194	9,561	5%	40	445,207	456,800	464,302	2%
	16	554,013	987,003	915,233	65,060	20,547	8,248	7%	37	912,380	919,007	945,346	2%
Com	17	-29,869	14,804	-10,002	6,580	1,761	1,350	66%	26	-11,308	-10,503	-8,371	15%
	18	-213,548	-146,790	-169,568	15,787	12,457	4,797	9%	24	-170,295	-165,157	-160,360	3%
Credit Spread	19	-44,762	308,931	118,169	79,811	68,919	23,247	68%	34	55,125	112,101	134,442	42%
	20	11,041,860	11,566,795	11,270,209	120,523	104,588	81,634	1%	34	11,193,577	11,276,192	11,325,020	1%
	21	58,793	76,624	65,135	3,063	2,059	1,510	5%	33	63,494	65,072	66,157	2%
	22	18,578	58,421	33,660	5,400	2,150	926	16%	35	32,528	33,454	34,424	3%
	23	-15,688	76,087	50,094	13,423	4,276	1,559	27%	32	49,313	50,861	53,097	4%
	24	161,882	216,896	202,278	12,630	10,388	1,582	6%	33	201,224	206,791	207,874	2%
	25	-21,698	3,431	-2,258	4,460	2,318	1,621	198%	29	-3,226	-1,812	-131	92%
	26	6,774,127	7,157,271	7,078,440	83,990	64,621	27,224	1%	33	7,010,390	7,119,414	7,140,201	1%
	27	-642,248	7,904	-136,945	203,714	203,714	6,241	149%	15	-90,876	-64,241	-58,000	22%
	28	-129,022	-3,378	-88,747	27,845	20,901	4,304	31%	25	-99,519	-95,215	-91,224	4%
All-in portfolio (1 to 28)**	29	3,881,446	7,202,913	6,086,405	1,090,278	1,090,278	311,697	18%	13	5,998,384	6,591,894	6,835,935	7%
Equity (1 to 7)**	30	-11,292,285	4,395,940	2,630,070	2,744,668	1,145,210	123,706	104%	33	1,623,304	3,889,924	3,930,994	42%
Interest rate (8 to 12)**	31	-16,483,871	-1,067,330	-15,818,693	2,567,927	67,662	29,596	16%	35	-16,275,992	-16,261,824	-16,200,567	0%
FX (13 to 16)**	32	153,032	2,502,047	619,764	367,927	129,921	78,934	59%	33	498,690	555,516	639,728	12%
Commodity (17 and 18)**	33	-204,374	-144,350	-165,158	15,957	13,444	10,439	10%	23	-177,442	-160,061	-151,792	8%
Credit spread (19 to 28)**	34	18,180,185	18,889,842	18,601,755	245,482	245,482	88,420	1%	14	18,319,353	18,753,514	18,760,258	1%
Correlation Trading	35	-3,487,924	5,162,515	2,840,057	2,574,701	2,574,701	374,847	91%	9	3,597,178	3,600,831	3,975,678	5%
	36	-2,448,586	1,819,699	-1,071,663	1,366,424	1,366,424	34,981	128%	9	-1,787,099	-1,755,571	-527,851	54%
	37	-316,836	455,657	207,662	241,829	241,829	53,825	116%	9	246,557	268,051	321,877	13%

[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 (29 to 34), 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

	IMV
Equity	16%
IR	8%
FX	7%
Commodity	9%
Credit spreads	17%
CTP	24%

The results of the extreme value analysis are summarised in Table 1 and Table 2. They depict 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 portfolios 25 and 27, as well as the CTP (portfolios 36 and 37). From a more aggregated risk-type perspective, interest rates and FX instruments show the lowest dispersion. Portfolios 1 and 10 were affected by different interpretations on the part of the banks.

In view of the small number of contributions, the high dispersion for CTP does not allow for any meaningful analysis or inferences. 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 facilitate a well-founded analysis.

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

Cluster detection analysis: number of banks by range

(X = ratio with the median)

		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.
Equity	1				15	9	8	5			37
	2			1	17	19	1				38
	3				18	20					38
	4				18	18					36
	5				19	20					39
	6				19	20					39
	7	2			16	20					38
IR	8				24	23					47
	9				24	24		1			49
	10		1		23	14	2	9			49
	11		3	1	18	23	1				46
	12				19	18					37
FX	13				21	21	1				43
	14		3		17	17	1	3			41
	15				21	20					41
	16				18	20					38
Com	17		1		12	12		1	1		27
	18				12	12		1			25
Credit Spread	19		5		12	8	9	2			36
	20				17	18		1			36
	21				16	17	1	1			35
	22			1	16	19		1			37
	23				16	15	1	2			34
	24				17	17		1			35
	25	2	4	7	1	6	3	3	4	1	31
	26				16	18		1			35
	27	2	1		4	6	1	2		1	17
	28		1		12	11	2	1			27
All-in portfolio (1 to 28)**	29				10	17	6	4	3	4	44
Equity (1 to 7)**	30				16	6	17			1	40
Interest rate (8 to 12)**	31				17	24	3				44
FX (13 to 16)**	32	1	1	2	14	18	3	2	2		43
Commodity (17 and 18)**	33				11	13	1	2			27
Credit spread (19 to 28)**	34				16	17	1	1			35
Correlation Trading	35				4	3	1	1			9
	36				4	2	1	1	1		9
	37			1	3	3		1	1		9

In particular, as shown in Table 3:

- Portfolio 1: a first group of banks reported the price of the future at the valuation date multiplied by the number of underlying. Therefore, there was no reference to the booking date. The second group of banks computed the IMV as the unrealised balance of '1-day P&L', since futures are margined daily.[10]

- Portfolio 10: some participating banks priced this swaption 'naked' (i.e. without considering the premium), while other banks considered the premium. At the interviews, some banks argued in favour of different choices regarding the discounting and forwarding curves used.

- Portfolio 19: in this sovereign CDS short position, the clusters derive from different assumptions on the running spreads among the participants. At the interviews, a couple of banks were found not to capture in a meaningful and appropriate way the basis risk due to the limitedness of their models based on a general risk only. However, other practices were found proper, with no infringement of the legal requirements, but those results were difficult to compare consistently.

- Portfolios 25 and 27: these trades are related to the iTraxx index and iTraxx Xover, where some banks' assumptions played a key role in pricing. For instance, the choice of on-the-run index, the adopted convention on the effective maturity of the option, misunderstandings related to the payer/receiver type, etc., appear to drive the variation observed for these portfolios.

- Other kinds of difficulties were found for CTP, principally as a result 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 a little more pricing consistency for the first CTP, portfolio 35, 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.

- 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

[10] As we will see in the VaR analysis section, the misinterpretation in this case did not affect the VaR computation, since P&L results are closer.

index for a shift in the credit curve for all underlying names) based on their proprietary pricing models.

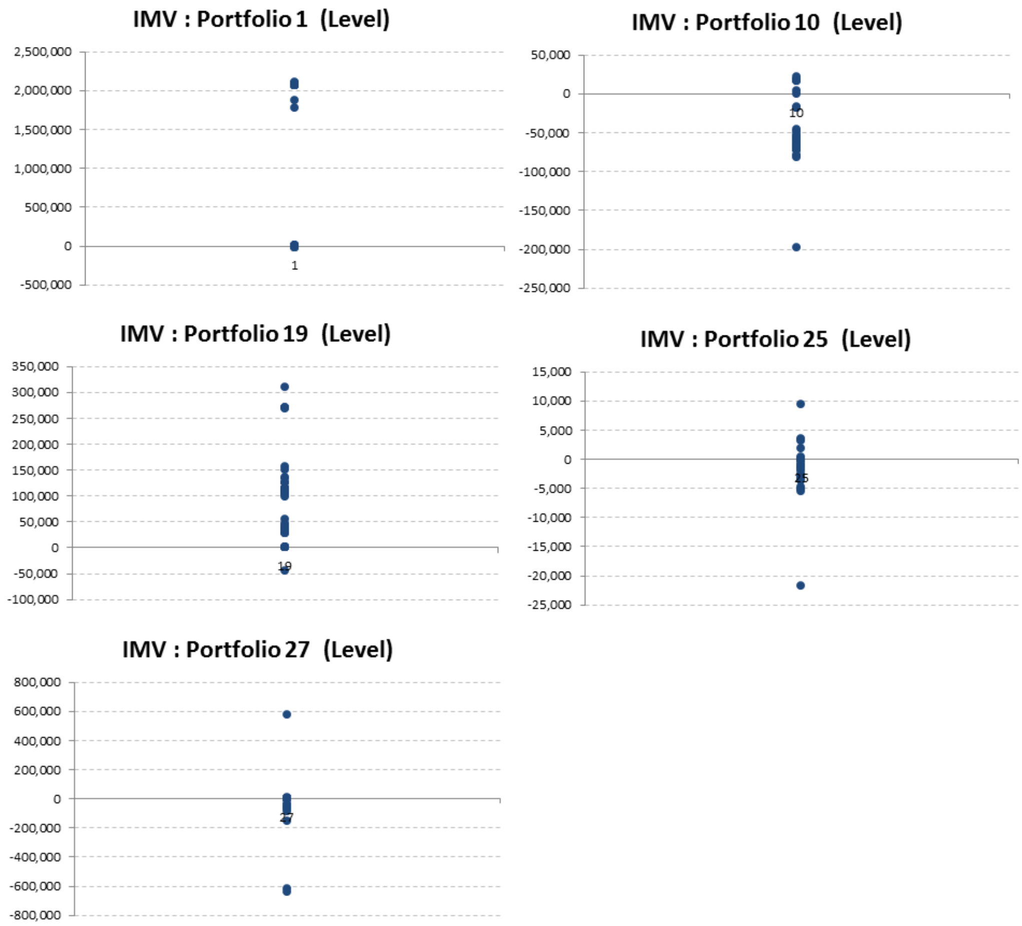
In general, a number of banks erroneously computed the IMV results as a P&L from the booking date to the valuation date. In order to achieve a uniform interpretation, the EBA issued a Q&A defining the IMV as the mark to market at the valuation date and time for each trade.[11] This should help in future exercises. In addition, during the interviews with the banks, the EBA asked banks to 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.

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

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 2.12.2016.

Figure 1: IMV scatter plot – clustered portfolios



The ‘concentration index’, given by the percentage of values within 50% and 150% of the median value in Table 3, shows that, overall, 87% of the observations lie between those ranges.

This result is an improvement on that reported following last year’s MR benchmarking exercise.

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 significantly in the next exercises.

For many hypothetical portfolios, the IMV variability may be 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

For **VaR and sVaR**, variability was assessed by using the banks' reported VaR and sVaR over a 2-week period (from 6 February 2017 to 17 February 2017). 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.

In the sample, 17 out of 51 banks (i.e. one third of the sample) calculated weekly sVaR measures. The remaining two thirds of the participating banks computed daily sVaR measures.

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.

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.

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]

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 a parametric approach, or another approach other than HS, cannot be subject to this assessment.

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]

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

[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.

