EBA REPORT

RESULTS FROM THE 2016 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)
EBA	European Banking Authority
ES	expected shortfall
EES	empirical estimate of expected shortfall
EQ	equity
EU	European Union
FRTB	Fundamental Review of Trading Book
FX	foreign exchange
HPE	hypothetical portfolio exercise
HS	historical simulation
IMV	initial market valuation
IQD	interquantile dispersion
IR	interest rates
IRC	incremental risk charge
ITS	implementing technical standards
LGD	loss given default
MC	Monte Carlo
MR	market risk
MRWA	market-risk-weighted asset(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 supervisory benchmarking study 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 and portfolios for the benchmarking exercises on internal models for market risk (MR).

It outlines the conclusions obtained from a market hypothetical portfolio exercise (HPE) that was conducted by the EBA during 2015/16. The main objective of this exercise was to assess the level of variability observed in market-risk-weighted assets (MRWA) produced by banks' internal models.

The exercise was performed on a sample of 50 European banks from 12 jurisdictions that submitted data for 35 market portfolios in all asset classes (equity (EQ), interest rates (IR), foreign exchange (FX), commodities (CO), credit spread (CS)) and three correlation trading portfolios (CTP), for a total of 38 portfolios.

These portfolios are described in Commission Implementing Regulation (EU) 2016/2070 of 14 September 2016 laying down implementing technical standards for templates, definitions and IT-solutions to be used by institutions when reporting to the European Banking Authority and to competent authorities in accordance with Article 78(2) of Directive 2013/36/EU (the CRD) of the European Union Parliament.[1] It was published and entered into force as Regulation EU 2016/2070 on 2 December 2016 in the *Official Journal of the European Union*, L 328.

The aim of this study is not only to assess the overall level of variability in MRWA produced by banks' internal models but also to examine and highlight the different drivers behind the dispersion observed. In particular, the assessment aims to examine differences between drivers produced by approaches explicitly contemplated in regulation and those related to other causes. Therefore, as envisaged by Article 78 of the CRD, the benchmarking exercise should reinforce and complement monitoring by national competent authorities (NCAs) on banks' internal models, but it does not replace the regular assessment and validation of internal models run by competent authorities (CAs).

In addition to the analytical part of the exercise, the EBA, jointly with CAs, conducted a set of interviews with banks' representatives to discuss the assumptions behind banks' models, the banks' results compared with the benchmarks and how banks carried out the benchmarking exercise. The dialogue with banks were helpful in bringing to light any missing risk factors, providing information on how additional risk factors were modelled and taken into account, and providing feedback to improve forthcoming benchmarking exercises.

[1] http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32016R2070.

Finally, NCAs were asked to provide the EBA with responses to a questionnaire about the actions they planned to perform, for each participating bank, based on the findings of the benchmarking exercise.

Main findings of the benchmarking analysis

The report presents the observed variability measures in terms of interquantile dispersion (IQD).[2] IQD is more robust than the usual coefficient of variation[3] when the sample comes from an unknown fat-tailed distribution. As in the previous exercises on MRWA variability, significant dispersion for all the risk measures provided by banks is observed in the IQD metric.

This has been the first benchmarking exercise on MRWA with widespread participation (50 EU banks with validated internal models for MR) and for many banks it was their first MR benchmarking exercise. As a consequence, many data quality issues were found and tentatively addressed to reduce spurious dispersion; therefore, the results should be treated with caution.

From a risk factor perspective, interest rates show a lower level of variability than the other asset classes because of the more consistent practices and more homogeneous assumptions used across the banks for modelling interest rate risk.

The analysis shows high dispersion in the initial market valuation (IMV) results as a result of the different interpretations and market practices adopted by banks. Some of these issues have been addressed and the quality of the data has improved thanks to successive resubmissions. The evidence collected will be taken into account in future exercises dealing with banks' pricing techniques, especially for complex derivatives, to achieve more harmonisation.

Regarding the single risk measures, across all asset classes, as expected the overall variability for value at risk (VaR) is lower than that observed for stressed VaR (sVaR) (respectively 23% and 30%).

More complex measures such as incremental risk charge (IRC) and all price risk (APR) show a much higher level of dispersion (respectively 42% and 52%).

To deepen the analysis of VaR and further investigate the variability drivers, different VaR metrics have been computed and compared with banks' reported VaR.

In particular:

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

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

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

- a comparable VaR, called HS VaR, which is the reported VaR only for those firms that use an HS approach.

According to the results obtained, variability slightly decreases when one of the above homogeneous VaR metrics is applied, leading to the conclusion that the model approach alone does not affect VaR variability. Others drivers such as ‘risks not captured in the model’ or the choice of absolute versus relative returns can explain further variability in the results.

Dispersion for sVaR is generally higher than that observed for regulatory VaR. In any case, the stressed period was not harmonised in the sample, so further discussion in relation to sVaR is not possible. Different choices for the stressed period are permitted by the Capital Requirements Regulation (CRR), and these choices are considered and challenged in the regulatory validation process.

It is clear that the variability observed could be produced by differences either in modelling or in the data period used to compute sVaR. However, allowing banks to use the stressed period that they apply in computing MR fund requirements helps to gain a closer estimation of implied capital needs from the HPEs, which is the main objective of this analysis.

In addition, a comparison across banks of the ratio between sVaR and VaR for the first 28 portfolios is included. There is evidence of high dispersion in the ratio for some trades, especially for credit risk trades, but, on average, the ratio is around 2.5.

A lack of consistent practice among banks for modelling some of the risk factors was found during some interviews with banks, especially with the most sophisticated ones. In particular, this is the case for the basis risk between a credit default swap (CDS) and its equivalent bond, the basis risk between an index and its components, the forward equity volatility surface and, in general, portfolios including sovereign risk. This last was clearly observed in relation to IRC risk. The results for those portfolios comprising sovereign positions exhibit a significantly higher level of dispersion (59%). In addition, during the interview process conducted with a subset of participating banks, it emerged that both banks’ modelling choices (especially the assumptions concerning the migration or transition matrix) and regulatory differences in the treatment of sovereign exposures for IRC play a role in the variability of the results. As a result, on average the variability for IRC is significantly higher than that observed for VaR. This confirms what has already been found in a previous analysis of MRWA variability.[4]

Regarding APR, the average variability is higher than that observed for all other metrics considered in the report (52%). However, the APR assessment suffers from a lack of contributions, since few banks are authorised for this risk metric and most banks are reducing their exposure to CTP, so these portfolios are in run-down mode.

The diversification benefits observed for VaR, sVaR and IRC in the aggregated portfolios were also analysed. As expected, larger portfolios generally exhibited greater diversification benefits than

[4] EBA, *Report on variability of risk weighted assets for market risk portfolios*, 17 December 2013.

smaller ones. The level of dispersion observed in diversification benefits is generally lower than that in the correspondent metric.

In light of the Fundamental Review of Trading Book (FRTB) proposed by the Basel Committee and already integrated into the CRR/CRD IV (currently under consultation), an assessment of the variability of empirical estimates of expected shortfall (EES) at a 95% confidence level has also been carried out. What arises from the analysis is that the dispersion in this metric across risk factors is lower than that found for VaR and for P&L VaR, especially for equity trades. EES tends to show the same variability among risk metrics for the other risk factors.

These findings are in line with those of previous exercises, so they have the same implications. Previous exercises were dedicated to a very small set of internationally based investment banking corporations, while this study includes all current (both general and specific) MR validated banks and sheds more light on the issues discussed. This assessment covers the entire population of EU banks with internal models on MR at the highest level of consolidation.

Dispersion in capital outcome

An assessment regarding possible capital requirements underestimations has been also conducted in parallel with the variability driver analysis. However, the analysis represents only a potential assessment of capital underestimation, as the results come from hypothetical portfolios and the capital requirements were defined using a proxy.

The proxy for the implied capital requirements from the hypothetical trades was defined as the sum of VaR and sVaR across all portfolios both multiplied by the common floor equal to 3 and multiplied by the total regulatory multiplier assigned to each bank by its supervisory CA.[5] This metric enables us to compare banks and assess their variability in this regard.

The average variability across the sample, measured by the IQD coefficient, is quite high, especially for the most complex portfolios (over 30%). A similar analysis for the aggregated portfolio was particularly difficult because of the poor quality of the results and the low number of contributions for each aggregated portfolio and its trade components.

The implied capital needs proxy has highlighted a few cases of underestimation with regard to the benchmarks, and these have been discussed, and further clarified, during interviews. Moreover, cases of capital overestimation were also investigated.

Supervisory recommendations

[5] The regulatory multiplier was set to zero when information was not available.

From the CAs’ assessment questionnaire, a few banks were made high priorities for intervention. Those banks were identified by the EBA for the interviews, and CAs have already planned some actions as part of their ongoing model monitoring activities.

This report also highlights some areas that may require further investigation by CAs, such as accentuated pricing variability for equity derivatives, commodities trades and credit spread products. Generally, FX trades and credit spread portfolios show more dispersion than other asset classes for the analysed risk metrics. When reviewing firms’ models, supervisors should pay attention to credit VaR models by challenging both VaR and sVaR assumptions and modelling choices. Similarly, particular attention has to be dedicated to any model extension to FX derivatives.

Furthermore, CAs should assess the materiality of risk factors not in VaR (‘risk not captured by the model’) and, where appropriate, challenge the models to improve the coverage (e.g. through internal model authorisation extension). For IRC models, supervisors should ensure that banks review the transition matrix in a prudent and adequate way.

2. Introduction and legal background

European legislators have acknowledged the need to ensure consistency in the calculation of risk-weighted assets (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 shall 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 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 the first MRWA variability assessment performed over a large sample of banks (50 banks at the highest level of consolidation in 12 jurisdictions within the EU). The banks participating in this exercise are those that have been granted permission to calculate their own funds requirements using internal models for one or more of the following risk categories:

- general risk of equity instruments;
- specific risk of equity instruments;
- general risk of debt instruments;
- specific risk of debt instruments;
- FX risk;
- commodities risk; and
- correlation trading portfolio.

Permission is required for each risk category. Since many banks do not have permission for all of the risk categories, the number of contributions for each hypothetical portfolio varies across the sample.

The assessed MR results, when provided and where applicable, are VaR, sVaR, IRC and APR for specific and aggregated trades. A preliminary assessment of IMV was done to detect the pricing ability of the participating banks.

Furthermore, banks using an HS approach for VaR have been requested to deliver 1 year of P&L data for each of the individual and aggregated portfolios modelled. The objective of requesting this additional P&L information was to use the data vector to perform alternative calculations for VaR, controlling, as far as possible, for the different options that banks can apply within regulation.

3. Main features of the 2016 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 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 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 market hypothetical portfolios composed of both non-CTP and CTP, as set out in Annex V to the Benchmarking ITS. The exercise includes 35 general portfolios (28 individual and 7 aggregated), capitalised under the VaR, sVaR and IRC models, comprising both 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 the less complex products; the second (portfolio 30) encompasses all products; the third (portfolio 31) is made up of all equity portfolios; the fourth (portfolio 32) is made up of all interest rate portfolios; the fifth (portfolio 33) is made up of all FX portfolios; the sixth (portfolio 34) is made up of all commodities portfolios; and, finally, the seventh (portfolio 35) 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 CDX.NA.IG index series 23 v1. The portfolios are constructed by hedging each index tranche with CDX.NA.IG index series 23 v1 5Y CDS to achieve zero CS01 as of 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.[6]

[6] https://www.eba.europa.eu/regulation-and-policy/other-topics/regulatory-and-implementing-technical-standards-on-benchmarking-portfolios

3.2 Data collection process

The data for the supervisory benchmarking exercise are submitted by banks to NCAs using the supervisory reporting infrastructure. Banks submitted the specified templates provided in the ITS, where applicable.

