



EBA REPORT RESULTS FROM THE 2024 MARKET RISK BENCHMARKING EXERCISE – PART 1 - IMA

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Contents

List of figures and tables

Abbreviations

1. Executive summary	9
1.1 Main findings of the benchmarking analysis	10
1.2 CAs' assessments based on supervisory benchmarks	15
1.3 Past exercises and future expected changes	15
2. Introduction of the 2024 market risk benchmarking exercise	17
2.1 Definition of the market risk hypothetical portfolios	17
2.2 Data collection process	18
2.2.1 IMV	18
2.2.2 Risk measures	18
2.3 Participating banks	19
2.4 Data quality	19
3. Market risk benchmarking framework	22
3.1 Outlier analysis	23
3.2 Risk and stressed measures assessment	32
3.2.1 Limitations	34
4. Overview of the results obtained	36
4.1 Analysis of VaR and sVaR metrics	36
4.2 A closer look at the VaR and sVaR results	40
4.2.1 Comparison of sVaR and VaR ratios	42
4.2.2 Drivers of variation	43
4.2.3 Supervisory actions	46
4.2.4 Modelling differences	46
4.2.5 Other drivers of variation	48
a. Size of the bank	49
b. Business model	50
c. Level of approval	51
d. Common stress period considered	52
4.2.6 Portfolio comparison	53

4.3	Analysis of IRC and APR	54
4.4	P&L analysis	57
4.5	Diversification benefit	58
4.6	Dispersion in capital outcome	60
4.7	Present value	60
5.	Competent authorities' assessment	62
6.	Conclusion	65
7.	Annex 1 – Additional tables	67
8.	Annex 2 – Legal background	148

List of figures and tables

Figures

Figure 1: IMV scatter plots – low-IQD instruments.....	30
Figure 2: IMV scatter plots – high-IQD instruments	31
Figure 3: Interquartile dispersion and coefficient of variation for IMV and risk metrics by portfolio	37
Figure 4: VaR submissions normalised by the median of each portfolio.....	41
Figure 5: sVaR submissions normalised by the median of each portfolio	42
Figure 6: sVaR–VaR ratio for the average VaR and sVaR by portfolio	43
Figure 7: Qualitative data: VaR methodological approaches.....	44
Figure 8: VaR submissions normalised by the median of each portfolio (by methodological approach)	44
Figure 9: Qualitative data: VaR time-scaling techniques	45
Figure 10: Qualitative data – length of VaR lookback period	45
Figure 11: Qualitative data – VaR weighting choices	45
Figure 12: Qualitative data: source of LGD for IRC modelling	55
Figure 13: Qualitative data – number of modelling factors for IRC.....	55
Figure 14: P&L chart example of low IQD	57
Figure 15: P&L chart example of high IQD	58
Figure 16: CAs’ own assessments of the levels of MR own funds requirements (BM exercise 2023)	63
Figure 17: CAs’ reported reasons for over-underestimation of MR own funds requirements (BM exercise 2023)	63
Figure 18: IMV scatter plots (all).....	92
Figure 19: VaR submissions normalised by the median of each portfolio (by asset class).....	109
Figure 20: sVaR submissions normalised by the median of each portfolio (by asset class)	114

Figure 21: sVaR submissions normalised by the median of each portfolio (by methodological approach)	119
Figure 22: VaR ratio with median (focus on small banks).....	121
Figure 23: VaR ratio with median (focus on medium-sized banks)	123
Figure 24: VaR ratio with median (focus on large banks)	125
Figure 25: Additional P&L charts with examples of low IQD	142
Figure 26: Additional P&L charts with examples of high IQD	144
Figure 27: Comparison between IMV and truncated STD deviation method to select outliers for risk measures	146