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 about the degree of market consensus on the relevant risk factors, in terms of both market dynamics and 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.

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 to missing, zero or unrealistically low results, which suggest that key underlying risk factors are not efficiently captured by the IRC internal model.

In the sample, 17 out of 31 banks (i.e. 55%) computed weekly IRC measures.

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

For **APR**, only a small number of contributions were submitted because of the scarcity of approved internal models on CTP, 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.

In the sample, 6 out of 8 banks (i.e. 75%) computed weekly APR measures.

Moreover, the **empirical estimated shortfall (EES)** was 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 = num. of days describing the 2.5 quantile rounded to the highest decimal

ES is the new risk metric introduced by the FRTB and is expected to enter into force from 01 January 2019.

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.

For the most inclusive portfolios, with the higher number of submissions, 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.

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. We also refer the reader to the following subsection, 'Limitations'.

Finally, to make the analysis more comprehensive, NCAs 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 interview, the EBA had the opportunity to discuss directly some issues raised by CAs when challenging the models in the ongoing assessment process.

Limitations

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 by 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.

From a methodological perspective, the sVaR metric could not be fully assessed, since the stress period has not been made consistent. It is clear that any variability observed could be produced either by differences in modelling or by the different data periods used for sVaR computation. One option would be to ask banks to use a common benchmarking stress period, but this would create an additional burden for them, and no consistent proxy for the implied own funds requirement could be defined. To allow more specific analyses on this aspect, in the next 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.

Another limitation is that there is no segregated analysis for institutions with partial model approval (e.g. general risk only), since this sample would be limited. Therefore, portfolios with specific risk may show further unwarranted dispersion of VaR figures. Among the banks invited for interview, one bank with partial model approval has been selected to gather more insights on how it approaches the benchmarking exercise. It has been found that, when dealing with the most complex trades, few banks apply manual adjustments that affect the results and lead to operational risks. In addition, since the model comprises only linear risk, non-linear risk factors are not included. This creates severe limitations in the exercise, along with difficulties in valuing trades retrospectively. In summary, partial use approval, along with the limitations of the model, raises concerns about the suitability of the inclusion of these results within the overall benchmarking exercise.

5. Overview of the results obtained

5.1 Analysis of VaR and sVaR metrics

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.

To check if submissions (by portfolio) were at least approximately symmetrically distributed around the mean and/or the median, we 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. In particular, portfolio 1 does not show separate clusters for VaR, as the figures are derived from the P&L distribution and are thus more homogenous.

Unexpected excess variability has been found in portfolios 5 and 7 within the equity asset class. Presumably, the dispersion found in portfolio 7 may be attributed to the banks' different assumptions on estimating the required 1-year term volatility parameter. It furthermore appears that banks have modelled the cross-currency basis swap (portfolio 14) differently; the cluster analysis identifies two (large) distinct clusters for this foreign exchange instrument. It is possible that the separate clusters can be attributed to whether a bank assumed an exchange of notional at maturity. The analysis also identifies clusters for portfolios 27 and 28 (credit spread). While the cause for portfolio 27 could be different choices of the on-the-run iTraxx Xover index, the clusters for portfolio 28 may be attributable to the interplay of simulated credit spreads and the running fees/notionals/FX rates from this trade booking.

Last but not least, the VaR values for CTP (portfolios 35–37) show substantial dispersion. Regrettably, the small sample size and scattering of results did not allow for 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.

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. Nevertheless, a more bespoke approach is therefore required in such cases.

Interquartile dispersion

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.

The IQD for VaR of portfolio 14, which is also a cluster portfolio (see Table 15 in the Annex), is particularly conspicuous (the coefficient of variation also shows a peak, but with a lower amplitude). In terms of risk type, the IQD for VaR for FX and credit spread portfolios are highest when compared with the other risk types. This differs from IMV, for which the IQD for FX portfolios is comparatively small.

As expected, the IQD for sVaR is higher than for VaR (see the bottom-most panel of Figure 2). One of the reasons for this is likely to be the difference in the 1-year stress period used across banks, which is chosen based on each participating bank's actual portfolio at the close of business on each reporting date within the 2-week period underlying the benchmarking analysis. In other words, the sVaR is not calculated with respect to the 1-year period that maximises VaR for the given hypothetical portfolio. The sVaR IQD for portfolios 14 and 27 is particularly high. During the interviews with banks, some portfolios with low sVaR were challenged and compared with banks that stated to adopt the same window stress period. It is apparent that modelling choices also play a key role in the dispersion.

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

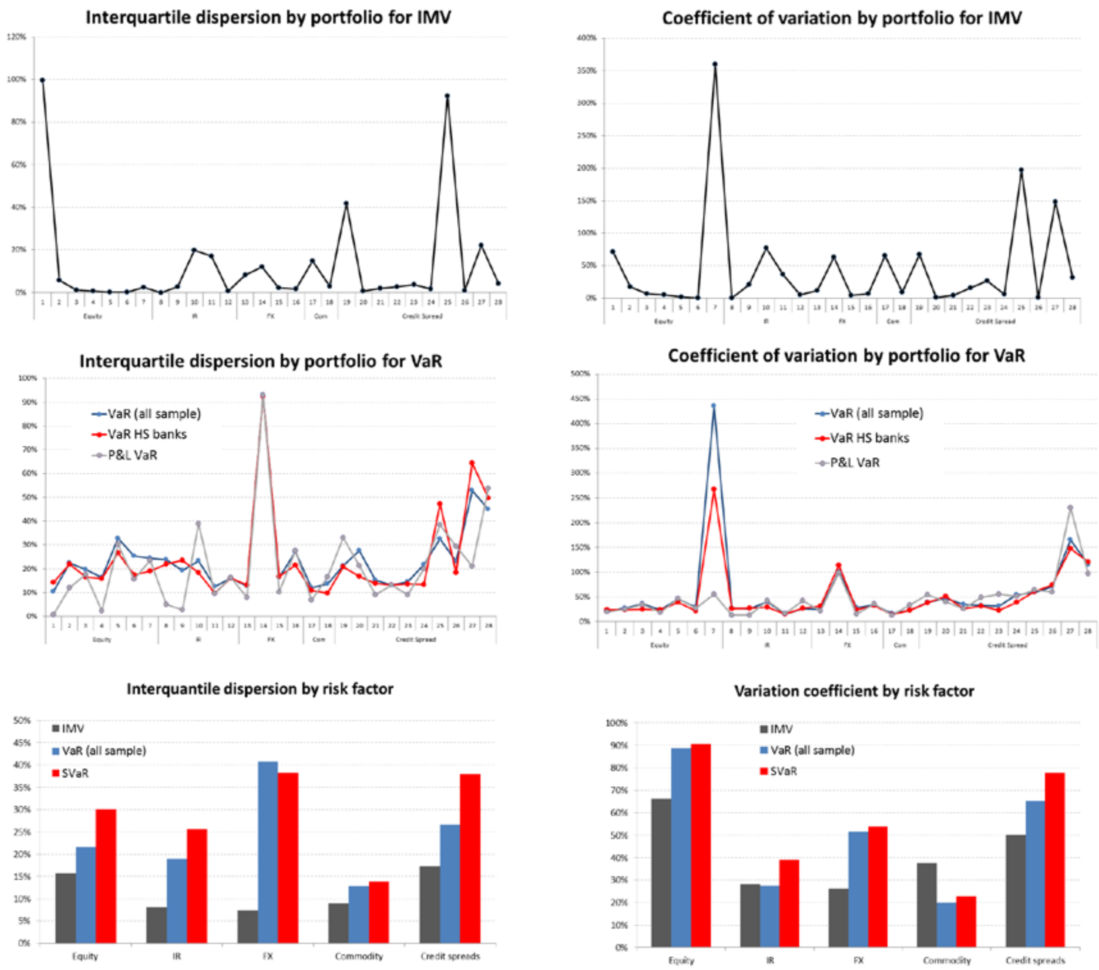


Table 4: Interquartile dispersion for IMV and risk metrics by risk factor

	IMV	*VaR (all sample)*	*SVaR*	*P&L VaR*	*VaR HS banks*	*VaR MC banks*	*Exp shortfall*
Equity	16%	22%	30%	15%	19%	26%	12%
IR	8%	19%	26%	15%	18%	9%	10%
FX	7%	41%	38%	37%	41%	41%	36%
Commodity	9%	13%	14%	12%	10%	15%	9%
Credit spr.	17%	27%	38%	25%	27%	19%	22%

Table 4 suggests that, with the exception of portfolios for which there seems to have been a misunderstanding, such as portfolios 10 and 27, 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 in line with both HS VaR and all-sample VaR, and, for some risk types, it tends to be lower.

When comparing variability for HS VaR and MC VaR, a clear conclusion could not be drawn, as the sample of MC banks is quite low. Regarding parametric banks, a similar analysis is not informative, as the total number of parametric banks is very low (i.e. 5 banks in the sample) and, furthermore, most of them could not provide results for many trades.

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, we used the sVaR–VaR ratio as one criterion for the ranking that determined if a bank should be invited for interview.

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 (portfolio 5), two interest rate trades (portfolios 9 and 10) and two credit spread trades (portfolios 27 and 28) 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	28.9%	68.4%	2.6%
	2	10.5%	86.8%	2.6%
	3	47.4%	50.0%	2.6%
	4	27.8%	72.2%	0.0%
	5	2.6%	69.2%	28.2%
	6	5.1%	94.9%	0.0%
	7	5.3%	92.1%	2.6%
IR	8	2.1%	83.0%	14.9%
	9	0.0%	77.6%	22.4%
	10	14.3%	63.3%	22.4%
	11	2.2%	89.1%	8.7%
	12	13.9%	83.3%	2.8%
FX	13	7.1%	90.5%	2.4%
	14	50.0%	47.5%	2.5%
	15	0.0%	97.5%	2.5%
	16	8.1%	89.2%	2.7%
Com	17	0.0%	100.0%	0.0%
	18	8.7%	91.3%	0.0%
Credit Spread	19	25.0%	75.0%	0.0%
	20	0.0%	93.8%	6.3%
	21	48.4%	51.6%	0.0%
	22	15.6%	84.4%	0.0%
	23	26.7%	73.3%	0.0%
	24	35.5%	64.5%	0.0%
	25	17.9%	78.6%	3.6%
	26	36.7%	60.0%	3.3%
	27	26.7%	53.3%	20.0%
	28	20.0%	48.0%	32.0%
All-in portfolio (1 to 28)**	29	4.7%	95.3%	0.0%
Equity (1 to 7)**	30	26.8%	73.2%	0.0%
Interest rate (8 to 12)**	31	0.0%	93.3%	6.7%
FX (13 to 16)**	32	18.6%	79.1%	2.3%
Commodity (17 and 18)**	33	11.5%	88.5%	0.0%
Credit spread (19 to 28)**	34	21.2%	78.8%	0.0%
Correlation Trading	35	0.0%	100.0%	0.0%
	36	25.0%	75.0%	0.0%
	37	25.0%	75.0%	0.0%