IMV

The reference date for IMV was 26 October 2015 4.30 p.m. London time (5.30 p.m. CET). Banks entered all positions on 15 October 2015 ('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 meant the marked to market of each hypothetical portfolio was delivered to the EBA in the last two weeks of July 2016.[7]

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 exclude to the extent possible counterparty credit risk when valuing the risks of the portfolios.

Banks should calculate 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 for the exercise.

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

All collected data were submitted for a preliminary analysis to spot any possible misinterpretation of the common instructions set out in ITS/RTS on benchmarking and any outliers, as defined hereafter.

3.3 Participating banks

A total of 50 banks representing 12 EU countries participated in the exercise (see Table 17: Banks participating in the 2015/16 EBA MR benchmarking exercise in the Annex). All EU banks with MR

[7] For this year's exercise, both IMVs and risk measures were delivered at the same time from mid-July to late November 2016.

internal models approved by CAs were asked to submit data for this benchmarking exercise at the highest level of consolidation.

NCAs are in charge of conducting similar benchmarking investigations for results at a 'solo' level within each own jurisdiction for eligible banks.

3.4 Data quality issues

The data collection process aims at ensuring the reliability and validity of the data obtained. In this regard, it is obvious that an unwanted variability driver (which would pollute the results obtained) could be produced by misunderstandings around the portfolios and the specific instruments included in them.

A preliminary IMV analysis was necessary to spot anomalies or misunderstandings regarding the interpretation of each portfolio. Where the price of the portfolio lay outside a certain range, more investigation had to be done by the NCA, which could if necessary ask the bank for a repricing and a resubmission. This process should guarantee that all the risk measures are provided according to a correct interpretation of the portfolios.

For the 2015/2016 exercise, the IMV and the risk measures were exceptionally submitted at the same time. For this reason, in many cases it was not possible to recompute the risk measures once a misinterpretation in the related IMV had been found. In addition, some banks mentioned many difficulties in computing repricing long after the prescribed valuation date. As a consequence, there were few resubmissions, and this has impacted the final quality of the data.

Another significant data issue was related to the aggregated portfolio figures. In particular, some banks reported the IMVs and the risk measures for the aggregated portfolios without including all the components.[8] As a result, those submissions were not taken into account, as they were not comparable with those valued in full. The percentage of figures discarded is reported in the following analysis.

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

[8] Some banks reported these values for aggregated portfolios taking into account the 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 capital purposes. This is reasonable and it allows a smaller but more homogeneous sample to be analysed when considering the aggregated portfolios.

Finally, during an interview with one bank, it was discovered to have misunderstood the exercise and how to carry it out; therefore, its contributions were discarded before the final benchmarks were computed.

4. Market risk benchmarking framework

The aim of the benchmarking exercise is to assess the variability in banks' MR models and identify which are 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 10, etc. Likewise, when modelling IRC, firms 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 (CRR), provided they have been agreed upon with the CA during the validation process. Therefore, given the wide range of approaches that 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 and which may cause variability, such as differences in simulation engines, differences in pricing model assumptions, volatility, correlations and other indirect risk factor estimates, additional risk factors considered in the models, different approaches to P&L computation and attribution, 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 through a limited portfolio exercise, since these effects are entirely portfolio-dependent. To assess these effects, it would be necessary to have a much more realistic portfolio, comprising thousands of instruments and including partial model approval. However, some of these supervisory actions can be properly assessed; in particular, 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 might include:

- misunderstandings regarding the positions or risk factors involved;
- model not fully implemented;
- missing risk factors not incorporated in the portfolio;
- differences in calibration or data series used in modelling simulation;
- additional risk factor incorporated in the portfolio;
- alternative model assumptions applied; and
- differences attributable to the methodology used (i.e. Monte Carlo (MC) versus HS or parametric).

4.1 Outlier analysis

Participating banks were asked to provide an IMV for all modelled portfolios. Some of the data points received were considered outlier values and excluded from the analysis.

The presence of clear outliers in the data used to assess variability is deemed inappropriate, since these data points are likely to weigh heavily in the results, creating a distorted picture of the normal level of variability observed.

Extreme values were initially defined as values outside a two standard deviations range from the median. The truncated standard deviation, which does not take into account extreme values (as it is computed excluding the values below the 5th and above the 95th percentile), was also considered. Since the data often 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.

The normal standard deviation is not appropriate because the quality of the data was very low for this year’s exercise.

If a bank’s IMV was found to be an extreme value for a particular portfolio, then all the risk measures related to that particular portfolio were removed from the computation of the final statistics. This approach has further increased the quality of the data, but, at the same time, it has led to a reduction in the observations available for the computation of the benchmarks.

Data scarcity has been the main issue, especially for the aggregated portfolios, as outlined in section 3.4, as the aggregated portfolios were populated when not all portfolios constituting the aggregated one were priced. This led to a number of extreme values over the total number of submissions, greater than 60% for some aggregate portfolios.

The dispersion across the contributions is summarised by the IQD coefficient, which is more robust when data come 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.

Table 1: IMV statistics and extreme values

Statistics for IMV

		Other statistics						Percentiles				
	Port.	Min	Max	Ave.	STDev	STDev_trun	Num obs. [3]	25th	50th	75th	Extreme Values % of total	Interquartile dispersion
Equity	1.1	-806,530	1,931,665	802,687	970,751	945,655	40	24,768	28,370	1,904,018	2%	97%
	1.2	140,096	11,025,824	498,990	1,754,094	28,482	38	203,740	210,573	217,927	13%	3%
	1.3	-5,992,468	1,044,280	703,463	1,086,648	23,952	40	862,478	869,866	881,179	20%	1%
	1.4	-315,503	-188,585	-231,317	22,948	17,146	37	-229,670	-228,089	-226,437	8%	1%
	1.5	-126,353	53,065	-43,456	36,801	26,684	24	-55,951	-44,612	-34,596	17%	24%
	1.6	50,397	172,028	122,476	27,213	23,394	35	114,133	130,610	137,262	14%	9%
	1.7	-135,096	50,903	-92,049	46,044	38,552	32	-117,800	-113,058	-80,034	13%	19%
IR	1.8	-17,333,638	-15,985,261	-17,071,534	326,288	281,092	47	-17,262,000	-17,260,859	-16,630,200	27%	2%
	1.9	-12,036	75,197	29,374	9,662	3,358	49	26,837	30,292	31,866	18%	9%
	1.10	-272,079	103,000	-83,922	58,398	40,637	48	-99,314	-95,770	-84,005	24%	8%
	1.11	925,696	1,222,933	1,130,323	58,317	44,500	34	1,097,497	1,142,946	1,167,833	3%	3%
	1.12	-779,890	-346,475	-701,828	63,729	15,094	36	-715,044	-712,180	-705,105	14%	1%
FX	1.13	-1,019,958	98,020	-814,427	179,613	76,453	46	-897,051	-853,197	-771,862	11%	8%
	1.14	-1,941,790	737,160	481,555	423,633	181,587	44	540,907	576,547	656,095	11%	10%
	1.15	-254,784	486,221	408,163	137,153	17,966	45	422,511	439,424	450,919	11%	3%
	1.16	0	0	0	0	-	30	0	0	0	3%	0%
Com	1.17	-941,730	72,000	-34,284	200,069	86,158	27	4,335	14,128	18,892	7%	63%
	1.18	-219,141	-117,535	-165,782	18,817	11,888	24	-173,831	-165,817	-159,173	16%	4%
Credit Spread	1.19	10,336	353,020	146,960	95,793	88,745	36	103,327	118,719	176,849	16%	26%
	1.20	8,628,961	12,467,656	11,337,872	674,584	460,366	35	11,072,180	11,441,360	11,657,409	14%	3%
	1.21	82,424	861,738	184,673	127,990	31,039	32	149,688	172,390	179,070	18%	9%
	1.22	-141,651	205,254	160,965	51,829	10,691	38	163,250	168,338	173,988	15%	3%
	1.23	3,035	366,966	164,478	57,293	36,457	34	148,810	153,689	159,869	14%	4%
	1.24	116,289	554,135	414,690	95,849	79,567	31	362,997	453,487	467,785	19%	13%
	1.25	-16,472	47,933	4,148	11,933	7,905	29	-1,681	989	11,343	13%	135%
	1.26	7,364,181	9,843,593	8,806,599	490,955	381,235	31	8,668,535	8,885,740	8,991,884	16%	2%
	1.27	-890,493	2,563	-344,754	360,068	360,068	18	-757,283	-84,164	-56,925	10%	86%
	1.28	-78,701	-6,160	-51,361	21,679	19,722	26	-67,211	-58,339	-45,747	22%	19%
All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29	1,575,197	6,775,361	4,239,527	1,543,974	1,543,974	16	3,155,988	4,211,822	5,375,265	63%	26%
All-in portfolio (1 to 28)**	1.30	3,731,926	8,775,797	6,067,972	1,281,829	1,281,829	14	5,064,890	6,483,442	6,835,317	69%	15%
Equity (1 to 7)**	1.31	-424,360	3,481,183	1,509,668	1,261,895	1,165,570	22	659,585	768,666	3,230,692	60%	66%
Interest rate (8 to 12)**	1.32	-17,136,687	-16,200,268	-16,765,175	341,495	327,456	27	-17,022,810	-16,948,259	-16,341,889	45%	2%
FX (13 to 16)**	1.33	-525,048	1,280,051	136,131	289,318	196,025	38	97,679	177,251	240,055	27%	42%
Commodity (17 and 18)**	1.34	-1,002,635	-59,181	-192,504	199,607	86,353	22	-156,508	-142,403	-125,440	19%	11%
Credit spread (19 to 28)**	1.35	19,901,150	22,849,940	21,191,317	873,627	873,627	14	20,516,436	20,990,960	21,515,075	66%	2%
Correlation Trading	2.1	-4,764,826	6,617,265	1,918,528	4,598,472	4,598,472	10	-4,517,370	4,187,796	4,589,074	0%	12700%
	2.2	-1,416,272	1,220,059	-340,847	1,070,057	1,070,057	10	-1,298,863	-640,884	405,683	0%	191%
	2.3	-386,661	386,433	73,006	319,305	319,305	10	-312,761	164,529	359,833	0%	1429%

15%	*Extreme values ratios above 15% have been highlighted in yellow*

Table 2: Average interquantile dispersion by risk factor

Average Interquantile dispersion by risk factor

	IMV
Equity	22%
IR	5%
FX	7%
Commodity	34%
Credit spreads	30%

The other results of this extreme value analysis are summarised in Table 1 and Table 2 both for each individual portfolio and at risk type level. As can be seen, the highest percentage of outliers is detected for the aggregated portfolios, for the reasons explained above. Credit spread portfolios also show an extreme value ratio above 15%, given the high dispersion.

Interest rates and FX instruments show the lowest dispersion, while the high dispersion for CTP does not allow any meaningful analysis to be performed.

On the other hand, interest rates have low dispersion but still a high extreme value ratio because the extreme value range is tighter.

To reinforce the analysis, a cluster analysis was also performed. It shows the dispersion of the IMVs by portfolio and helps in identifying clusters in the pricing of the portfolios that could explain the high dispersion for some trades. What arises from this analysis is that some portfolios show clusters that are very probably generated by different interpretations of the portfolios.