Tables

Table 1: Average IQD by asset class - VaR.....	11
Table 2: IMV statistics and extreme values.....	25
Table 3: Average IMVs’ interquartile dispersion by asset class	26
Table 4: IMV cluster analysis – number of banks by range.....	28
Table 5: Interquartile dispersion for IMV, risk metrics and SBM OFR by risk factor	38
Table 6: sVaR–VaR ratio by range (number of banks as a percentage of the total)	39
Table 7: Coefficient of variation for regulatory VaR (controlling for HS) by modelling choice (%) .	48
Table 8: Average regulatory VaR by modelling choice.....	48
Table 9: Asset class comparison for VaR in terms of banks’ size	50
Table 10: Asset class comparison for VaR within the same business model (cross-border universal bank).....	51
Table 11: Asset class comparison for VaR in terms of level of approval.....	52
Table 12: Asset class comparison for sVaR in terms of the time window applied.....	52
Table 13: Portfolio comparison for VaR, sVaR and IRC	53
Table 14: IRC statistics and cluster analysis	56
Table 15: Coefficient of variation for regulatory IRC by modelling choice (%)	57
Table 16: Diversification benefit statistics	59

Table 17: Interquartile dispersion for capital proxy.....	60
Table 18: Banks participating in the 2024 EBA MR benchmarking exercise.....	67
Table 19: Instruments/portfolios underlying the HPE	68
Table 20: VaR cluster analysis – number of banks by range	84
Table 21: VaR statistics.....	85
Table 22: sVaR statistics	86
Table 23: P&L VaR statistics	87
Table 24: Empirical expected shortfall statistics	88
Table 25: sVaR/VaR statistics	89
Table 26: P&L VaR/VaR statistics	90
Table 27: VaR statistics (small banks only).....	120
Table 28: VaR statistics (medium-sized banks only)	122
Table 29: VaR statistics (large banks only)	124
Table 30: VaR statistics (small TB banks only).....	126
Table 31: VaR statistics (medium TB banks only).....	127
Table 32: VaR statistics (large TB banks only)	128
Table 33: VaR statistics (same business model – cross-border universal bank)	129
Table 34: VaR statistics (low L3 A&L banks only)	130
Table 35: VaR statistics (medium L3 A&L banks only)	131
Table 36: VaR statistics (high L3 A&L banks only)	132
Table 37: VaR statistics (IR and CS asset classes – only banks with general and specific IR risk approval)	133
Table 38: VaR statistics (IR and CS asset classes – only banks with general IR risk approval)	134
Table 39: VaR statistics (EQ asset class – only banks with general and specific EQ risk approval)	134
Table 40: VaR statistics (EQ asset class – only banks with general EQ risk approval)	135
Table 41: Stress VaR statistics (2008-2009 stress period only).....	136
Table 42: PV statistics.....	137

Table 43: IRC – modelling choice: source of LGD – market convention	138
Table 44: IRC – modelling choice: source of LGD – non-market convention	139
Table 45: IRC – modelling choice: source of LGD – 1-2 modelling factors.....	140
Table 46: IRC – modelling choice: source of LGD – >2 modelling factors	141

Abbreviations

APR	all price risk
CA	competent authority
CDS	credit default swap
CO	commodities
CRD	Capital Requirements Directive
CRR	Capital Requirements Regulation
CS	credit spread
CS01	credit spread value of 1 basis point changes
CTP	correlation trading portfolio
CV	coefficient of variation
EBA	European Banking Authority
EQ	equity
ES	expected shortfall
EU	European Union
FRTB	fundamental review of the trading book
FX	foreign exchange
HPE	hypothetical portfolio exercise
HS	historical simulation
IMV	initial market valuation
IQD	interquartile dispersion
IR	interest rates
IRC	incremental risk charge
IT	information technology
ITS	implementing technical standards
LGD	loss given default
MC	Monte Carlo
MR	market risk
MRWA	market-risk-weighted asset
OFR	Own Funds Requirements
P&L	profit and loss
PD	probability of default
Q&A	question and answer
RTS	regulatory technical standards
RWA	risk-weighted asset
sVaR	stressed value at risk
SBM	Sensitivities Based Method
VaR	value at risk