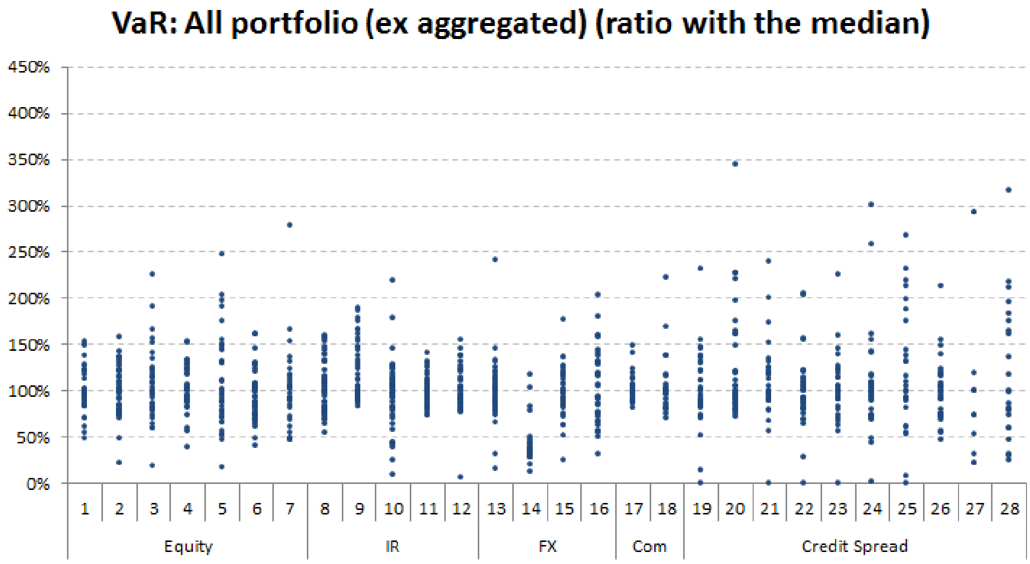
5.2 A closer look at the VaR and sVaR results

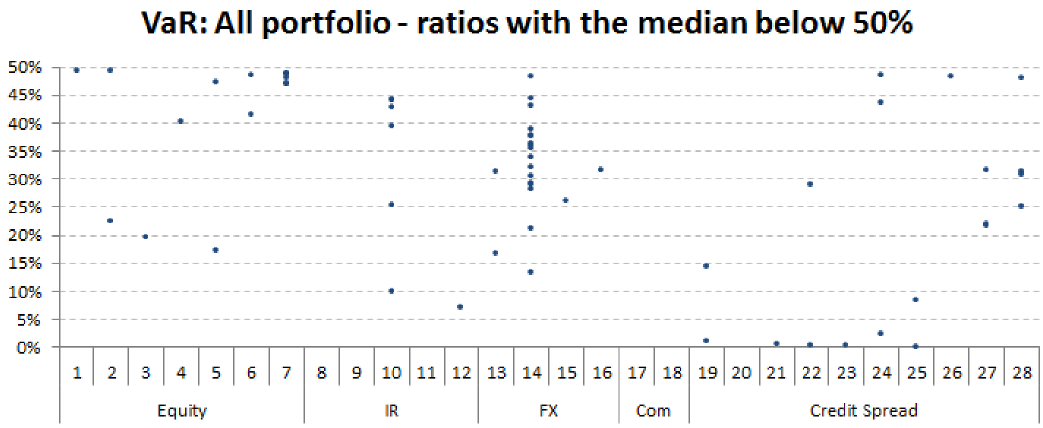
Figure 3 and Figure 4 give an overview of the VaR and sVaR results for portfolios 1 to 28, i.e. they do not include the aggregated portfolios, where fewer observations were available for the reasons explained above (see Section 3.4).

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

Especially for sVaR, the credit spread portfolios show a higher level of dispersion than the other asset classes. This is due to the higher complexity of some of these products and to the different banks' choices regarding the stress period.

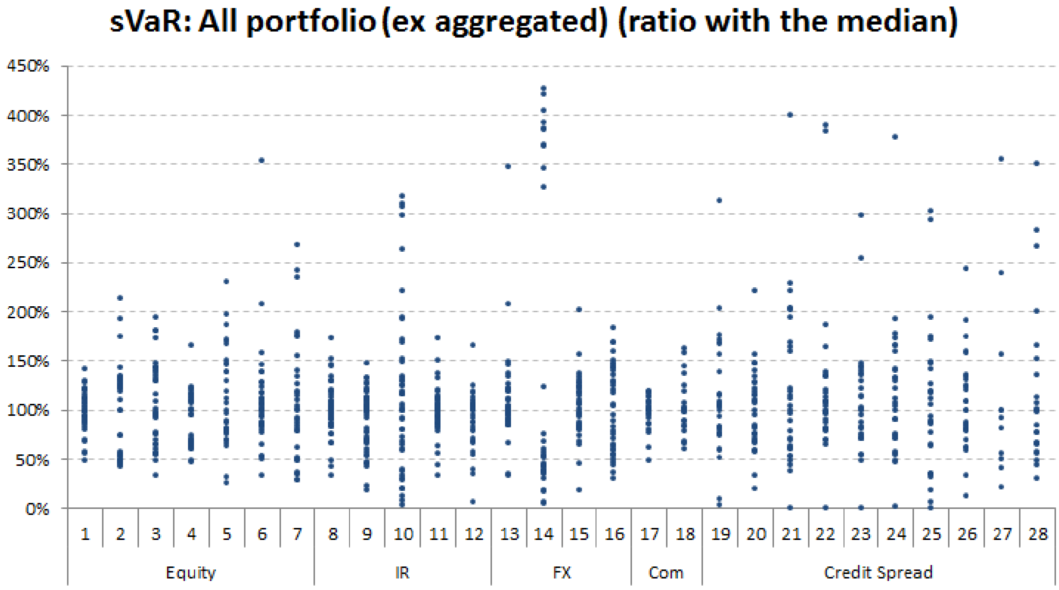
Figure 3: VaR submissions normalised by the median of each portfolio





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

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



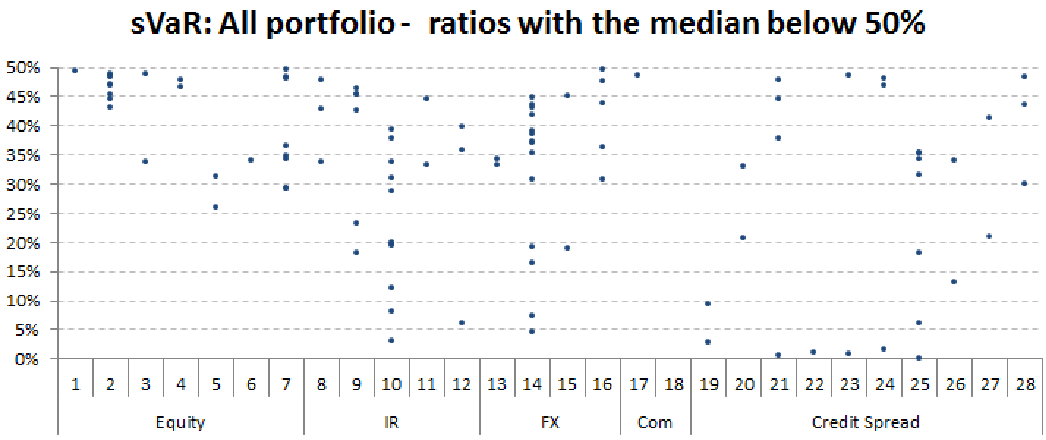


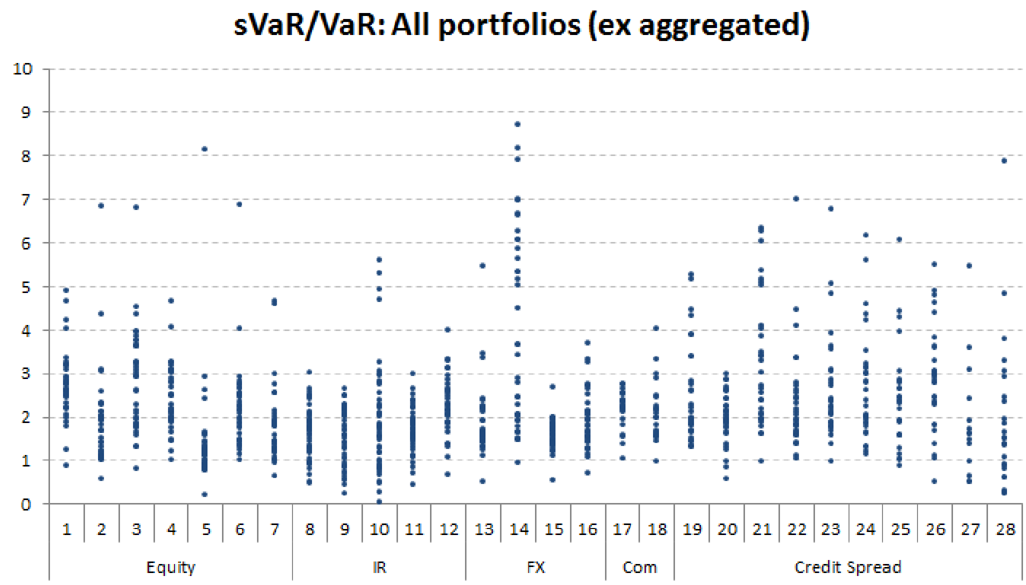
Table 16 and Table 17 in the Annex report VaR and sVaR statistics along with EU benchmarks for all HPE trades.

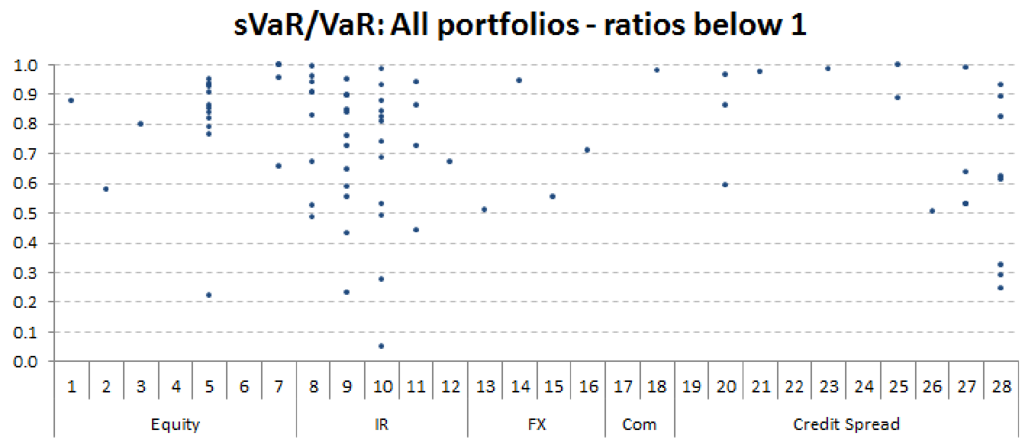
Comparison of sVaR to VaR ratios

Banks were ranked in relation to the full sample not only by their VaR and sVaR values but also by their sVaR–VaR ratio. In general, we would expect sVaR to be at least as high as VaR, as sVaR is calibrated to a 1-year period of significant stress. 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.