Table 3: IMV cluster analysis

IMV cluster analysis: number of banks by range

(X = ratio with the median)

		300% < X	200%> X >150%	150% > X >100%	100% > X >50%	50%> X >0	0 > X >-100%	-100% >X > -200%	X < -200%	Num obs. (including outliers)	Interquartile dispersion
Equity	1.1	17		3	15	3	1		1	40	97%
	1.2	1		17	20					38	3%
	1.3			20	19				1	40	1%
	1.4			18	19					37	1%
	1.5		2	8	8	2	1	1		22	24%
	1.6			17	15	3				35	9%
	1.7			16	11	3	2			32	19%
IR	1.8			23	24					47	2%
	1.9			23	24		1			48	9%
	1.10		3	20	14	8	1	1		47	8%
	1.11			17	17					34	3%
	1.12			18	17	1				36	1%
FX	1.13			23	21	1	1			46	8%
	1.14			22	17		4		1	44	10%
	1.15			22	21		2			45	3%
	1.16										
Com	1.17	3		9	6	3	3		3	27	63%
	1.18			12	12		1			25	4%
Credit Spread	1.19		2	9	13	5	1			30	26%
	1.20			17	18		1			36	3%
	1.21	1		15	15	1	1			33	9%
	1.22			19	18		2			39	3%
	1.23		1	14	16	1	1			33	4%
	1.24			15	15	1	1			32	13%
	1.25	11		2	2	1	4	4	5	29	135%
	1.26			15	16		1			32	2%
	1.27	7		1	6	2	3			19	86%
	1.28			13	8	5	1			27	19%
All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29		1	9	15	4	2	3	8	42	26%
All-in portfolio (1 to 28)**	1.30			11	15	3	4	2	6	41	15%
Equity (1 to 7)**	1.31	15		10	12		1			38	66%
Interest rate (8 to 12)**	1.32			24	17	1	1			43	2%
FX (13 to 16)**	1.33	1	4	14	12	2	1	2	7	43	42%
Commodity (17 and 18)**	1.34	2		9	9	2	3			25	11%
Credit spread (19 to 28)**	1.35			18	14	1	2			35	2%
Correlation Trading	2.1		1	4	2			3		10	12700%
	2.2		2			1	2	2		7	191%
	2.3		2			2		1	2	7	1429%

100	*Range containing more than 10% of the total observations for that particular portfolio*

In particular, as shown in Table 3:

- Portfolio 1.1: a first group of banks reported the price of the future at the valuation date multiplied by the number of underlyings. Therefore, there was no reference to the booking date. The second group of banks computed the IMV as the unrealised balance (i.e. the profit or loss that would be made if the position were closed out (or 'unwound') but that has not yet been realised) between the booking date (15 October 2015) and the valuation date and time (26 October 2015, 5.30 p.m. CET).[9]

[9] 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.

- Portfolios 1.25 and 1.27: these trades are related to iTraxx index and iTraxx Xover, where some banks' assumptions played a key role in pricing. During the interviews, some of these interpretations were discussed with the banks' representatives, especially those that were more market practice oriented.

- Other kinds of difficulties were found for CTP (portfolios 2.1, 2.2 and 2.3), principally as a result of the scarcity of contributions and the complex nature of these trades, along with their spread hedging.

In general, the concentration index, given by the percentage of values within 50% and 150% of the median value, shows that, overall, 88% of the observations lies between those ranges.

This range might be acceptable for the first exercise, but our aim should be to decrease this IMV empirical range significantly in the next exercise.

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 7 December 2015 to 18 December 2015). 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 two weeks.

In addition, **P&L VaR** values produced by the EBA using the data from banks using an HS approach were analysed. Those banks delivered a yearly 1-day P&L vector for each of the individual and aggregated portfolios modelled, and 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, in doing so, to control for the different modelling options explicitly contemplated in regulation that banks apply.

Additional checks have been 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' P&L daily values. Additional checks regarding the 1-day P&L versus the 10-day P&L (either overlapped or not) were performed where applicable. A useful check across the HS banks can be made by calculating the ratio between P&L VaR and the provided regulatory VaR, which can be expected to be close to 1.

Clearly, the P&L VaR assessment is possible only for firms applying an HS approach. Accordingly, firms applying an MC or a parametric approach, or another approach different from HS, cannot be subject to the same level of assessment.

The P&L VaR was computed as the empirical 1st percentile of the P&L vector rescaled to 10 days applying the square root of time, without applying any data weighting scheme, and, finally, taken with the positive sign:

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

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 around the risk factors, in terms of market dynamics, and, also importantly, volatility levels. Obviously, this analysis, like most of those discussed here, relies on enough 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. However, a variability analysis was also performed.

For **APR**, only a small number of contributions were submitted because of the scarcity of validated 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 addition, the **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 and taken with the positive sign as defined below:

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

n = num. of days describing the 2.5 quartile rounded to the highest decimal

ES is the new risk metric introduced by the FRTB and is expected to enter in force from 1 January 2019.

For the aggregated portfolios, any **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, 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, in particular with regard to diversification benefits, since these effects are entirely portfolio-dependent. We refer the reader to the following sub-section, '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.

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 assessment by CAs. Nevertheless, any conclusions on the total levels of capital derived from the hypothetical data should treated with due caution. The hypothetical portfolios are very different from real portfolios (in terms of size and structure). In addition, the data cannot reflect all actions taken by supervisors.

Furthermore, the sVaR metric could not be fully assessed, since the stressed 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. An option would be to ask banks to use a benchmarking stressed period, but this would create an additional burden for them, and no consistent proxy for the implied own funds requirement could be defined.

Finally, 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.

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 by the outcome of the IMV extreme value analysis. As explained, firms' 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, we checked for any significant differences between the mean and median values for the truncated sample. The results for portfolio 1.14 clearly fall into at least two groups. Table in the Annex reports the banks' VaR results in relation to the median aggregated into six buckets. This is very useful for detecting unexpected clusters. As can be seen, some clusters that were evident for IMV were not reflected in VaR. In particular, portfolio 1.1 does not show separate clusters for VaR, as the figures come from the P&L distribution and so are more homogenous.

It appears probable that firms have modelled the hypothetical trade (the resetting currency swap portfolio 1.14) differently; it is possible that the separate clusters can be attributed to whether a firm assumed an exchange of notional at maturity or not. A cluster analysis also identifies portfolio 1.28 as clustered, even though the mean and median are close in value.

This has relevance when performing 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. A more bespoke approach is therefore required in such cases.

The VaR values for CTP (portfolios 2.1-2.3) show substantial dispersion. However, the small sample size and scattering of results did not allow a deeper analysis to be carried out.

Interquantile dispersion

Figure 1 and Table 4 summarise the variability results, measured by IQD, for the three VaR measures (VaR; VaR for HS firms only; and VaR calculated from a 1-year P&L series for HS firms).

The IQD for VaR is high for portfolios 1.14, 1.25 and 1.28, which are clustered portfolios (see also Table in the Annex). In terms of risk type, the IQD for VaR for FX and credit spread portfolios are at the highest levels. This differs from IMV, for which the IQD is small for FX portfolios.

The IQD for sVaR is higher than for VaR, as expected.

One of the reasons for this is that the 1-year sVaR periods are different for each firm and depend on the firm's actual portfolio as at the close of business date. That is, they are not calculated with respect to the 1-year period that maximises VaR for the given hypothetical portfolio.

As was the case for VaR, the IQD for portfolios 1.14 and 1.28 is high. In addition, the IQD for portfolios 1.21 and 1.27 is high.

Figure 1: Interquartile dispersion for IMV and risk metrics by portfolio

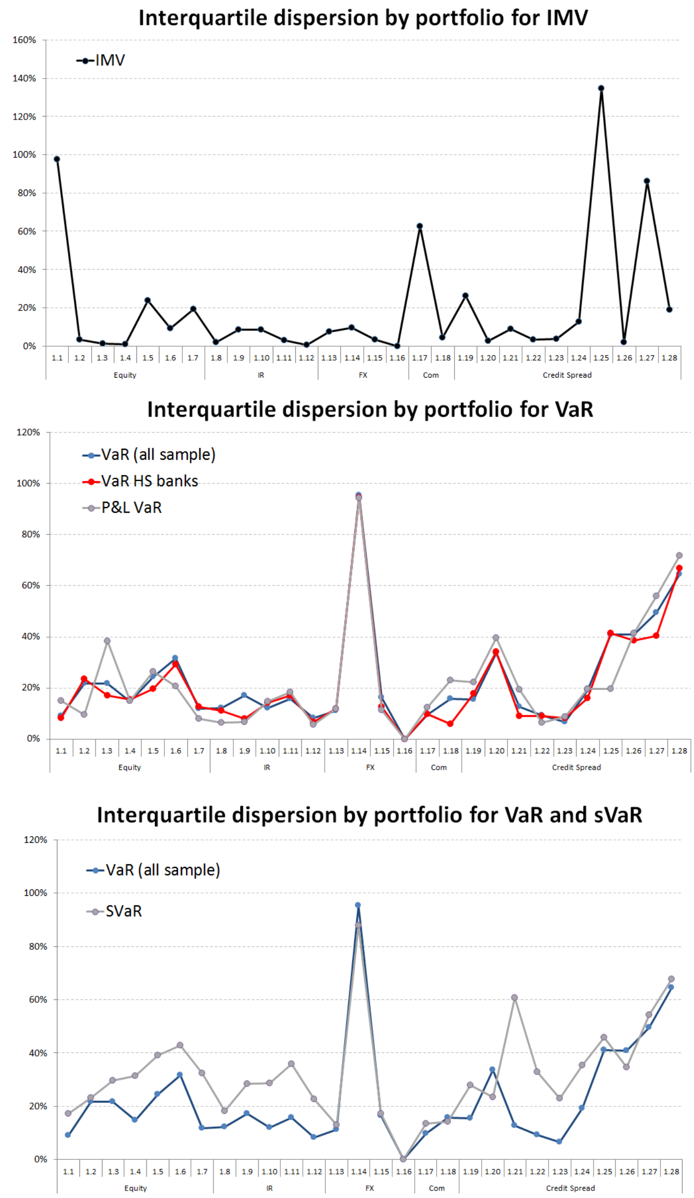


Table 4: Interquartile dispersion for IMV and risk metrics by risk factor

Average Interquartile dispersion by risk factor

	IMV	VaR (all sample)	SVaR	P&L VaR	VaR HS banks	VaR MC banks	Exp shortfall
Equity	22%	19%	31%	19%	17%	15%	16%
IR	5%	13%	27%	10%	11%	8%	10%
FX	7%	41%	39%	39%	41%	37%	40%
Commodity	34%	13%	14%	18%	12%	13%	16%
Credit spreads	30%	29%	41%	30%	17%	25%	28%

There is evidence that when a homogeneous subset of firms is considered (i.e. HS firms) the VaR results show less dispersion than is observed in the total sample. This is confirmed across all asset classes except credit spread trades, where there is substantial invariance. With regard to the P&L VaR, it is observed that the dispersion is in line with both HS VaR and all-sample VaR except for commodities where HS models are more harmonised.

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

The behaviour of the ratio between sVaR and VaR was also analysed across the sample. Some banks have ratios below 1 for many portfolios, while other banks have extremely high ratios for some portfolios. In light of these results, we used the sVaR–VaR ratio as a criterion for the ranking that determined if a bank should be called for an interview.

In general, there is higher dispersion of this ratio for FX and credit spread positions (with the exception of portfolio 1.28), as can be seen in Table 5, which reports the average of this ratio by risk factor. It is worth noting that three interest rate trades and one credit spread trade have a significant proportion of ratios below 1, which indicates that the (firm-level) stressed period used for those banks was not appropriate for these particular hypothetical trades.