1. Executive summary

1. This report presents the results of the 2024 supervisory benchmarking exercise pursuant to Article 78 of the Capital Requirements Directive (CRD) and the related regulatory and implementing technical standards (RTS and ITS) that define the scope, procedures and portfolios for benchmarking internal models for market risk (MR).
2. The report summarises the conclusions drawn from a hypothetical portfolio exercise (HPE) conducted by the EBA during 2023/24. The primary objective of the exercise is to assess the level of variability observed in risk-weighted assets (RWA) for market risk produced by banks' internal models.
3. The exercise was performed on a sample of 43 European banks from 13 jurisdictions. The relevant institutions submitted data for 105 instruments recombined into 77 market portfolios across all major asset classes, i.e., equity (EQ), interest rates (IR), foreign exchange (FX), commodities (CO) and credit spreads (CS), as well as five correlation trading instruments recombined into four portfolios (CTPs), for a total of 82 benchmark portfolios. Thus, the exercise covers the entire population of EU banks with internal models for MR at the highest level of consolidation.
4. As summarised in this report, the analytical part of the exercise delivered by the EBA provided the competent authorities (CAs) with a list of outliers to be examined in detail. The banks with the most significant number of outliers were also highlighted to their CAs, which addressed the issues reported bilaterally with their banks. CAs and the EBA also collected feedback on improving forthcoming benchmarking exercises where possible.
5. Finally, considering the benchmarking exercise's results, CAs were asked to provide the EBA with responses to a questionnaire on the actions they plan to take regarding each participating bank's internal model.

1.1 Main findings of the benchmarking analysis

6. The report measures variability in terms of the interquartile dispersion (IQD)¹ and the coefficient of variation (CV)² observed within each benchmark portfolio. The IQD is more robust than the CV when the sample is drawn from an unknown, fat-tailed distribution. As far as the market-risk-weighted asset (MRWA) variability, the IQD metric suggests a level of dispersion for all the risk measures provided by banks that need to be monitored.
7. The primary considerations are that the 2024 results show an increase in the dispersion of the initial market valuation (IMV) versus the 2023 exercise concerning all assets classes asset class; see, for instance, Table 2. Equity and Interest Rate and CS remains relatively low (4%, 4% and 5% respectively, compared to 2%, 2% and 3% respectively in 2023). Nonetheless, the FX average IQD increased significantly to 19% (it was 8% in 2023 and 3% in 2022). The reason for this is that FX FD instruments (301, 302, 310 and 311) present an IMV quite dispersed (especially instrument 301 with 1766% IQD). Instrument 301 (Fx FWD) is not a new instrument in the sample, with a low IMV, but also there are banks that report IMV of similar magnitude but opposite sign, which means that there are still some issues linked to the common understanding of the booking for this instrument. A clarification on the booking of the Fx Fwd should improve the consistency of the Fx asset class booking in the future exercise. CO remains a substantially high IQD (16%, vs 14% in 2023 and vs 24% in 2022) asset class, which is driven by two instruments (401 and 402), over a total of 5 CO instruments (which is very limited), as well as the total number of submissions, with a negative effect on the average IQD of this asset class.
8. Therefore, even if the average IQD of the IMV has increased, this is due to a very restricted sample of instruments with substantially high IQD (the mentioned 301, but 223, 221, and 121). The rest of the instruments have comparable low dispersion with respect the previous exercise. Therefore, based on this year's observations, we can conclude that the quality of the data submitted did not decreased. The quality of the data is extremely important for the benchmarking exercise, and the banks should pay great attention when submitting these data. It should be stressed that to substantially increase the data quality, several rounds of iteration with submitters would be required, which is not feasible within the short time frame of the exercise. The continuous improvement and clarification of the details for the instruments is also an objective that the EBA is always pursuing.
9. Dispersions have been examined and most of them have been justified by the banks and CAs. A minority of the outlier observations remain unexplained and are expected to be part of the ongoing activities of supervisors, who are expected to monitor and investigate the situation (see Chapter 5 of this report).