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 0.90 and 5.80. The portfolios with the lowest levels of dispersion for the sVaR–VaR ratio (excluding outliers) are portfolios 15 (FX knockout option) and 17 (commodity trade gold forward).

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





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

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. In general, we found that banks using absolute returns had a higher sVaR than banks using relative returns and, therefore, a higher sVaR–VaR ratio. During the interviews with the banks, it has been detected that absolute returns seem more commonly used for interest rates and credit spreads. Particular attention should be devoted to the MC simulations when very low rate and low credit spread environments have to be considered.

The strong dependence of sVaR on the specification of risk factor returns in the model is something (N)CAs should pay close attention to when reviewing banks' credit spread VaR models. In particular, banks' justification of their modelling choices should be challenged not only for the most recent historical period used for VaR but also for the corresponding 1-year sVaR period.

Drivers of variation

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 (67%). Although the majority of banks use the same methodological approach (i.e. HS), the dispersion of VaR remains significant, as other modelling choices play a key role (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

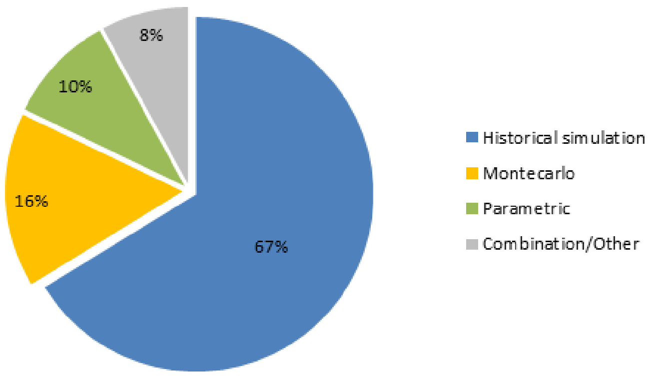
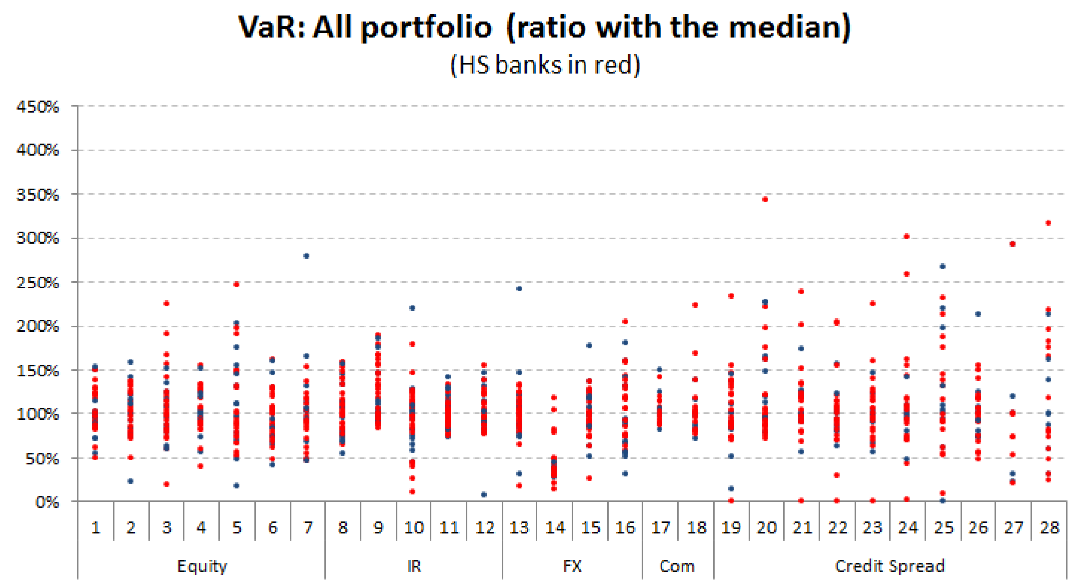
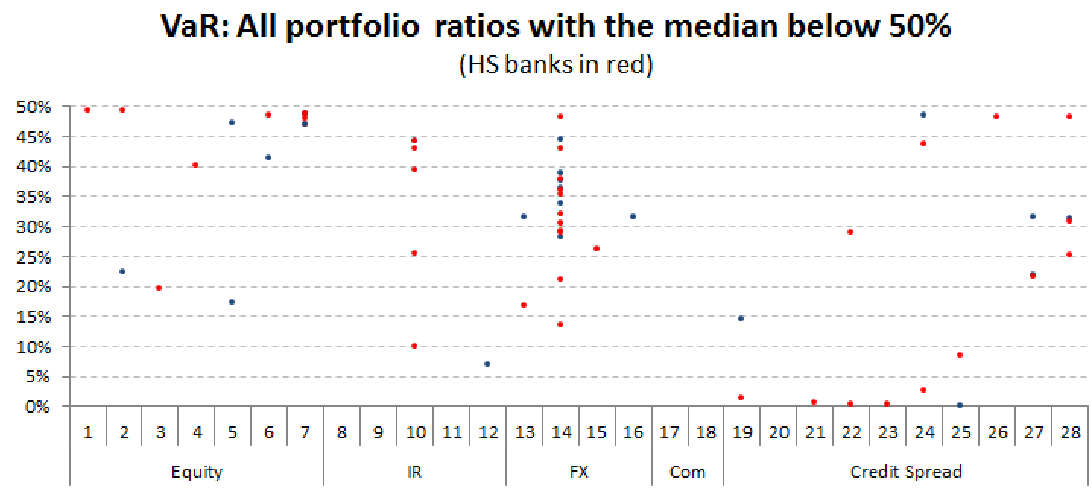


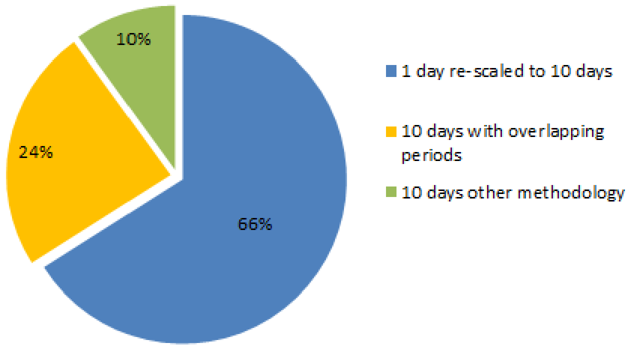
Figure 7: VaR submissions normalised by the median of each portfolio (by methodological approach)





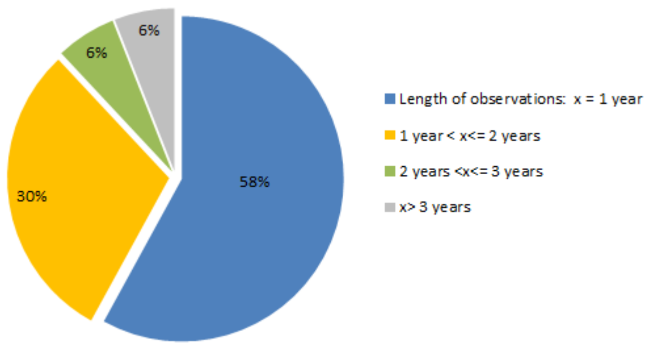
With regard to the regulatory 10-day VaR computation, the preferred method is rescaling the 1-day VaR to the 10-day VaR using the square-root-of-time approximation.

Figure 8: Qualitative data: VaR time scaling techniques



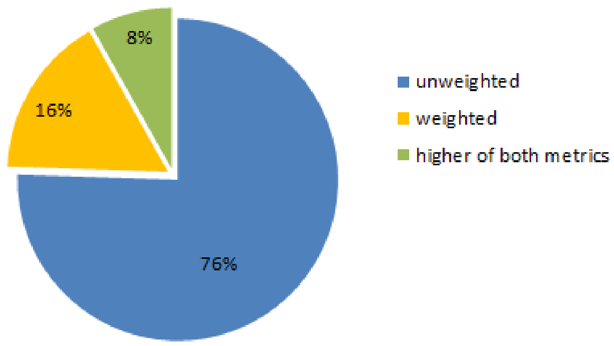
Concerning the historical lookback period used to calibrate banks' VaR models, more than half of the banks use the minimum period of 1 year (58%). Another 30% of the banks use a 2-year period.

Figure 9: Qualitative data: VaR lookback period length



As for the possible use of a data weighting scheme, most banks' models use unweighted data in the regulatory VaR computation (37 out of 49 respondents, or 76%).

Figure 10: Qualitative data: VaR weighting choices



Finally, with regard to supervisory actions on regulatory add-ons, 65% 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 3.5, with a maximum of 4.9. 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 NCAs for their supervised banks, and also from discussions with some banks during the interviews.

These responses suggest that the observed variation may be due to a number of different drivers. We have chosen to present our analysis using the following broad headings:

1. Supervisory actions;
2. Modelling differences; and
3. Other drivers of variation.

Supervisory actions

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 NCA 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).

Including the multipliers in our 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.

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.

Modelling differences

As explained in Section 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 to around 10 banks, since controlling for the subsequent modelling choices, and picking up banks with all completed results, drastically reduces the sample size.

The portfolios – portfolios 1, 11, 13 and 21 – 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).

As shown in Table 6 and Table 7, there is evidence that the modelling choices matter. For instance, for the subsamples of banks using the HS methodological approach, the choice of regulatory VaR stemming from a scaled 1-day VaR, a lookback period greater than 1 year, and use of unweighted returns seems to produce lower dispersion and more conservative VaR results (i.e. higher average VaR figures).

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 1	21%	25%	29%	17%	12%	29%
IR 11	17%	10%	15%	17%	20%	15%
FX 13	10%	21%	32%	17%	7%	42%
CS 21	17%	26%	19%	23%	18%	18%
mean	16%	20%	24%	18%	14%	26%

Table 7: Average regulatory VaR by modelling choice

	Average VaR subsamples					
	1-day	*10-day*	*1y*	*>1y*	*unweighted*	*weighted*
EQ 1	186,506	127,081	160,850	187,292	170,639	168,384
IR 11	190,118	179,277	182,763	175,917	178,659	174,838
FX 13	821,337	746,083	661,303	806,008	771,629	702,971
CS 21	80,158	78,633	72,453	81,828	76,063	68,002

Other drivers of variation

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

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.

Another driver of variation may be that certain risks are not captured in a model. Evidence of non-modelled risk factors can be obtained from the results for those hypothetical portfolios that are specifically designed to isolate individual risks, for example portfolio 28, which is mainly sensitive to the Quanto CDS basis. Relatively low submissions for these portfolios are most likely explained by banks not including this risk factor in their models. On the other hand, we need to keep in mind that banks may not have material exposure to this risk factor in their actual portfolios.