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

Distribution of sVaR / Var ratio over portfolios

(X = ratio with the median)

% of the total

		X>3	3≥ X >1	1≥ X
Equity	1.1	13%	88%	0%
	1.2	6%	91%	3%
	1.3	58%	42%	0%
	1.4	0%	100%	0%
	1.5	10%	85%	5%
	1.6	0%	94%	6%
	1.7	7%	93%	0%
IR	1.8	0%	77%	23%
	1.9	0%	61%	39%
	1.10	0%	70%	30%
	1.11	33%	64%	3%
	1.12	10%	87%	3%
FX	1.13	10%	90%	0%
	1.14	38%	59%	3%
	1.15	3%	93%	5%
	1.16	0%	0%	0%
Com	1.17	8%	92%	0%
	1.18	5%	95%	0%
Credit Spread	1.19	47%	53%	0%
	1.20	6%	90%	3%
	1.21	67%	33%	0%
	1.22	45%	52%	3%
	1.23	50%	50%	0%
	1.24	73%	27%	0%
	1.25	32%	64%	4%
	1.26	22%	78%	0%
	1.27	27%	73%	0%
	1.28	19%	62%	19%
All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29	6%	94%	0%
All-in portfolio (1 to 28)**	1.30	8%	92%	0%
Equity (1 to 7)**	1.31	6%	94%	0%
Interest rate (8 to 12)**	1.32	8%	92%	0%
FX (13 to 16)**	1.33	18%	82%	0%
Commodity (17 and 18)**	1.34	5%	95%	0%
Credit spread (19 to 28)**	1.35	42%	58%	0%
Correlation Trading	2.1	29%	57%	14%
	2.2	33%	67%	0%
	2.3	17%	83%	0%

5.2 A closer look at VaR and sVaR results

Figures 2 and 3 give an overview of the VaR and sVaR results for portfolios 1.1 to 1.28, excluding the aggregated portfolios, for which no meaningful analysis could be carried out, for the reasons explained above.

For each firm, the average of VaR and sVaR over the 10-day submission period is shown. The portfolio median is the median of the average VaR and sVaR over the submission period.

Figures 2 and 3 are limited to VaR–median and sVaR–median less than or equal to 600%. Therefore, the fact that portfolio 1.14 is bimodal cannot be seen in the figures. Extreme outliers, such as portfolios 1.1, 1.8 and 1.18 for VaR, or portfolios 1.7, 1.8, 1.17 and 1.18 for sVaR, cannot be seen in Figures 2 and 3 either.

The credit spread portfolios (portfolios 1.19-1.28) show a higher level of dispersion than the other asset classes, especially for sVaR. There are also more extreme outliers for the credit spread portfolios, which, again, are not visible in Figures 2 and 3.

Figure 2: VaR submissions normalised by the median of each portfolio

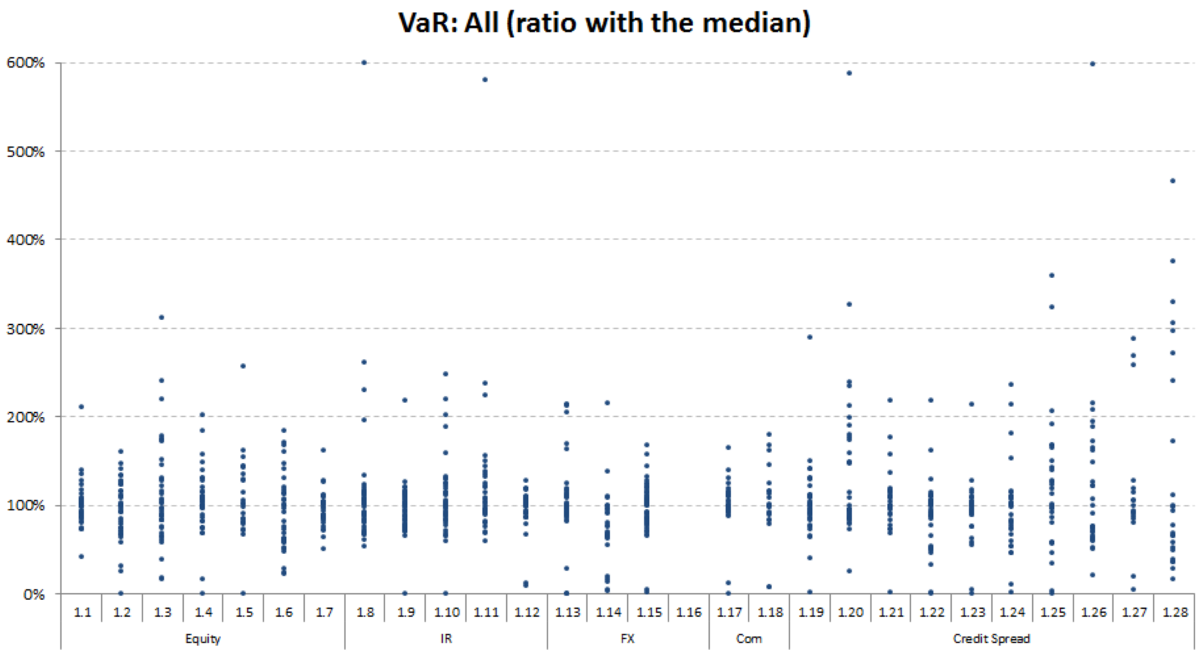
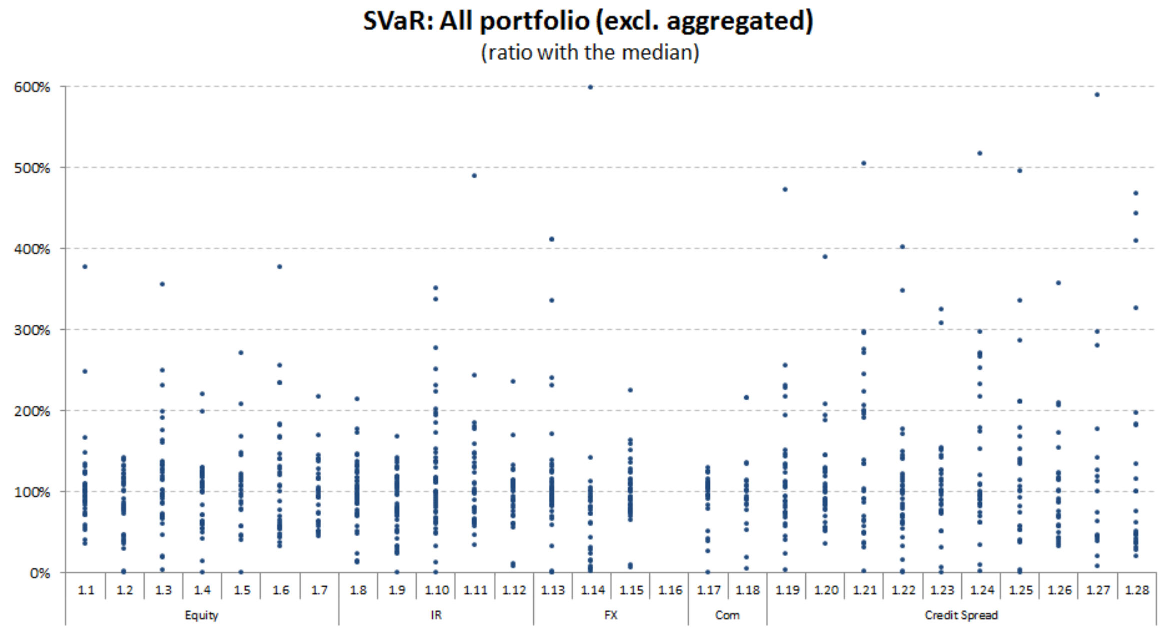


Figure 3: sVaR submissions normalised by the median of each portfolio

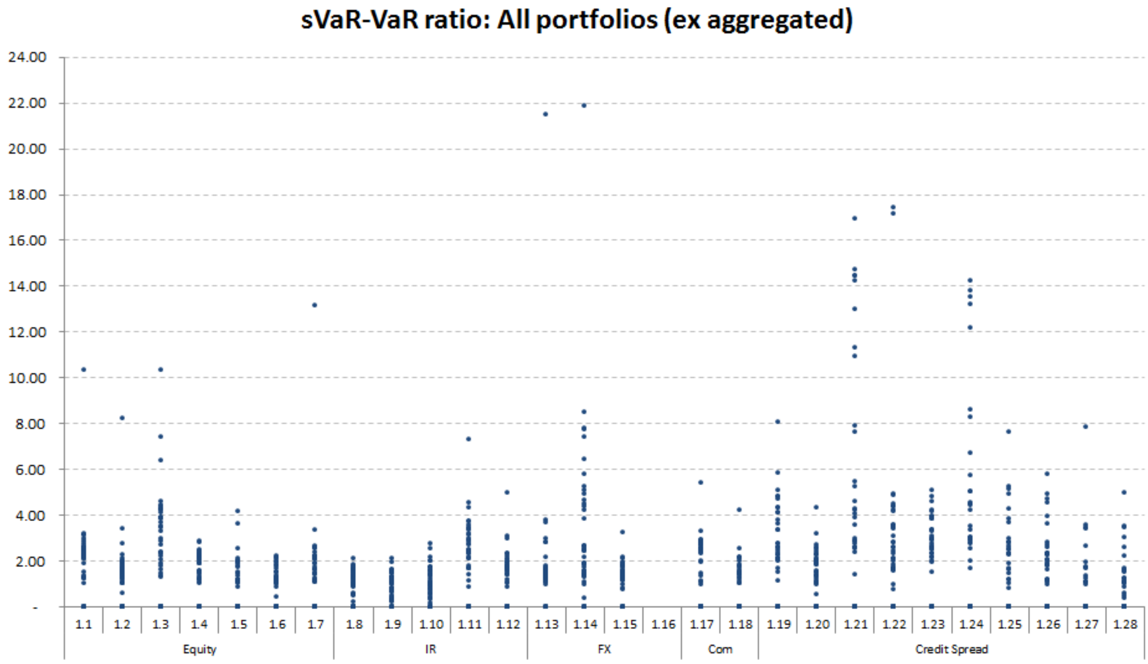


Comparison of sVaR to VaR ratios

Firms were ranked in relation to the full sample not only by their VaR and sVaR values but also by the sVaR–VaR ratio. In general, we would expect that sVaR would be at least as big as VaR, as sVaR is calibrated to a 1-year period of significant stress. However, because the stressed period is calibrated on a firm-by-firm basis on the basis of firms' actual portfolios, for the hypothetical portfolios used for the HPE the sVaR–VaR ratio could conceivably be smaller than 1 in some instances.

Figure 4 shows the ratio of the average sVaR to the average VaR for each portfolio. The sVaR–VaR ratio varies strongly depending on portfolio. Excluding outliers, the average sVaR–VaR ratio varies between 0.85 and 4.86. The portfolios with the lowest levels of dispersion for the sVaR–VaR ratio (excluding outliers) are portfolio 1.6 (equity barrier option), portfolio 1.8 (IR, long long-term and short short-term treasuries), portfolio 1.9 (IR swap) and portfolio 1.18 (commodity, short oil put option).

Figure 4 : 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.

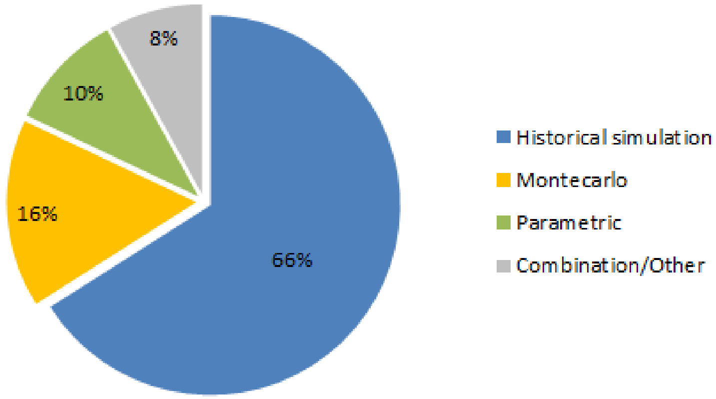
The dispersion for credit spread portfolios is observed to be higher than that for the other asset classes. In general, we found that firms using absolute returns had a higher sVaR than firms using relative returns, and therefore a higher sVaR–VaR ratio. The strong dependency of sVaR on how risk factor returns are specified in the model is something to which NCAs should pay close attention when reviewing firms' credit VaR models. In particular, firms' justification of 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

From the qualitative information provided by banks (Figures 5-8), the most common methodological approach used by banks for MR models is HS (66%).

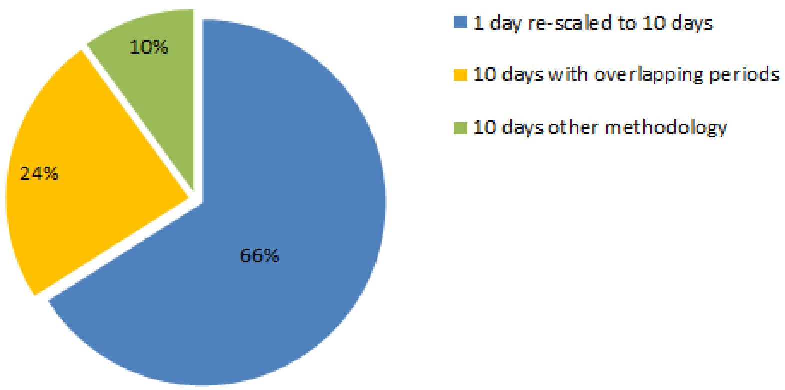
Although the majority of banks use the same methodological approach (i.e. HS), as seen above the dispersion of VaR remains significant, especially when other modelling choices play a key role (e.g. differences in time scaling and/or weighting scheme choices, absolute versus relative returns for different asset classes, etc.).

Figure 5: Qualitative data: VaR methodological approaches



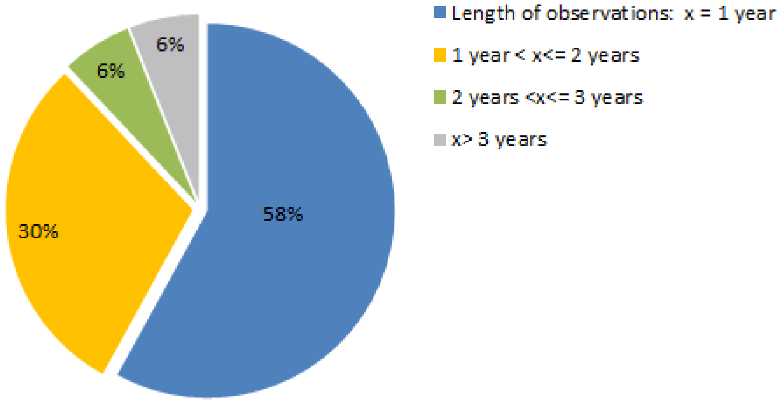
With regard to the regulatory 10-day VaR computation, the preferred method is given by the 1-day VaR rescaled to the 10-day VaR via the square-root-of-time rule.

Figure 6: Qualitative data: VaR time scaling techniques



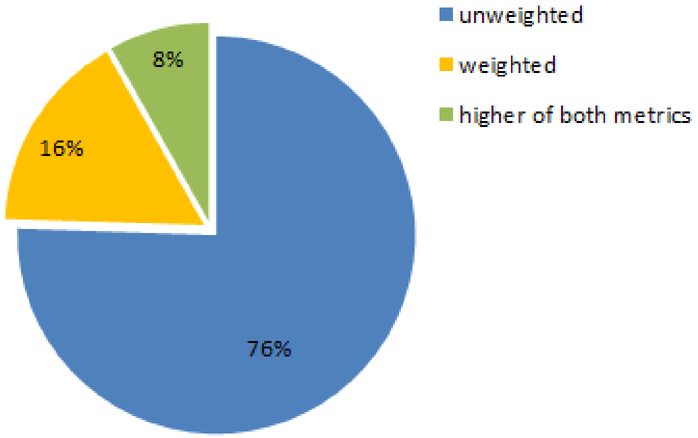
Concerning the historical lookback period used to calibrate firms' VaR models, more than half of the banks use the minimum period of 1 year (58%). Another 30% of the banks use a 2-year period.

Figure 7: Qualitative data: VaR lookback period length



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

Figure 8: Qualitative data: VaR weighting choices



Finally, with regard to the supervisory actions on regulatory add-ons, 65% of the banks in the sample have a total multiplier greater than the minimum of 3, which includes the addend resulting from the number of overshootings (Table 1 in Article 366 of the CRR) and the supervisory extra charge. The total multiplier, in this sample, is on average equal to 3.5 with a maximum equal to 4.9. In addition, there are some banks with other added penalties that encompass risk not in VaR and additional amounts for IRC and APR charges.

From these responses, there is evidence that a number of different possible drivers of variation exist. 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 fully include in the analysis. The effect of an increased VaR or sVaR multiplier, for example imposed by an NCA because of model weaknesses, can be studied by comparing a proxy given by the following data:

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

where m_{vaR} and m_{sVaR} are the total regulatory multipliers and consist of 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 change the results significantly in terms of variability across the sample; that is, different positioning across the sample changed, but, on average, the extent of the dispersion did not.

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

Modelling differences

As explained above, the CRR permits firms to make different VaR modelling choices.

To test the impact of different modelling choices in a controlled way, four sample portfolios were selected.

The portfolios – portfolios 1.1, 1.9, 1.13 and 1.22 – cover the main asset classes (i.e. equity, interest rates, FX and credit). For these portfolios, VaR and sVaR were calculated using a reference HS VaR model implementation with the capability to vary the model features selected from the qualitative responses. These results were then compared with the results submitted by firms using the same modelling choices.

For clarity, the different modelling choices considered were:

- length of the historical lookback period;
- relative or absolute risk factor returns;
- 1-day scaled or 10-day overlapping returns; and
- use of weighting.

The risk measures were calculated using only modelling choices known to be used by firms. Table 6 shows a description of the four selected portfolios and which underlying instrument was chosen to model each portfolio. For the comparison with sVaR, the stressed periods used by firms together with the relevant modelling choices were used to reproduce sVaR.

Table 6: Representative portfolios

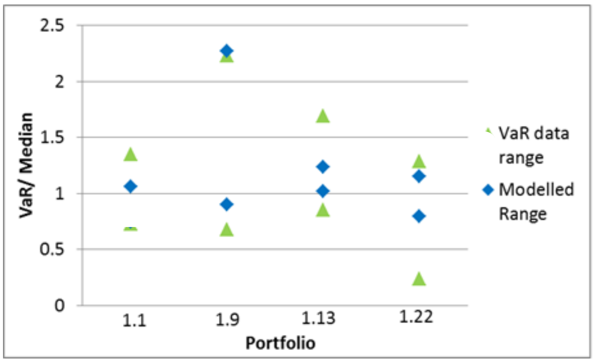
Portfolio	*Description*	*Modelled by*
1.1	*EQ: Long delta on FTSE 100 index futures*	FTSE 100 index
1.9	*IR: 10y IR swap*	EUR 10y swap rate
1.13	*FX: Short 3-m EUR/USD forward and short 3-m put EUR call USD*	EUR/USD FX rate
1.22	*CS: Short CDS index ITRAXX 5y*	ITRAXX

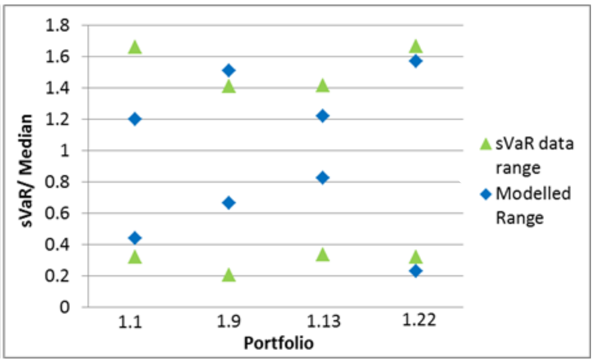
Figure 9 compares the dispersion of the submitted VaR and sVaR results with the reproduced VaR and sVaR results. The average VaR and sVaR over the 10-day calculation period are shown as a proportion of the corresponding median values. Only the maximum and minimum VaR and sVaR are shown for each portfolio. Clear outliers have been omitted. Figure 9 shows the proportion of the variation in the VaR and sVaR values submitted by firms that can be reproduced by the reference VaR model using different permitted modelling choices. We note that the highest VaR value submitted for portfolio 1.9 would be flagged as an outlier based on a statistical analysis of the data, but that it can in fact be closely reproduced with the same set of modelling choices used by the firm. In this case, the result can be explained by the use of 10-day overlapping returns and the short 1-year lookback period. Euro interest rates increased by a factor of around 100% over a 10-day period in May 2015, and the effect of this large movement is 'dampened' for firms using either 1-day returns or longer lookback periods. The The level of dispersion when using the reference model is noticeably smaller for the FX and credit spread portfolios, namely portfolios 1.13 and 1.22 respectively.

A possible explanation for portfolio 1.13 is that it consists of a delta-hedged option, for which the reference VaR model uses a full revaluation pricing approach. We expect that at least some firms may be using pricing approximations based either on sensitivities or partial revaluation ladders/grids, and that these could (in principle) produce significantly different results. The use of weighting further increases the range of results; for portfolio 1.1 the dispersion increases mostly on the upside, and for portfolios 1.13 and 1.22 mostly on the downside.

For sVaR, in addition to the different modelling choices, different stressed periods come into play. The dispersion observed for sVaR is greater than the dispersion observed for VaR. The increase in dispersion is reproduced in the modelled range.

Figure 9: VaR and sVaR ratio with the median for representative portfolios





For a subset of 13 firms using HS VaR, sufficient information was available to (approximately) estimate what the firms' VaR and sVaR submissions should have been using the reference model. Table 7 shows the number of firms for which such an analysis was possible for each portfolio and the subset for which the estimated VaR or sVaR measures agreed well with the submitted risk measures.

The deviation between submitted and estimated risk measures is generally smaller for VaR than for sVaR. The closest agreement is for portfolio 1.1, for which 80% of the reproduced VaR results differ by less than 10% from the VaR values submitted by the firms. Even for sVaR, the submitted and recalculated values show relatively good agreement, with 50% of firms with less than 10% deviation. For portfolio 1.13, the agreement between the estimated and submitted sVaR values is, at 50%, as good as the agreement for portfolio 1.1.

Table 7: VaR and sVaR submissions for a subset of HS banks

	VaR			sVaR		
Portfolio	Total n. banks	<10% dev. (n.banks)	<10% dev. (% of total)	Total n. banks	<10% dev. (n.banks)	<10% dev. (% of total)
1.1	10	8	80%	10	5	50%
1.9	13	5	38%	12	0	0%
1.13	9	5	56%	10	5	50%
1.22	11	4	36%	11	1	9%

Even though a relatively simplistic reference VaR model was compared with firms' models, this further confirmed that the modelling choices discussed in this section can explain some of the variation observed in firms' results. For example, firms using absolute returns have a higher sVaR for credit spread portfolios than firms using relative returns, at least in the prevailing market conditions in December 2015. Another observation is that the use of weighting increases the range of possible returns, on the upside for portfolio 1.1 and on the downside for portfolios 1.13 and 1.22. However, not all variations can be explained by these modelling choices alone. It has to be kept in mind that the models used by firms are more sophisticated and therefore also differ in aspects other than those represented here.