Moreover, the use of proxies leads to spurious variability in some of the hypothetical portfolios characterized by less liquid risk factors, for example some credit spreads. This consideration also applies to the sVaR. Furthermore, from some interviews with the banks, a lack of consensus around modelling of the basis risk between CDS and the equivalent bonds, and between the iTraxx index and its single names components, was found as a potential justification of the most remarkable deviations for the affected hypothetical trades.

Portfolio comparison

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, we would expect a more diversified portfolio to produce a lower VaR than a more concentrated portfolio.

This hypothesis can be analysed using portfolios 21 and 24 (Table 8). Both of these portfolios involve corporate instruments, yet portfolio 21 is more concentrated than portfolio 24. Against this background and in view of the specific portfolio definitions, one would expect the following result:

$$60\% \times VaR_{Portfolio\ 24} < VaR_{Portfolio\ 21};$$

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

Table 8: Portfolio comparison for VaR, sVaR and IRC

	*60% * VaR(port.24) < VaR(port.21)*	*60% * sVaR(port.24) < sVaR(port.21)*	*60% * IRC(port.24) < IRC(port.21)*
Num of banks	**2 out of 33**	**1 out of 33**	**0 out of 30**

The comparison between the two portfolios with respect to regulatory VaR shows that only 2 out of 33 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, all banks fulfil our *a priori* expectation.

When compared with last year's results, this finding provides evidence for the conjecture that banks are more consistent in their risk measure results.

5.3 Analysis of IRC

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).

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

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.

The number of submissions is particularly low 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.

As 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 Section 5.6, the expected diversification relationship holds for all submitted banks. In this case, the comparison can be based on missing risk factors, as extractable from portfolios for which banks submitted unrealistically low IRC results, such as zero. This is the case for the following portfolios:

- portfolio 8: Tenor basis – 5 banks do not appear to model this risk;
- portfolio 25: CDS-index basis – 8 banks do not appear to model this risk;
- portfolio 27: short index put on iTraxx Xover – 16 banks do not appear to model this risk; and,
- portfolio 28: Quanto CDS basis – 9 banks do not appear to model this risk.

It is recommended that (N)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.

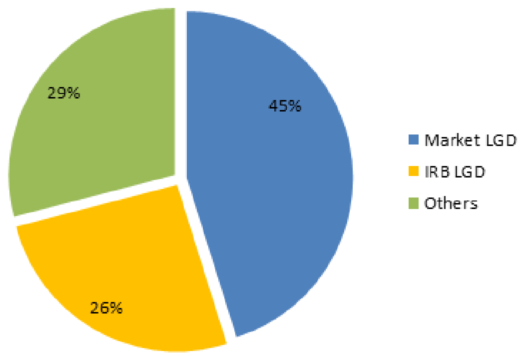
Particular attention from (N)CAs should be devoted to portfolio 8, a 'curve flattener' sovereign position on German government bonds, for which some banks have stated that their IRC result of zero is due to them assigning a zero PD to Germany owing to its AAA rating. IRC risk shows a higher level of dispersion for portfolio 8 than the dispersion observed in other credit spread portfolios, especially the simplest ones. In this regard, as reported above (see Section 5.2), regulatory differences in the treatment of sovereign exposures were identified as a driver of variation; some jurisdictions, for example, require a non-zero floor for the PD, while others allow banks to exclude sovereign exposure from the default component of IRC risk.

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.

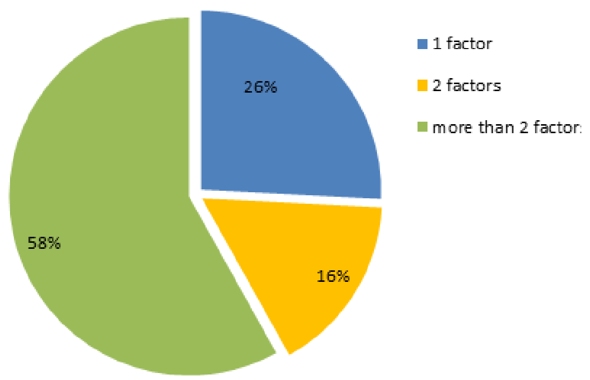
The responses to the qualitative questionnaire relating to the IRC methodological aspects suggest that the use of market LGD predominates across respondents (Figure 11). Both PD (15 respondents out of 26, or 58%) and transition matrices are mostly taken from rating agencies (20 respondents out of 26, or 77%). As it may be a key driver for the observed variability, the different choice for computing the transition matrices is an issue to be discussed with the selected subsample of banks during their respective interviews.

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



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 (17 respondents out of 26, or 65%).

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



Hence, in the context of IRC, the modelling practices across the sample of banks participating in the benchmarking exercise seem to be fairly 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	8	0	658,143	136,567	134,829	89,595	67,438	99%	28	45,356	122,273	187,700
Credit Spread	19	170,427	1,999,771	876,138	473,360	405,053	361,882	54%	25	475,500	887,791	1,207,500
	20	12,985	1,273,488	304,698	308,304	244,041	152,891	101%	27	97,735	189,794	458,358
	21	458,674	1,153,600	825,325	201,407	190,865	164,773	24%	26	662,003	841,216	988,472
	22	335,800	6,033,000	1,002,555	1,088,522	365,861	180,891	109%	26	519,122	616,995	1,114,000
	23	585,369	3,017,000	1,188,739	482,544	287,350	189,764	41%	25	915,163	1,058,895	1,423,188
	24	229,669	2,055,021	965,627	354,774	247,860	150,536	37%	26	783,052	973,180	1,049,000
	25	0	3,016,000	178,473	621,666	64,113	8,922	348%	23	72	8,922	133,500
	26	167,417	2,082,499	658,115	526,341	455,050	108,457	80%	28	397,451	459,147	671,670
	27	37,299	1,684,454	583,113	513,379	513,379	342,537	88%	12	181,118	485,700	934,810
	28	0	687,600	151,782	198,122	198,122	82,884	131%	22	7,695	88,369	210,671
All-in portfolio (1 to 28)**	29	2,017,599	5,538,100	3,305,385	1,229,325	1,229,325	776,646	37%	12	2,374,324	2,987,730	3,978,217
Credit spread (19 to 28)**	34	2,097,500	5,521,000	3,464,322	1,199,845	1,199,845	752,247	35%	13	2,406,499	3,055,540	4,019,143

[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 (29 to 34), 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 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, 25 banks provided results for IRC in relation to the IR and CS hypothetical trades, net of the aggregated portfolios where missing values were predominant. The trade with the lowest contribution was the 27th, the 'short index put on iTraxx Xover', primarily because of the perceived high complexity of this trade among some banks, already discussed in the previous sections.

5.4 Analysis of APR

In their responses to the qualitative questionnaire relating to the APR methodological aspects, all respondents, i.e. all 8 banks with an authorisation for CTP, stated that they use more than 2 modelling factors at the overall CTP model level.

With regard to the source of LGD estimates at the overall CTP model level, 50% of the respondents use market LGD, 2 banks (or 25%) use the LGD underlying their internal ratings-based approach for credit risk, and the remaining 2 banks (or 25%) use other sources. As in the case of IRC, the source for PD estimates (6 respondents out of 8, or 75%) and transition matrices (6 respondents out of 8, or 75%) are mostly rating agencies. The liquidity horizon applied at the portfolio level for the CTP model is predominantly between 9 and 12 months (7 respondents out of 8, or 88%).

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.

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 is 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.

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 parameters simulations (i.e. credit spreads, recovery rates, default correlations, CDS/Index basis, etc.) and transition matrices for rating migrations.

The average variability for the APR charge is around 50% 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 meaning for analysis, for example with respect to VaR, is possible. Table 10 should thus 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	*35*	808,295	7,715,352	2,836,629	2,822,080	2,822,080	419,639	99%	6	1,006,474	1,327,023	4,835,604
	36	108,563	1,475,272	504,176	498,156	498,156	123,832	99%	6	234,379	362,399	482,043
	37	15,580	4,598,376	801,860	1,860,020	1,860,020	21,815	232%	6	30,518	44,864	76,961

[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 (29 to 34), 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.*

5.5 P&L analysis

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.[15] 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.

This analysis allows us to detect banks that systematically exhibit a high or a low correlation level in their P&L. We 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. We 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.

Across the 28 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.

Another useful check for the submitted P&L results was a comparison of the ratio between the P&L VaR computed by 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.

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

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

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

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.

As expected, there is evidence that larger aggregated portfolios exhibited greater diversification benefits than smaller ones. The diversification benefit for all-in portfolios 29 (all portfolios) and 34 (credit spread), 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, we 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 28)**	29	67%	10%	13	57%	70%	74%	13%
Equity (1 to 7)**	30	46%	9%	35	41%	47%	51%	11%
Interest rate (8 to 12)**	31	49%	8%	35	47%	51%	54%	7%
FX (13 to 16)**	32	34%	41%	31	3%	5%	87%	93%
Commodity (17 and 18)**	33	28%	7%	22	23%	26%	31%	15%
Credit spread (19 to 28)**	34	49%	11%	15	42%	48%	51%	10%

sVaR

		Other statistics			Percentiles			
	Port.	Ave.	STDev	Num obs.[3]	25th	50th	75th	Interquartile dispersion
All-in portfolio (1 to 28)**	29	66%	9%	13	60%	68%	70%	8%
Equity (1 to 7)**	30	40%	20%	35	27%	45%	54%	33%
Interest rate (8 to 12)**	31	49%	6%	35	45%	50%	53%	8%
FX (13 to 16)**	32	30%	32%	32	7%	11%	45%	73%
Commodity (17 and 18)**	33	14%	5%	22	11%	12%	15%	14%
Credit spread (19 to 28)**	34	54%	11%	15	51%	54%	60%	8%

IRC

		Other statistics			Percentiles			
	Port.	Ave.	STDev	Num obs.[3]	25th	50th	75th	Interquartile dispersion
Credit spread (19 to 28)**	29	47%	11%	11	39%	49%	52%	14%

5.7 Dispersion in capital outcome

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: (1) using the banks' total multiplication factor; and (2) 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.

An analysis of the dispersion of these variables suggests that the average dispersion of the implied capital outcome tends to be lower than the average dispersion observed for the other risk metrics. Clearly, the proxy tends to smooth the dispersion of each individual addend. This is most visibly the case for the interest rate and commodities risk factors (Table 12). In the case of FX risk, it is worth recalling the clusters observed in the portfolio 14 results. This portfolio is the cross-currency basis swap, where, as discussed during some interviews, the discounting and forwarding curves, as well as the intra-year cross-currency basis, are supposed to be important drivers.

Table 12: Interquartile dispersion for capital proxy

	Capital proxy (banks own mult)	*Capital proxy (fixed mult, =3)*
Equity	26%	25%
IR	19%	14%
FX	40%	38%
Commodity	13%	11%
Credit spr.	34%	33%

Accordingly, it may be deduced that the idiosyncratic factors that drive variability in an individual portfolio do not compound when they are aggregated. On the contrary, they tend to compensate for one another when MR metrics are summed.