Other drivers of variation

In addition to the drivers of variation discussed in the two sub-sections above, there may be other drivers of variation. In the sub-section 'Modelling differences', only results obtained with HS VaR are discussed, although the methodology 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 1.28, which is mainly sensitive to the Quanto CDS basis. Relatively low submissions for these portfolios are most likely explained by the firms not including this risk factor in their model. We need to keep in mind, however, that the firms may not have material exposure to this risk factor in their actual portfolios.

Furthermore, from some of the interviews with banks, a lack of consensus around modelling of the basis risk between a CDS and its equivalent bond, and between an index and its components, was found; the same was true of the estimation of the forward volatility surface, and in general where the level of liquidity is tight.

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 lower VaR than a more concentrated portfolio.

Table 8 shows relationships between VaR results for some credit spread portfolios that are provisionally expected to hold, and the corresponding number of firms for which this is not the case. The numbers in brackets are the total numbers of submissions for the compared portfolios.

Table 8: Portfolio comparison for VaR

	Expected results			
	1.22<1.23	*1.23<1.21*	*1.24<2*1.21*	*1.26*5/4<1.21*
n. banks with unexpected results vs (total banks)	25 *(34)*	25 *(31)*	1 *(30)*	28 *(30)*

With regard to these portfolios, some initial expectations about the VaR results were expected due to their definitions.

Results for portfolio 1.22 are bigger than the VaR results for portfolio 1.23 for the majority of firms. This was unexpected, as portfolio 1.22 is more diversified. Only the ratios for portfolios 1.21 and 1.24 fulfilled our expectations.

These comparisons suggest that bond–CDS basis risk is a significant driver of risk. It would suggest that NCAs should pay close attention to the modelling of bond–CDS basis risk when reviewing firms' credit VaR models. Although the firms to be interviewed are not considered outliers with respect to this analysis, nevertheless this will be an area to follow up on to validate the findings.

5.3 Analysis of IRC

A smaller number of firms have permission for IRC than for VaR; only firms with approval to use internal models for specific risk of debt instruments are permitted to use IRC models. Table 9 shows the number of IRC submissions by portfolio, as well as the number of firms that submitted a very low result for a given portfolio, suggesting that an important risk factor (in the context of the HPE) has not been modelled. The firms shown under 'risk factor not modelled' are those for which the results are considered very low; this should not be taken to mean that firms with higher IRC results include all risk factors from a given portfolio in their model.

Table 9: IRC submissions and potential risk factors not modelled

Portfolio	Submissions	Risk factors not modelled
1.8	24	4
1.19	29	0
1.2	29	7
1.21	29	0
1.22	30	0
1.23	30	0
1.24	28	0
1.25	25	14
1.26	28	0
1.27	14	0
1.28	20	4
1.29	31	0
1.3	30	0
1.35	31	0

The number of submissions is particularly low for some of the all-in portfolios (portfolios 1.29-1.35) and therefore no conclusion can be drawn regarding these. A prerequisite for consideration of firms' submissions for the all-in portfolios is that a firm needs to be able to model all the corresponding underlying portfolios. As noted above, IRC being zero or unrealistically low suggests that the key underlying risk factors (for that portfolio) are not captured by the IRC model.

As for VaR, 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.

Our initial expectations were that the relationships shown in Table 9 would hold for certain credit spread portfolios (portfolios 1.19-1.28). Table 10 shows the number of firms for which the expected results do not hold. The numbers in brackets are the number of submissions for the portfolios.

Table 10: Portfolio comparison for IRC

	Expected results			
	1.22<1.23	1.23<1.21	1.24<2*1.21	1.26*5/4<1.21
n. banks with unexpected results vs (total banks)	3 (29)	10 (29)	0 (28)	13 (28)

Unlike for VaR, the expected relationships are shown to hold for the majority of firms. This suggests that outright default risk is a more material contributor to risk than, for example, bond–CSD basis risks. In two cases, there are a relatively significant number of firms deviating from the expected results: portfolios 1.23 and 1.21, with 10 exceptions; and portfolios 1.26 and 1.21, with 13 exceptions.

There may be different reasons why the IRC ratios deviate from expectations for these firms. The most plausible explanations are likely to be that different interpretations of the portfolios have been used, or that the IRC models are missing risk factors that are important in the context of these portfolios (but which may not be material risks for the firm).

In some cases, missing risk factors can be identified by identifying portfolios for which firms submit unrealistically low IRC results, for example zero, as shown above.

This is most notably the case for the following portfolios:

- portfolio 1.8: Tenor basis – 7 firms do not appear to model this risk;
- portfolio 1.25: CDS-index basis – 16 firms do not appear to model this risk; and
- portfolio 1.28: Quanto CDS basis – 8 firms do not appear to model this risk.

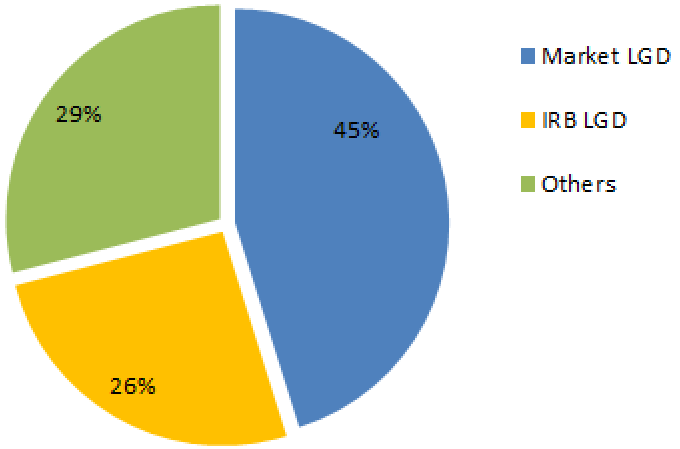
It is recommended that NCAs assess the extent to which these missing risk factors are important in the context of firms' overall risk, and whether or not they need to be added to the model.

There is a range of permitted modelling approaches for IRC. For example, firms need to decide:

- the 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.

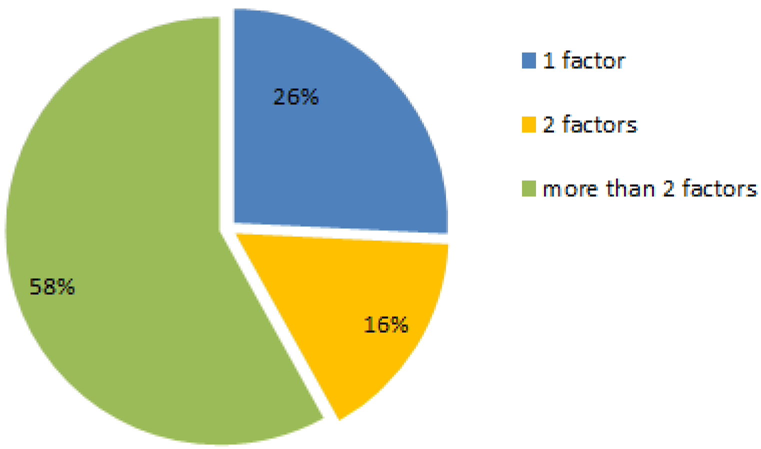
From the responses to the qualitative questionnaire relating to the IRC methodological aspects, Figure 10 shows that the use of market LGD predominates across respondents. PD estimates come mostly from rating agencies (15 respondents out of 26). Similarly, the transition matrices also come mostly from rating agencies (20 respondents out of 26).

Figure 10: Qualitative data: source of LGD for IRC modelling



A majority of respondents stated that they used more than two systemic modelling factors at the overall IRC model level (Figure 11).

Figure 11: Qualitative data: number of modelling factors for IRC



The liquidity horizon applied at the portfolio level for the IRC model is predominantly between 9 and 12 months (17 respondents out of 26).

Overall, we found that there were many common IRC modelling practices across the sample.

IRC risk shows a significantly higher level of dispersion for the 'curve flattener' sovereign position on German government bonds (portfolio 1.8) than that observed in other credit spread portfolios, especially the simplest ones. In this regard, regulatory differences in the treatment of sovereign exposures were also identified as a driver of variation; for example, some jurisdictions require a non-zero floor for the probability of default, some jurisdictions allow banks to exclude sovereign exposure from the default component of the IRC risk, etc.

Table 11: IRC statistics and cluster analysis[10]

Statistics for IRC

	Port.	Main statistics						Percentiles				
		Min	Max	Ave.	STDev	STDev_tri	Num obs.	25th	50th	75th	MAD	Interquartile dispersion
IR	1.8	0	1,322	159	307	307	17	35	88	136	53	59%
Credit Spread	1.19	185	1,771	963	481	463	25	521	1,068	1,324	358	44%
Credit Spread	1.20	15	1,430	278	305	214	29	90	214	319	118	56%
Credit Spread	1.21	522	1,804	975	362	357	25	736	828	1,055	156	18%
Credit Spread	1.22	202	5,967	907	1,079	428	28	510	604	994	173	32%
Credit Spread	1.23	352	5,740	1,285	1,016	516	28	900	985	1,212	145	15%
Credit Spread	1.24	644	2,517	1,658	424	376	25	1,424	1,611	1,952	229	16%
Credit Spread	1.25	0	2,975	166	645	47	21	0	5	23	5	96%
Credit Spread	1.26	202	1,766	782	437	389	26	498	691	1,040	258	35%
Credit Spread	1.27	79	1,885	508	493	493	12	254	310	550	95	37%
Credit Spread	1.28	0	324	53	81	81	16	17	28	50	17	50%
All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29	1,365	12,071	3,236	2,501	2,501	16	2,147	2,528	3,444	458	23%
All-in portfolio (1 to 28)**	1.30	1,303	5,789	3,611	1,227	1,227	13	3,124	3,389	3,945	501	12%
Credit spread (19 to 28)**	1.35	1,262	4,652	3,275	880	880	12	3,007	3,279	3,549	270	8%

IRC Cluster analysis: number of banks by range

(X = ratio with the median)

	Port.	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. [1]
IR	1.8	1	3	2	4	6	8				24
Credit Spread	1.19			2	11	7	9				29
Credit Spread	1.20	2	3	2	7	6	9				29
Credit Spread	1.21		3	2	10	14					29
Credit Spread	1.22	3	1	5	6	13	2				30
Credit Spread	1.23	2	1	3	9	14	1				30
Credit Spread	1.24			2	11	14	1				28
Credit Spread	1.25	11		1	1	2	10				25
Credit Spread	1.26	1	4	3	6	8	6				28
Credit Spread	1.27	3	1		4	5	1				14
Credit Spread	1.28	2	1	6	2	6	3				20
All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29	1		1	9	18	2				31
All-in portfolio (1 to 28)**	1.30	2	1	2	7	15	3				30
Credit spread (19 to 28)**	1.35	2	1	2	8	15	3				31

[1] Including extreme values

100 — *Range containing more than 10% of the total observations for that particular portfolio*

[10] MAD stands for Median Absolute Deviation.

The table 11 shows that the IRC average variability is higher than that observed for VaR. However, for more plain vanilla portfolios (portfolios 19-24) it decreases, and if we consider only the corporate risk portfolios (portfolios 21-24) it decreases further. It is also worth noting that for the aggregated portfolios (portfolios 29, 30 and 35) IRC dispersion tends to decrease significantly.

Finally, during the interviews, it became clear that, for some banks, with regard to IRC, a key driver was the migration matrix, for which there is no common rule on periodic review.

5.4 Analysis of APR

In their responses to the qualitative questionnaire relating to the APR methodological aspects, all of the respondents, that is, banks with an authorisation for CTP, 8 out of 8, stated that they used 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, market LGD is used by 4 respondents out of 8, the LGD used in the internal ratings-based approach is adopted by 2 banks, and the remaining 2 banks use other sources.