Table 12, moreover, suggests that variability does not seem to be influenced by regulatory add-ons. With the exception of interest rate products, the ranges of capital value dispersion remain broadly the same whether or not the banks actual multiplication factors are used. The effect is more pronounced for interest rate products, because many more banks contribute to this risk class. Therefore, there is more impact on regulatory add-ons across banks.

The EBA used implied capital outcome as another criterion for identifying banks to invite for interview. Looking at this capital outcome proxy by risk category, we can arrive at a ranking of the banks on the basis of how they are distributed below the first quartile or above the third quartile.

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

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 8 and 9 of the draft RTS on supervisory benchmarking. This section highlights some key information derived from these assessments.

The EBA designed a questionnaire regarding this assessment, which asked NCAs 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 NCAs' ongoing monitoring activities.

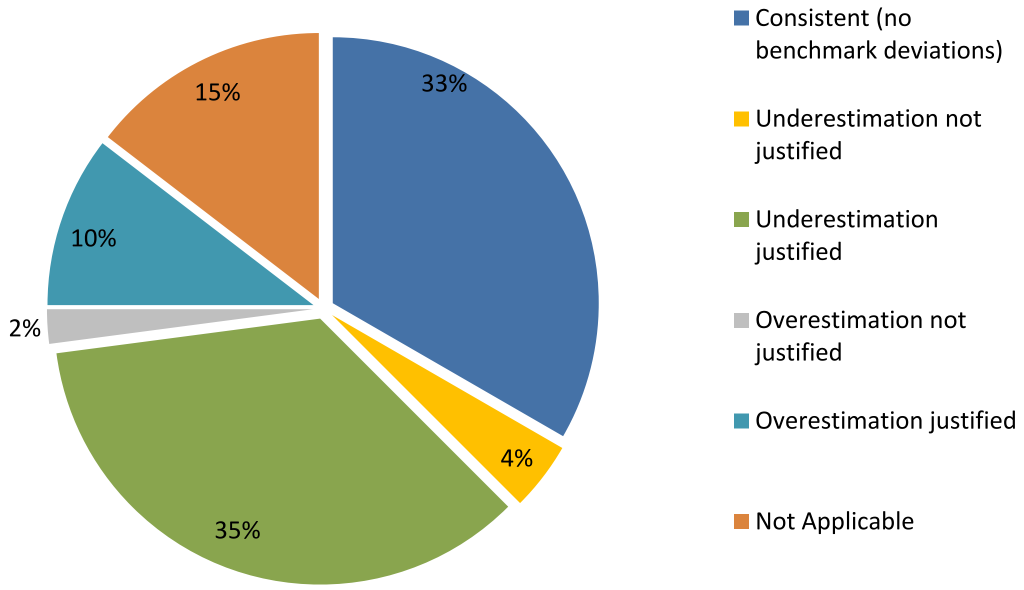
A total of 48 questionnaires, provided by the NCAs, from 12 jurisdictions, have been considered in this assessment of the MR benchmarking exercise.

Regarding the level of priority of the assessments, 13 banks (around 27%) are reported to be 'high priority' for intervention by NCAs. NCAs gave high priority to those banks that were either an outlier in the analysis or identified by the EBA 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.

Figure 13 reports the CAs' own overall assessments of the levels of own funds requirements. When it comes to benchmark deviations, justified or not, 25 banks were reported by CAs as under- or overestimating MR own funds requirements, of which 22 provided justifications for this. Obviously, 'not justified' implies that further and targeted CA investigation is required. Finally, 16 banks had consistent results (i.e. no benchmark deviations).

Briefly, CAs' assessments acknowledge 3 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 much 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



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.

Two banks were identified for possible underestimation, not justified, during the banks' internal validation 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.

CAs planned some actions for 17 banks (e.g. reviewing the banks' internal VaR and IRC models, alongside the TRIM (Targeted Review of Internal Models) in-depth assessment, where applicable within the Single Supervisory Mechanism countries; a supervisory extra charge; stringent conditions on any extension of the internal model approach; further internal model investigation at peer level; etc.).

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

7. Conclusion

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.

It must be 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 lead to conclusions regarding real under- or overestimations for the MR capital charge. However, the analysis will certainly help in determining possible supervisory activities to address uniformity and harmonisation, and in promoting more in-depth future investigations on this matter.

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 across the banks.

In particular, the report provides inputs for CAs on areas that may require their further investigation, such as accentuated IMV variability for some complex 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. As a general remark, particular attention should be devoted to further enhancement of the internal models, ensuring the consistent representation of and adequate conservatism for a low rates environment (both for interest rates and credit spread rates).

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.

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 (N)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.

Annex

Table 13: Banks participating in the 2016/17 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	BHF Bank
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, SA
ES	Banco Bilbao Vizcaya Argentaria, SA
ES	Banco Santander SA
ES	Criteria Caixa Holding, SA
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	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 Plc
GR	Alpha Bank SA

GR	Eurobank Ergasias SA
GR	National Bank of Greece SA
IT	Banca Popolare di Milano Scarl
IT	Banco BPM SpA
IT	Intesa Sanpaolo SpA
IT	UniCredit SpA
NL	ABN AMRO Groep NV
NL	Coöperatieve Rabobank UA
NL	ING Groep NV
NL	NIBC Holding NV
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**
No. of banks	*2*	*2*	*8*	*2*	*4*	*4*	*14*	*3*	*4*	*4*	*1*	*3*

Table 14: Portfolios underlying the HPE

Risk factor	Port.ID	Portfolio description
EQUITY	1	Equity index futures on FTSE 100
	2	Bullish leveraged trade on Google
	3	Volatility trade on S&P 500
	4	Volatility trade on FTSE 100
	5	Covered call on Generali
	6	Collar strategy on Sanofi
	7	long strangle 12-m maturity on Aviva
IR	8	Curve flattener trade on sovereign treasuries
	9	Interest rate swap
	10	2y swaption on 10y IRS
	11	IRS USD 10y vs 1y
	12	Infation zero coupon swap
FX	13	Covered FX call on EUR/USD
	14	Mtmkt Cross Crcy Basis Swap 2y USD 3m LIBOR vs. EUR 3m EURIBOR swap
	15	Knock-out currency option
	16	Double no touch binary currency option
COMMODITIES	17	Long short-term ATM OTC Ldn Gold fwd & Short long-term ATM OTC Ldn Gold fwd
	18	Short oil put options
CREDIT SPREAD	19	Sovereign CDS portfolio
	20	Sovereign bond/CDS portfolio
	21	Sector concentration portfolio
	22	Diversified index portfolio
	23	Diversified index portfolio with higher concentration
	24	Diversified corporate portfolio
	25	Index basis trade on iTraxx 5y EU
	26	CDS bond basis
	27	Short index put on iTraxx EU Xover
	28	Quanto CDS on ES with delta hedge
ALL IN	29	All-in portfolio
ALL EQ	30	All Equity portfolios
ALL IR	31	All IR portfolios
ALL FX	32	All FX portfolios
ALL COM	33	All commodity portfolios
ALL CS	34	All credit spread portfolios
CTP 1	35	Long position in spread hedged equity tranche of CDX.NA.IG index
CTP 2	36	Long position in spread hedged mezzanine tranche of CDX.NA.IG index
CTP 3	37	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

(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			2	16	19	1	38
	2			1	17	18	2	38
	3		1	4	14	18	1	38
	4			2	15	18	1	36
	5		2	5	11	19	2	39
	6			2	15	20	2	39
	7	3	1	2	14	12	6	38
IR	8			4	21	22		47
	9			10	17	22		49
	10		1	1	23	18	6	49
	11				23	23		46
	12			1	17	17	1	36
FX	13		1		20	19	2	42
	14	17			2	4	17	40
	15			1	20	18	1	40
	16		1	4	13	18	1	37
Com	17				11	13		24
	18		1	1	10	11		23
Credit Spread	19		1	1	13	15	2	32
	20	1	3	5	7	16		32
	21		2	2	11	15	1	31
	22		2	2	10	16	2	32
	23		1	1	11	16	1	30
	24	1	1	2	10	14	3	31
	25		4	3	8	11	2	28
	26	1	1	1	12	14	1	30
	27	3	2		3	4	3	15
	28	3	2	5	3	8	4	25
All-in portfolio (1 to 28)**	29		1	2	17	18	5	43
Equity (1 to 7)**	30			3	14	23	1	41
Interest rate (8 to 12)**	31				20	23	2	45
FX (13 to 16)**	32		1	1	17	11	13	43
Commodity (17 and 18)**	33		1	1	9	13	2	26
Credit spread (19 to 28)**	34		2	2	11	15	3	33
Correlation Trading	35	1	1		1	4	1	8
	36	1		1	1	2	3	8
	37	2		1		3	2	8

Table 16: VaR statistics

		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
Equity	1	88,010	238,189	162,074	33,454	26,243	13,169	21%	24	149,624	159,038	184,191
	2	17,521	123,238	79,259	21,487	17,627	17,712	27%	35	60,969	78,113	96,319
	3	48,932	559,400	260,234	95,299	74,567	47,848	37%	36	202,650	248,603	302,293
	4	79,374	305,836	205,839	50,490	42,451	34,809	25%	31	176,500	197,825	245,264
	5	5,171	73,514	32,811	14,968	12,737	9,475	46%	35	21,713	29,725	42,900
	6	13,760	53,448	32,734	9,796	8,792	7,838	30%	35	24,422	33,100	40,938
	7	963	196,971	7,451	32,501	903	422	436%	36	1,449	2,044	2,391
IR	8	59,200	170,700	110,394	30,769	26,923	24,177	28%	40	83,774	107,099	136,333
	9	88,825	201,000	124,040	32,518	28,004	9,067	26%	40	101,323	106,142	149,746
	10	2,600	56,800	25,129	10,305	8,371	5,450	41%	39	19,300	25,820	31,000
	11	130,829	233,984	176,018	27,418	23,502	21,128	16%	41	150,268	176,614	192,821
	12	11,800	258,167	171,372	45,243	32,315	22,864	26%	32	146,808	166,857	203,367
FX	13	134,769	1,174,774	787,679	195,787	156,222	102,402	25%	39	700,169	803,502	905,904
	14	11,573	1,134,000	432,391	438,529	427,835	70,815	101%	34	31,200	85,645	862,612
	15	48,257	327,500	181,893	51,680	39,787	29,980	28%	34	157,100	184,063	218,179
	16	51,105	179,200	103,699	35,474	32,649	31,048	34%	34	75,025	99,456	131,044
Com	17	62,635	114,831	79,504	13,525	10,983	8,300	17%	22	68,422	76,664	87,279
	18	111,264	262,535	159,929	36,489	26,832	22,852	23%	20	132,332	155,184	173,773
Credit Spread	19	733	137,035	61,794	24,380	15,885	12,725	39%	27	49,787	58,900	76,670
	20	91,534	436,006	167,236	79,496	61,269	25,900	48%	29	115,608	126,600	204,300
	21	404	144,879	77,023	26,847	18,553	13,992	35%	27	65,095	72,072	88,399
	22	89,398	285,100	148,513	49,282	41,208	17,972	33%	27	121,100	139,072	157,926
	23	75,163	295,700	142,791	45,500	31,199	21,395	32%	25	120,800	131,261	161,511
	24	1,619	194,000	69,838	38,060	26,978	10,465	54%	27	48,107	64,404	74,869
	25	4	69,186	29,539	17,335	14,577	9,926	59%	24	18,549	25,860	36,563
	26	36,600	368,570	86,887	61,231	26,303	18,524	70%	28	56,777	75,863	90,801
	27	6,291	373,156	61,212	101,477	101,477	10,437	166%	12	18,217	28,655	59,139
	28	7,019	259,260	48,214	55,812	30,551	12,863	116%	22	20,700	27,883	54,542
All-in portfolio (1 to 28)**	29	816,648	2,215,040	1,309,342	415,199	415,199	272,654	32%	12	965,563	1,279,436	1,511,293
Equity (1 to 7)**	30	314,483	613,750	422,375	85,671	77,366	50,078	20%	28	360,550	392,452	454,402
Interest rate (8 to 12)**	31	208,906	440,223	319,302	63,032	57,641	39,278	20%	32	266,237	319,615	357,500
FX (13 to 16)**	32	2,899	1,711,702	799,720	537,673	502,047	325,172	67%	27	191,600	1,072,789	1,232,004
Commodity (17 and 18)**	33	15,139	332,065	171,762	58,676	32,171	19,434	34%	21	145,687	164,469	183,903
Credit spread (19 to 28)**	34	281,268	878,372	456,862	165,478	165,478	72,586	36%	13	355,691	429,797	491,100
Correlation Trading	35	22,824	1,475,039	478,161	474,682	474,682	130,940	99%	7	258,268	283,158	617,751
	36	15,482	371,984	113,612	120,596	120,596	48,796	106%	7	34,678	83,474	137,875
	37	5,953	67,088	24,272	22,764	22,764	6,275	94%	7	8,474	12,228	43,007

[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 (29 to 34), 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

		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
Equity	1	291,671	605,599	437,578	68,876	53,259	46,121	16%	24	397,127	425,700	488,160
	2	59,127	293,525	130,905	60,673	54,000	47,421	46%	35	68,744	137,479	177,114
	3	230,092	1,328,954	721,052	295,770	272,519	262,606	41%	36	429,021	682,478	947,567
	4	242,742	657,031	470,069	134,719	127,866	122,163	29%	31	343,906	519,253	590,915
	5	8,582	183,980	44,969	36,192	27,139	9,835	80%	35	26,287	32,900	49,357
	6	21,791	133,317	64,495	20,616	15,683	11,009	32%	35	53,750	64,000	75,565
	7	1,000	249,399	10,516	41,004	2,114	1,531	390%	36	1,941	3,416	5,056
IR	8	57,000	291,900	173,316	48,317	36,255	26,722	28%	40	144,328	169,076	201,740
	9	37,940	308,359	190,171	65,375	53,845	47,178	34%	40	142,858	208,918	235,869
	10	3,481	137,366	46,224	34,355	31,026	14,733	74%	39	17,042	43,240	56,000
	11	99,166	515,541	296,168	75,194	49,634	35,407	25%	41	256,901	298,593	331,618
	12	25,400	681,621	367,108	122,831	93,219	51,700	33%	32	286,117	411,676	432,963
FX	13	439,668	4,576,403	1,405,232	607,943	285,019	143,932	43%	39	1,181,200	1,318,765	1,562,708
	14	18,948	2,582,960	947,777	851,884	811,136	394,130	90%	34	161,656	418,869	1,695,000
	15	54,467	449,200	283,060	79,312	64,158	51,744	28%	34	237,600	287,734	342,806
	16	71,088	360,295	198,179	84,564	79,009	79,511	43%	34	115,470	195,643	274,492
Com	17	85,128	209,096	168,465	30,744	24,238	14,717	18%	22	151,441	174,900	189,458
	18	196,398	517,823	325,872	88,211	74,367	58,614	27%	20	265,386	326,765	371,409
Credit Spread	19	3,798	408,000	144,255	78,477	54,094	30,981	54%	27	99,710	130,691	181,057
	20	64,557	694,100	313,972	131,123	102,671	89,850	42%	29	220,473	312,807	398,874
	21	1,564	501,987	244,633	140,907	127,623	85,200	58%	27	134,200	219,400	369,467
	22	163,700	972,446	314,231	201,009	156,033	47,892	64%	27	205,300	250,087	335,342
	23	149,516	913,500	342,903	176,027	130,468	87,018	51%	25	227,199	307,036	399,582
	24	2,606	589,000	175,756	109,031	66,466	63,141	62%	27	110,671	156,269	221,533
	25	6	212,300	74,859	55,783	47,258	34,006	75%	24	24,900	70,291	101,243
	26	28,105	517,204	232,186	98,595	74,654	47,343	42%	28	170,316	212,243	281,114
	27	9,275	682,838	153,483	233,800	233,800	25,729	152%	12	30,568	44,400	131,666
	28	16,461	694,812	82,241	146,084	53,129	14,716	178%	22	25,100	37,668	62,655
All-in portfolio (1 to 28)**	29	1,436,300	3,728,804	2,627,637	670,292	670,292	305,612	26%	12	2,388,274	2,578,297	3,092,427
Equity (1 to 7)**	30	441,985	2,420,967	1,077,640	357,918	221,901	167,216	33%	28	876,520	1,070,288	1,224,900
Interest rate (8 to 12)**	31	209,323	778,153	543,149	125,806	105,643	77,996	23%	32	482,160	573,690	612,753
FX (13 to 16)**	32	11,815	3,535,540	1,615,624	842,859	713,220	310,672	52%	27	1,018,749	1,783,528	2,035,302
Commodity (17 and 18)**	33	55,176	534,509	309,377	110,108	84,039	41,066	36%	21	249,403	290,200	331,266
Credit spread (19 to 28)**	34	573,248	1,319,696	857,363	212,034	212,034	114,698	25%	13	644,439	848,506	919,432
Correlation Trading	35	28,954	1,769,201	700,253	541,192	541,192	159,437	77%	7	331,199	631,665	791,102
	36	21,081	599,679	276,698	234,430	234,430	144,062	85%	7	59,850	165,143	478,295
	37	10,645	91,901	43,490	31,284	31,284	16,067	72%	7	19,125	26,711	68,780

[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 (29 to 34), 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

		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
Equity	1	114,533	250,996	147,107	29,373	29,373	1,549	20%	17	137,591	139,140	139,760
	2	3,110	131,948	90,803	23,168	12,441	9,930	26%	25	82,219	90,663	104,513
	3	98,031	572,372	264,713	91,363	59,173	43,935	35%	25	216,799	259,067	310,068
	4	160,334	326,632	190,184	36,666	22,779	3,842	19%	24	174,827	179,610	183,412
	5	11,065	56,921	23,136	10,978	8,347	5,247	47%	24	15,811	19,631	29,634
	6	12,649	32,938	19,678	5,437	4,718	1,679	28%	26	16,118	17,323	22,136
	7	1,398	9,487	2,772	1,557	596	564	56%	24	1,959	2,419	3,162
IR	8	76,058	148,386	98,753	13,652	9,001	4,993	14%	28	92,691	98,031	102,606
	9	52,380	135,978	103,897	13,571	7,142	3,020	13%	28	100,531	103,550	106,494
	10	6,325	44,430	24,561	10,558	9,462	8,347	43%	26	14,573	26,438	33,084
	11	128,515	235,698	169,849	27,969	24,538	16,179	16%	28	151,190	166,417	182,703
	12	9,487	377,462	159,662	67,316	41,869	26,548	42%	25	134,114	159,644	186,574
FX	13	177,088	1,109,042	756,597	169,172	114,250	64,216	22%	29	704,469	736,811	828,244
	14	23,008	1,135,258	439,124	436,000	421,100	43,418	99%	25	30,801	66,426	847,729
	15	158,114	288,792	195,192	31,037	24,507	23,518	16%	26	168,070	194,028	206,147
	16	29,314	151,478	94,270	34,395	30,820	23,947	36%	25	66,408	86,248	116,880
Com	17	66,976	110,711	81,094	10,739	10,739	2,026	13%	15	75,764	76,424	87,023
	18	3,029	171,643	125,277	42,240	42,240	16,760	34%	14	114,101	122,837	159,444
Credit Spread	19	25,763	151,789	63,561	34,900	29,235	19,143	55%	22	37,286	56,862	74,241
	20	86,472	359,529	141,170	57,389	33,707	24,645	41%	24	104,528	122,083	161,276
	21	47,583	142,666	81,392	21,262	15,489	7,278	26%	22	74,694	83,739	89,641
	22	94,979	439,557	153,149	75,444	40,724	17,791	49%	22	113,842	128,471	148,627
	23	78,772	483,828	148,812	83,636	32,542	13,241	56%	21	115,819	123,509	139,140
	24	21,782	192,899	74,471	38,123	25,861	12,284	51%	21	50,596	69,490	75,857
	25	3	97,205	36,746	23,539	23,539	14,025	64%	19	23,951	28,460	53,759
	26	36,749	276,770	80,114	48,252	21,850	15,811	60%	23	48,339	72,732	88,544
	27	7,099	373,155	52,208	120,405	120,405	3,162	231%	9	10,326	12,649	15,811
	28	6,325	177,170	46,868	45,415	45,415	25,858	97%	17	18,974	36,281	63,246
All-in portfolio (1 to 28)**	29	742,258	1,834,958	1,087,679	408,227	408,227	134,835	38%	8	771,596	891,762	1,398,751
Equity (1 to 7)**	30	281,695	553,408	368,779	65,352	47,864	20,066	18%	20	335,363	347,851	379,473
Interest rate (8 to 12)**	31	203,995	332,039	275,174	36,554	32,471	26,829	13%	23	241,798	282,217	306,867
FX (13 to 16)**	32	94,868	1,456,450	713,714	488,001	488,001	315,952	68%	19	135,280	976,459	1,092,421
Commodity (17 and 18)**	33	68,071	179,689	140,309	29,424	29,424	14,784	21%	14	126,491	138,693	162,746
Credit spread (19 to 28)**	34	270,915	801,331	422,353	165,355	165,355	90,968	39%	10	295,743	379,473	487,886
Correlation Trading	35	262,149	597,670	481,722	150,788	150,788	44,245	31%	4	385,665	533,533	577,778
	36	36,888	201,431	106,273	75,962	75,962	47,964	71%	4	45,423	93,387	167,123
	37	13,147	46,596	30,422	15,981	15,981	12,882	53%	4	16,990	30,971	43,853

[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 (29 to 34), 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