The liquidity horizon applied at the portfolio level for the CTP model is predominantly between 9 and 12 months (7 respondents out of 8).

The sources of PD estimates applied at the portfolio level for the CTP model are mostly rating agencies (6 respondents out of 8).

The sources of the transition matrices applied at the portfolio level for the CTP model are also mostly rating agencies (6 respondents out of 8).

It should be highlighted that all these options are, in principle, acceptable under the current regulatory framework and that it is up to banks and CAs to agree during the validation process on the most appropriate ones to be applied by each bank, with particular reference to the banks' proprietary 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, difference in approximations when repricing positions, etc.

Table 12 shows that the average variability for the APR charge is around 50% when it is 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.

The VaR values for CTP, owing to the small sample size and scattering of results, did not allow for a meaningful analysis.

During the interviews it was found that one firm had chosen to submit APR results for the CTP on the basis that the firm has regulatory approval outside the EU for this model. However, this legal entity has not been granted permission by its EU NCA and, in accordance with the RTS on benchmarking, should not have submitted these results.

Table 12: APR statistics and cluster analysis

Statistics for APR

		Main statistics						*Percentiles*				
	Port.	*Min*	*Max*	*Ave.*	*STDev*	*STDev_trunc* [1]	*Num obs.* [3]	*25th*	*50th*	*75th*	*MAD*	*Interquantile dispersion*
Correlation Trading	*2.1*	1,895	5,978	3,303	1,479	1,479	7	**1,969**	**2,984**	**4,434**	1,015	38%
	2.2	350	4,595	1,458	1,568	1,568	7	**495**	**718**	**2,523**	281	67%
	2.3	1	185	102	66	66	7	**58**	**105**	**173**	47	50%

APR 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.* [3]
Correlation Trading	*2.1*		1		2	4					*7*
	2.2	2			1	3	1				*7*
	2.3			2	1	3	1				*7*

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. From these series, the correlation matrices between banks and for all portfolios were computed. Because of the extreme high dimensionality, for each portfolio all banks with a high correlation (greater than 80%) and all banks with a low correlation (less than 40%) with each other were grouped and counted.

This analysis allows us to detect the banks that systematically show a high or a low correlation level in their P&L. As shown by Table 13, we computed the percentage of banks for each correlation bucket (high, low and medium) by risk category. We also examined the top 10 high- and low-correlated banks. We found evidence that, for many portfolios, banks with high correlation also tend to be aligned between them. The same is much more evident for low-correlated banks. That means that, for many portfolios, high-correlated P&L vectors tend to come from banks with a homogeneous method for their actual P&L computation.

Table 13: Percentage of banks by correlation range and risk category

Percentage of banks by correlation range and risk category

All sample

	High (corr > 80%)	Medium (80%<corr>40%)	Low (corr < 40%)
Equity	32%	11%	57%
IR	37%	10%	53%
FX	24%	13%	63%
Commod	28%	10%	62%
Credit spreads	16%	12%	72%
Aggregated portfolios	15%	18%	67%

Top 10 highly correlated banks

	High (corr > 80%)	Medium (80%<corr>40%)	Low (corr < 40%)
Equity	51%	18%	31%
IR	60%	11%	28%
FX	30%	18%	52%
Commod	45%	20%	35%
Credit spreads	27%	12%	61%
Aggregated portfolios	19%	27%	55%

Top 10 low correlated banks

	High (corr > 80%)	Medium (80%<corr>40%)	Low (corr < 40%)
Equity	23%	9%	68%
IR	26%	5%	69%
FX	12%	8%	80%
Commod	23%	5%	72%
Credit spreads	12%	8%	80%
Aggregated portfolios	11%	12%	77%

As can be seen, highly correlated banks tend to be more aligned with each other, while low correlated banks tend to be significantly misaligned.

For each portfolio, the standard deviation of each bank's P&L series was computed. This metric is called P&L volatility. Therefore, each trade has a series of banks' P&L volatility.

In the analysis, the 5th percentile and the 95th percentile were computed for each trade from portfolios 1.1-1.28. Banks that are systematically over the 95th percentile or below the 5th percentile were found.

Three banks from the sample are systematically below the 5th percentile and two are systematically above the 95th percentile.

Across the 28 non-CTP, these are the HS banks for which the level of variability observed in the P&L is least harmonised in the sample of all HS banks.

This is an important point because it reflects the differences in how the actual P&L is computed across the banks.

Another metric that was computed by the EBA from the P&L series provided by HS banks is EES. EES results have the same level of dispersion as the P&L VaR, but the level of dispersion is lower for equity products (see Table 4 in section 5.1).

5.6 Diversification benefit

The diversification benefits observed for VaR, sVaR and IRC in the aggregated portfolios were analysed. In general, larger aggregated portfolios exhibited greater diversification benefits than smaller ones. The VaR diversification benefit is computed as the absolute benefit (i.e. the sum of the single VaR from each individual position minus the VaR of the aggregated portfolio) over the sum of the single VaR from each individual portfolio. It is defined in the same way for sVaR and IRC.

Table 14 summarises the analysis results.

Table 14: Diversification benefit statistics

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 (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29	56%	15%	16	52%	58%	62%	8%
All-in portfolio (1 to 28)**	1.30	67%	23%	13	66%	77%	81%	11%
Equity (1 to 7)**	1.31	72%	7%	23	68%	70%	74%	4%
Interest rate (8 to 12)**	1.32	60%	16%	28	59%	64%	66%	6%
FX (13 to 16)**	1.33	32%	43%	35	3%	7%	83%	93%
Commodity (17 and 18)**	1.34	28%	14%	24	20%	25%	33%	25%
Credit spread (19 to 28)**	1.35	48%	14%	17	35%	51%	53%	20%

sVaR

		Other statistics			Percentiles			
	Port.	Ave.	STDev	Num obs. [3]	25th	50th	75th	Interquartile dispersion
All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29	51%	16%	16	44%	52%	62%	16%
All-in portfolio (1 to 28)**	1.30	66%	28%	13	70%	75%	82%	8%
Equity (1 to 7)**	1.31	76%	8%	23	71%	76%	80%	6%
Interest rate (8 to 12)**	1.32	53%	18%	28	52%	58%	62%	8%
FX (13 to 16)**	1.33	31%	40%	36	5%	10%	59%	84%
Commodity (17 and 18)**	1.34	35%	15%	24	26%	37%	44%	26%
Credit spread (19 to 28)**	1.35	53%	11%	17	49%	54%	60%	10%

IRC

		Other statistics			Percentiles			
	Port.	Ave.	STDev	Num obs. [3]	25th	50th	75th	Interquartile dispersion
Credit spread (19 to 28)**	1.29	48%	9%	10	44%	46%	50%	7%

The dispersion is significantly higher for some portfolios than for others, and, in some cases, it is quite comparable to that observed for VaR, sVaR and IRC.

5.7 Dispersion in capital outcome

For each individual position, a variable given by the sum between the regulatory VaR and sVaR was computed. This variable was used in two ways, with and without the banks' total multiplier. The results were averaged between the trades that belong to the same risk factor category, thus arriving at a proxy for the implied capital outcome.

We analysed the dispersion of these variables. For the aggregated portfolios, it is lower than the average dispersion observed for the other risk metrics. Evidently, the proxy tends to smooth the dispersion of each individual addend. This also happens for the interest rate, commodities and credit spread risk factors (Table 15).

Table 15: Interquartile dispersion for capital proxy

Average Interquartile dispersion by risk factor

	Capital proxy (with mult)	*Capital proxy (without mult)*
Equity	28%	27%
IR	22%	20%
FX	41%	40%
Commodity	14%	12%
Credit spreads	39%	37%

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.

Variability was not influenced by regulatory add-ons. The ranges of capital values dispersion remain broadly the same.

The implied capital outcome was used by the EBA to sort the banks and, along with other criteria, to identify firms to invite for an 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 (Table 16).

Table 16: Capital proxy rankings

Ranking for (VaR+sVaR)

Below the threshold (25th)

(without total mult)

	Ranked by number of outliers (< 25th percentile)					
Position	Equity	IR	FX	Commod	Credit spreads	Total
1	BANK_4	BANK_21	BANK_5	BANK_23	BANK_19	**BANK_19**
2	BANK_5	BANK_19	BANK_23	BANK_14	BANK_2	**BANK_23**
3	BANK_37	BANK_4	BANK_14	BANK_11	BANK_7	**BANK_27**
4	BANK_36	BANK_1	BANK_11	BANK_50	BANK_27	**BANK_41**
5	BANK_41	BANK_5	BANK_27	BANK_41	BANK_34	**BANK_39**
6	BANK_21	BANK_37	BANK_13	BANK_25	BANK_39	**BANK_37**
7	BANK_13	BANK_36	BANK_25	BANK_20	BANK_37	**BANK_36**
8	BANK_39	BANK_41	BANK_50	BANK_1	BANK_36	**BANK_5**
9	BANK_19	BANK_39	BANK_19	BANK_5	BANK_26	**BANK_4**
10	BANK_20	BANK_11	BANK_4	BANK_27	BANK_38	**BANK_2**

Ranking for (VaR+sVaR)

Above the threshold (75th)

(without total mult)

	Ranked by number of outliers (> 75th percentile)					
Position	Equity	IR	FX	Commod	Credit spreads	Total
1	BANK_29	BANK_26	BANK_29	BANK_35	BANK_47	**BANK_29**
2	BANK_35	BANK_40	BANK_31	BANK_9	BANK_46	**BANK_35**
3	BANK_47	BANK_35	BANK_40	BANK_10	BANK_29	**BANK_47**
4	BANK_9	BANK_34	BANK_35	BANK_32	BANK_35	**BANK_10**
5	BANK_34	BANK_10	BANK_44	BANK_45	BANK_13	**BANK_46**
6	BANK_43	BANK_22	BANK_9	BANK_46	BANK_11	**BANK_40**
7	BANK_10	BANK_42	BANK_38	BANK_34	BANK_10	**BANK_43**
8	BANK_38	BANK_29	BANK_10	BANK_43	BANK_24	**BANK_24**
9	BANK_24	BANK_47	BANK_42	BANK_24	BANK_31	**BANK_31**
10	BANK_11	BANK_43	BANK_47	BANK_29	BANK_40	**BANK_38**

From these results, a few banks were identified as aggressive, and their approaches and results were challenged during the interviews. Other banks contributed to the dispersion of the results because of their high values.

6. Competent authorities' assessment

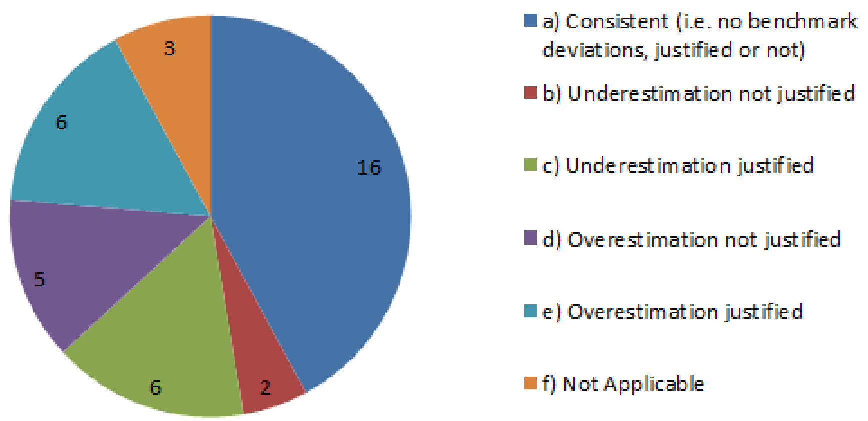
The CAs provided individual assessments for each participating institution of any potential underestimation of the capital requirement as required by Article 78(4) of the CRD and Articles 8 and 9 of the draft RTS on supervisory benchmarking. This section highlights some key information derived from these assessments.

A total of 38 bank respondents, represented by their NCAs, from 10 jurisdictions, took part in this assessment of the MR benchmarking exercise.

Regarding the level of priority of the assessments, 7 banks (18.42%) 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 to the ratio of sVaR to VaR across all portfolios.

Figure 12 reports the CAs' own overall assessments of the levels of own funds requirements. When it comes to benchmark deviations, justified or not, 19 banks were reported by CAs as under- or overestimating MR own funds requirements, of which 12 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).

Figure 12: CAs own assessments of the levels of MR own funds requirements



The main factors and reasons that may explain possible underestimations are weaknesses in pricing model assumptions, 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 more than 70% of applicable respondents

In three banks, NCAs identified possible underestimation, not justified, during the bank's internal validation process. CAs are currently undertaking some monitoring activities (both ongoing and on-site) of the internal models to check all the related issues.

CAs planned some actions for 12 banks (e.g. reviewing the bank's internal VaR and IRC models, a supervisory extra charge, stringent conditions on any extension of the internal model approach, further internal model investigation at peer level, etc.).

Currently, two 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 variability in these hypothetical portfolios, but that cannot lead to conclusions regarding real under- or overestimations for the MR 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 equity derivatives, commodities trades and credit spread products. Other reported findings are in line with previous MR benchmarking exercises. Generally, credit spread portfolios show more dispersion than other asset classes for the analysed metrics. There is evidence that how risk factor returns are taken into account in the models plays a key role in this (e.g. relative versus absolute returns for different asset classes). Supervisors should pay attention to this when reviewing firms' credit VaR models, by challenging both VaR and sVaR assumptions and modelling choices.

Supervisors might also look at other possible ways of improving harmonisation, such as assessing the materiality of risk factors not in VaR and, where appropriate, challenging the models to improve the coverage (e.g. with regard to inflation), and applying conservatism when allowing banks to periodically review the transition matrix and with regard to computing the implied default probabilities and correlations for sovereign positions in IRC models. Importantly, the conclusions reached in regular supervisory model monitoring activities should 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 aims to provide a framework that could 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 NCAs, the graphs and tables created, the methodology defined, the discussions held during the interviews, etc.) sets a path for future investigations and activities on these issues.

Annex

Table 17: Banks participating in the 2015/16 EBA MR benchmarking exercise

Country	Bank name
AT	Erste Group Bank AG
AT	Raiffeisen-Landesbanken-Holding GmbH
BE	Belfius Banque SA
BE	KBC Group NV
DE	BHF Bank AG
DE	Commerzbank AG
DE	Deutsche Bank AG
DE	Deutsche Zentral-Genossenschaftsbank AG
DE	Landesbank Baden-Württemberg
DE	Landesbank Hessen-ThüringenGirozentrale
DE	NORD/LB Norddeutsche Landesbank Girozentrale
DE	Westdeutsche Genossenschafts-Zentralbank AG
DK	Danske Bank A/S
DK	Nykredit Realkredit A/S
ES	Banco Bilbao Vizcaya Argentaria, SA
ES	Banco Santander SA
ES	BFA Tenedora De Acciones, SA
ES	Criteria Caixa Holding, SA
FR	BNP Paribas SA
FR	Groupe BPCE
FR	Groupe Crédit Agricole
FR	Société Générale SA
GB	Barclays Plc
GB	Citigroup Global Markets Europe Ltd
GB	Credit Suisse International
GB	Credit Suisse Investments (UK)
GB	Goldman Sachs Group UK Ltd
GB	HSBC Holdings PLC
GB	ICBC Standard Bank PLC (formerly 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 Popolare Società Cooperativa
IT	Intesa Sanpaolo SpA
IT	UniCredit SpA
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**
N. banks	*2*	*2*	*8*	*2*	*4*	*4*	*14*	*3*	*4*	*3*	*1*	*3*

Table 18: HPE

	Portfolio ID	Portfolio description	IMV submissions
Equity	1.1	Equity index futures on FTSE 100	41
	1.2	Bullish leveraged trade on Google	39
	1.3	Volatility trade on S&P 500	41
	1.4	Volatility trade on FTSE 100	38
	1.5	Equity variance swaps on Eurostoxx 50	24
	1.6	Barrier option on S&P 500	36
	1.7	Quanto index call on Eurostoxx 50	32
IR	1.8	Curve flattener trade on sovereign treasuries	48
	1.9	Interest rate swap	50
	1.10	2y swaption on 10y IRS	49
	1.11	LIBOR range accrual	34
	1.12	Infation zero coupon swap	36
FX	1.13	Covered FX call on EUR/USD	48
	1.14	Mtmkt Cross Crcy Basis Swap 2y USD 3m LIBOR vs. EUR 3m EURIBOR swap	44
	1.15	Knock-out currency option	47
	1.16	Double no touch binary currency option	31
Commodity	1.17	Long short-term ATM OTC Ldn Gold fwd & Short long-term ATM OTC Ldn Gold fwd	28
	1.18	Short oil put options	24
Credit Spread	1.19	Sovereign CDS portfolio	35
	1.20	Sovereign bond/CDS portfolio	35
	1.21	Sector concentration portfolio	32
	1.22	Diversified index portfolio	38
	1.23	Diversified index portfolio with higher concentration	34
	1.24	Diversified corporate portfolio	31
	1.25	Index basis trade on iTraxx 5y EU	29
	1.26	CDS bond basis	31
	1.27	Short index put on iTraxx EU Xover	18
	1.28	Quanto CDS on ES with delta hedge	26
Sub All-in portfolio	1.29	All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	16
All-in portfolio	1.30	All-in portfolio (1 to 28)**	14
All Equity portfolios	1.31	Equity (1 to 7)**	22
All IR portfolios	1.32	Interest rate (8 to 12)**	27
All FX portfolios	1.33	FX (13 to 16)**	39
All commodity portfolios	1.34	Commodity (17 and 18)**	22
All credit spread portfolios	1.35	Credit spread (19 to 28)**	14
Correlation Trading	2.1	Long position in spread hedged equity tranche of CDX.NA.IG index	10
	2.2	Long position in spread hedged mezzanine tranche of CDX.NA.IG index	10
	2.3	Short position in spread hedged super senior tranche of CDX.NA.IG index	10

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

Table 19: VaR cluster analysis

VaR cluster 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	Num obs. [1]
Equity	1.1	1	1		18	20	1	41
	1.2			1	17	16	3	37
	1.3	1	2	5	11	18	3	40
	1.4		1	2	17	15	2	37
	1.5		1	2	10	10	1	24
	1.6			4	11	16	4	35
	1.7			1	13	18		32
IR	1.8	1	2	1	21	22		47
	1.9		1		21	26	1	49
	1.10		3	2	18	24	1	48
	1.11	1	2	1	13	17		34
	1.12				19	15	2	36
FX	1.13		4	2	16	20	4	46
	1.14	17	1		3	18	5	44
	1.15			2	21	19	2	44
	1.16							
Com	1.17			1	13	12	2	28
	1.18	1		3	7	11	2	24
Credit Spread	1.19		1	1	16	16	2	36
	1.20	3	3	6	5	17	1	35
	1.21	1	1	2	12	14	1	31
	1.22		1	1	14	17	5	38
	1.23		1		14	17	2	34
	1.24		2	2	10	13	4	31
	1.25	2	1	5	8	9	4	29
	1.26	1	2	5	5	17	1	31
	1.27	1	3		5	7	2	18
	1.28	6	3	1	1	9	6	26
All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29	1	2	2	10	26	4	45
All-in portfolio (1 to 28)**	1.30	4	1	2	13	22	2	44
Equity (1 to 7)**	1.31	1	1	5	13	18	3	41
Interest rate (8 to 12)**	1.32	2	1	2	17	23	2	47
FX (13 to 16)**	1.33	2	4	1	20	5	16	48
Commodity (17 and 18)**	1.34	1		3	10	8	6	28
Credit spread (19 to 28)**	1.35	1	2	4	8	17	5	37
Correlation Trading	2.1	1			2	3	1	7
	2.2		1		2	1	2	6
	2.3	2			1	2	1	6

[1] *Including extreme values*

100 — *Range containing more than 10% of the total observations for that particular portfolio*

Table 20: VaR statistics

Statistics for VaR

		Main statistics						Percentiles				
	Port.	Min	Max	Ave.	STDev	STDev_trunc[1]	Num obs.[3]	25th	50th	75th	MAD	Interquantile dispersion
Equity	1.1	114	17,414	626	2,837	39	37	140	157	168	14	9%
	1.2	0	681	409	141	115	33	319	425	496	97	22%
	1.3	38	485	218	94	77	32	167	201	258	46	22%
	1.4	1	231	113	40	28	34	94	114	126	16	15%
	1.5	1	346	143	66	35	20	108	135	178	32	24%
	1.6	62	237	128	50	46	31	80	129	154	41	32%
	1.7	183	460	279	57	42	28	245	283	311	31	12%
IR	1.8	83	918	174	141	51	34	130	153	166	18	12%
	1.9	0	415	182	56	30	41	148	190	209	29	17%
	1.10	40	165	71	25	19	37	59	67	76	8	12%
	1.11	95	927	200	145	62	33	145	160	199	30	16%
	1.12	21	270	199	54	42	31	191	212	226	17	8%
FX	1.13	1	1,973	962	442	330	41	833	924	1,042	100	11%
	1.14	1	1,268	476	527	519	39	25	37	1,060	35	95%
	1.15	9	381	225	64	49	39	188	228	262	38	16%
	1.16											
Com	1.17	1	92	55	18	13	25	52	55	63	6	10%
	1.18	15	6,182	488	1,306	57	21	172	189	236	31	16%
Credit Spread	1.19	0	111	41	17	9	30	34	38	47	5	15%
	1.20	34	808	196	142	83	31	118	134	238	29	34%
	1.21	1	445	68	78	15	27	48	54	62	6	13%
	1.22	31	206	93	30	20	33	83	94	100	11	9%
	1.23	48	184	86	23	13	30	79	86	90	7	7%
	1.24	38	194	84	38	30	26	61	82	90	13	19%
	1.25	0	76	25	16	11	25	14	24	33	10	41%
	1.26	35	989	214	178	87	27	115	166	274	62	41%
	1.27	7	1,086	214	263	263	15	108	123	318	24	50%
	1.28	3	136	36	36	29	21	11	17	53	12	65%
All-in (1, 2, 4, 8, 9, 13, 17, 18, 19, 20, 21, 24, 26)**	1.29	788	25,052	2,830	5,958	5,958	16	979	1,135	1,537	190	22%
All-in portfolio (1 to 28)**	1.30	655	5,127	1,743	1,525	1,525	13	970	1,155	1,565	256	23%
Equity (1 to 7)**	1.31	289	22,795	1,857	5,585	5,585	16	383	447	545	80	17%
Interest rate (8 to 12)**	1.32	208	1,682	366	316	150	24	260	276	315	27	10%
FX (13 to 16)**	1.33	0	4,604	1,013	1,149	1,153	33	136	932	1,139	670	79%
Commodity (17 and 18)**	1.34	15	287	173	70	57	20	143	190	209	31	19%
Credit spread (19 to 28)**	1.35	246	817	487	173	173	12	395	433	589	100	20%
Correlation Trading	2.1	240	1,834	704	536	536	7	326	581	843	256	44%
	2.2	49	277	133	83	83	6	59	131	152	47	44%
	2.3	5	789	151	313	313	6	14	17	65	8	65%

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