		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
Equity	1	128,758	283,703	158,382	34,111	34,111	1,126	22%	17	147,847	152,223	152,916
	2	4,357	121,900	98,453	22,163	9,927	1,405	23%	25	94,673	98,621	111,019
	3	106,990	537,060	256,332	83,373	54,340	9,885	33%	25	227,576	241,914	289,290
	4	152,371	363,863	205,251	39,213	18,131	2,104	19%	24	189,117	195,770	204,881
	5	15,825	64,510	33,726	11,021	8,502	1,820	33%	24	26,704	31,806	37,637
	6	15,284	38,832	21,610	5,656	4,463	933	26%	26	17,929	20,191	24,666
	7	0	3,450	2,209	994	981	199	45%	26	1,852	2,271	3,162
IR	8	80,773	127,025	100,306	10,250	8,341	1,752	10%	28	95,064	99,627	105,711
	9	67,776	134,623	110,085	12,068	7,818	1,006	11%	28	106,319	108,815	113,449
	10	6,325	39,987	26,683	10,096	9,219	2,283	38%	26	19,460	28,094	35,312
	11	146,930	244,235	176,830	23,008	18,763	3,950	13%	28	158,904	174,311	185,001
	12	11,068	314,097	174,882	57,379	38,596	3,740	33%	25	171,215	183,412	194,663
FX	13	189,737	1,042,787	813,915	147,015	77,808	13,253	18%	29	781,601	820,615	880,642
	14	24,141	1,018,780	449,823	441,089	435,035	16,315	98%	25	31,524	75,733	889,127
	15	164,231	267,079	195,786	27,206	23,181	4,164	14%	26	175,143	192,832	204,494
	16	36,777	163,384	103,181	35,677	31,989	9,239	35%	25	73,348	99,081	132,289
Com	17	76,088	95,987	82,817	6,097	6,097	1,000	7%	15	78,354	82,746	85,673
	18	3,368	172,940	123,283	41,246	41,246	4,742	33%	14	116,135	120,123	151,069
Credit Spread	19	37,148	157,416	81,280	24,153	15,313	2,542	30%	22	69,570	74,864	90,878
	20	96,593	415,501	149,971	67,140	36,696	9,417	45%	24	105,086	129,317	175,386
	21	51,816	185,742	97,080	25,484	13,830	1,875	26%	22	90,905	96,975	102,762
	22	118,542	342,712	189,716	46,294	29,198	2,786	24%	22	171,215	177,764	186,704
	23	104,405	365,243	173,828	53,021	27,870	3,998	31%	21	154,750	167,394	174,364
	24	23,070	169,182	83,671	28,945	17,855	1,909	35%	21	75,895	81,165	87,203
	25	3	76,437	38,517	21,044	21,044	3,997	55%	19	27,105	31,709	56,982
	26	39,528	298,203	84,724	52,792	24,849	6,892	62%	23	52,347	74,656	96,449
	27	8,112	386,948	57,870	123,589	123,589	1,285	214%	9	12,649	15,067	27,557
	28	8,362	171,134	58,138	52,561	52,561	10,172	90%	17	17,788	53,143	67,813
All-in portfolio (1 to 28)**	29	849,072	2,357,757	1,298,940	520,271	520,271	66,083	40%	8	941,816	1,058,045	1,592,484
Equity (1 to 7)**	30	325,715	616,899	380,815	75,768	53,404	5,557	20%	20	338,963	352,067	382,963
Interest rate (8 to 12)**	31	204,065	347,323	289,691	37,494	31,810	8,167	13%	23	268,067	290,402	323,785
FX (13 to 16)**	32	109,099	1,325,031	735,562	488,519	488,519	61,513	66%	19	138,613	1,010,685	1,132,608
Commodity (17 and 18)**	33	74,865	187,158	149,036	28,778	28,778	3,040	19%	14	140,194	142,721	173,102
Credit spread (19 to 28)**	34	351,343	1,169,184	549,386	235,244	235,244	15,701	43%	10	455,368	472,412	581,859
Correlation Trading	35	324,317	687,795	523,879	151,020	151,020	26,795	29%	4	421,324	541,702	626,434
	36	34,830	194,602	98,187	71,560	71,560	11,743	73%	4	44,523	81,658	151,850
	37	15,514	46,520	29,720	15,160	15,160	3,630	51%	4	16,943	28,423	42,497

[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 (29 to 34), 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

		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
Equity	1	0.88	4.90	2.75	0.79			29%	38	2.36	2.64	3.16
	2	0.58	6.85	1.86	1.09			59%	38	1.13	1.67	2.09
	3	0.80	6.82	2.87	1.14			40%	38	1.88	2.94	3.64
	4	1.02	4.66	2.44	0.76			31%	36	1.95	2.24	3.04
	5	0.22	8.13	1.41	1.20			85%	39	0.93	1.16	1.34
	6	1.02	6.87	2.23	0.97			43%	39	1.55	2.17	2.53
	7	0.66	4.66	1.81	0.86			47%	38	1.27	1.67	2.02
IR	8	0.48	3.01	1.65	0.59			36%	47	1.20	1.71	1.99
	9	0.23	2.64	1.60	0.64			40%	49	1.05	1.69	2.17
	10	0.05	5.60	1.94	1.22			63%	49	1.03	1.75	2.37
	11	0.44	3.00	1.73	0.50			29%	46	1.50	1.73	1.95
	12	0.67	4.00	2.26	0.67			29%	36	1.88	2.16	2.62
FX	13	0.51	5.47	1.87	0.77			41%	42	1.51	1.63	2.18
	14	0.94	8.71	3.91	2.26			58%	40	1.91	3.17	5.91
	15	0.55	2.70	1.62	0.33			20%	40	1.43	1.65	1.84
	16	0.71	3.70	1.93	0.66			34%	37	1.52	1.79	2.15
Com	17	1.05	2.77	2.18	0.43			20%	24	2.08	2.25	2.43
	18	0.98	4.04	2.11	0.68			32%	23	1.59	2.00	2.36
Credit Spread	19	1.31	5.25	2.50	1.12			45%	32	1.69	1.98	2.97
	20	0.60	2.98	1.99	0.58			29%	32	1.74	1.99	2.41
	21	0.98	6.34	3.25	1.49			46%	31	2.01	2.71	4.05
	22	1.04	7.00	2.30	1.15			50%	32	1.61	1.93	2.59
	23	0.99	6.79	2.63	1.21			46%	30	1.85	2.24	3.01
	24	1.14	6.18	2.70	1.23			45%	31	1.87	2.40	3.14
	25	0.89	6.07	2.40	1.15			48%	28	1.59	2.34	2.80
	26	0.51	5.49	2.87	1.18			41%	30	2.31	2.89	3.52
	27	0.53	75.57	6.84	18.41			269%	15	1.18	1.63	2.75
	28	0.25	7.86	1.96	1.66			85%	25	0.89	1.51	2.44
All-in portfolio (1 to 28)**	29	1.01	3.55	2.08	0.49			24%	43	1.76	1.98	2.40
Equity (1 to 7)**	30	1.07	4.07	2.59	0.72			28%	41	2.18	2.59	3.06
Interest rate (8 to 12)**	31	0.48	2.90	1.82	0.52			28%	45	1.53	1.84	2.25
FX (13 to 16)**	32	0.50	12.47	3.00	3.01			100%	43	1.61	1.81	2.61
Commodity (17 and 18)**	33	1.05	3.64	1.87	0.63			34%	26	1.45	1.63	2.01
Credit spread (19 to 28)**	34	1.31	4.76	2.23	0.91			41%	33	1.55	1.94	2.79
Correlation Trading	35	1.02	2.79	1.72	0.59			34%	8	1.25	1.56	2.16
	36	1.36	5.71	2.46	1.37			56%	8	1.70	1.83	2.47
	37	1.17	7.70	2.86	2.26			79%	8	1.52	1.69	2.98

[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 (29 to 34), 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

		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
Equity	1	0.66	1.68	1.13	0.24			21%	27	1.00	1.10	1.26
	2	0.56	21.16	1.66	3.91			236%	26	0.74	0.90	1.02
	3	0.68	2.74	1.07	0.37			34%	27	0.94	0.98	1.07
	4	0.65	1.64	1.09	0.23			21%	26	0.99	1.03	1.16
	5	0.35	9.38	2.02	1.71			85%	27	1.00	1.45	2.37
	6	0.90	2.73	1.85	0.51			28%	27	1.46	2.01	2.17
	7	0.32	1.28	0.82	0.22			27%	25	0.65	0.88	0.95
IR	8	0.55	1.75	1.22	0.28			23%	33	1.04	1.18	1.45
	9	0.85	2.50	1.26	0.36			29%	35	1.00	1.06	1.51
	10	0.41	1.57	1.00	0.21			21%	35	0.89	1.00	1.14
	11	0.88	1.29	1.07	0.12			11%	32	0.97	1.04	1.18
	12	0.66	10.75	1.46	1.84			126%	27	1.00	1.12	1.26
FX	13	0.80	1.52	1.12	0.19			17%	32	0.96	1.07	1.28
	14	0.57	1.83	1.09	0.28			26%	31	0.93	1.01	1.17
	15	0.60	1.95	0.99	0.26			26%	30	0.81	1.04	1.08
	16	0.77	2.06	1.24	0.33			27%	27	1.02	1.06	1.35
Com	17	0.74	1.41	0.99	0.17			17%	17	0.88	0.99	1.05
	18	0.91	44.65	3.97	10.51			265%	16	0.99	1.23	1.59
Credit Spread	19	0.53	2.57	1.28	0.52			41%	26	0.86	1.11	1.64
	20	0.84	1.78	1.14	0.22			19%	26	1.00	1.06	1.24
	21	0.61	1.67	1.03	0.23			22%	25	0.89	1.02	1.10
	22	0.65	1.67	1.08	0.24			22%	26	0.95	1.08	1.18
	23	0.61	1.76	1.06	0.25			23%	24	0.93	1.04	1.16
	24	0.62	1.44	1.05	0.23			22%	25	0.93	1.01	1.27
	25	0.37	1.48	0.93	0.34			37%	23	0.62	1.00	1.25
	26	0.50	1.94	1.10	0.34			31%	25	0.91	1.01	1.33
	27	1.00	5.31	2.37	1.48			63%	11	1.31	1.76	2.55
	28	0.33	2.17	1.11	0.42			38%	20	0.87	1.04	1.20
All-in portfolio (1 to 28)**	29	0.24	1.98	1.11	0.29			26%	31	0.95	1.10	1.25
Equity (1 to 7)**	30	0.77	1.64	1.13	0.19			17%	29	1.03	1.12	1.20
Interest rate (8 to 12)**	31	0.38	1.59	1.15	0.25			22%	33	1.01	1.13	1.35
FX (13 to 16)**	32	0.80	36.37	2.34	6.12			262%	32	1.04	1.17	1.41
Commodity (17 and 18)**	33	0.74	1.93	1.24	0.31			25%	19	1.01	1.17	1.40
Credit spread (19 to 28)**	34	0.54	1.92	1.12	0.28			25%	27	0.99	1.11	1.26
Correlation Trading	35	0.51	1.27	0.92	0.25			27%	5	0.81	0.99	1.03
	36	0.44	1.59	1.04	0.37			36%	5	0.94	1.04	1.18
	37	0.49	1.12	0.82	0.27			33%	5	0.50	0.93	1.05

[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 (29 to 34), 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.*

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