¹ IQD is defined as the absolute value of the ratio of the interquartile range (Q3 – Q1) divided by the sum of the quartiles (Q3 + Q1). The higher the IQD is, the higher the dispersion in the data.

² CV is computed as the ratio of the standard deviation to the mean.

10. From a risk factor perspective, FX portfolios exhibit a lower level of dispersion than the other asset classes. In general, variability is substantially lower than in the previous exercise. This is likely due to an improvement in the data submission, which impacted the dispersion of the risk measures, decreasing the dispersion in general (see Table 5: Interquartile dispersion for IMV, risk metrics and SBM OFR by risk factor).
11. Regarding the single risk measures, the overall variability for value at risk (VaR) is lower than the observed variability for stressed VaR (sVaR) (14% and 21%, compared to 16% and 21% in 2023, compared to 21% and 28% in the 2022 exercise, with 27% and 31% in 2021 and with 18% and 29% in 2020).³ More complex measures, such as the incremental risk charge (IRC), show a higher level of dispersion (44%, it was 42% in 2023 exercise, 45% in the 2022, 43% in 2021 and 49% in 2020).
12. The variability of risk measures, especially the VaR, is marginally lower than the previous exercise and overall, this exercise mark the lowest level of dispersion of the risk measures since the exercise has started, as shown in the table below.

Table 1: Average IQD by asset class - VaR

Average Interquartile dispersion by asset class - VAR

	Interquartile range 2024 exercise	Interquartile range 2023 exercise	Interquartile range 2022 exercise	Interquartile range 2021 exercise	Interquartile range 2020 exercise	Interquartile range 2019 exercise	Interquartile range 2018 exercise	Interquartile range 2017 exercise
Equity	16%	17%	25%	24%	18%	14%	23%	22%
IR	15%	16%	21%	19%	13%	16%	9%	19%
FX	9%	12%	11%	27%	12%	22%	17%	41%
Commodity	14%	17%	18%	19%	20%	24%	21%	13%
Credit spreads	16%	18%	28%	37%	23%	28%	26%	27%
CTP								

13. As for the past exercise, to deepen the analysis of VaR and further investigate the variability drivers, different VaR metrics were computed and compared with the banks' reported VaR, in particular:
- an alternative estimation of VaR, called profit and loss (P&L) VaR, computed by the EBA using the 1-year daily P&L series submitted by banks using a historical simulation (HS) approach; and
 - a comparable VaR, called HS VaR, corresponds to the regulatory VaR reported by those banks that use an historical simulation (HS) approach (only).
14. When comparing the variability between the regulatory VaR and these alternative risk measures, a decrease in the IQD when considering a more homogeneous sample is confirmed (i.e., HS banks only). In fact, for all the risk types, the dispersion observed for the P&L VaR tends to be lower but is still not negligible. This finding suggests that the modelling approach is not the only driver of the observed VaR variability. Other drivers, such as risks not captured in the

³ These values are derived as a simple average of the IQD across all non-correlation trading portfolios.

model or the choice of absolute versus relative returns, offer further explanations for the results' variability (see Table 5: Interquartile dispersion for IMV, risk metrics and SBM OFR by risk factor).

15. Even so, within the subset of banks using an HS approach, modelling choices (see Table 7: Coefficient of variation for regulatory VaR (controlling for HS) by modelling choice) seem to make a noticeable difference. Modelling configurations produce mixed results depending on the different asset classes. The same can be said in terms of conservativeness, where different calibrations have different effects depending on the asset class (see Table 8: Average regulatory VaR by modelling choice). But this analysis is extremely sensitive to the different portfolios used to produce the statistic, the low number of subjects available, and the passage of time from one exercise to another. Different model settings impact differently the dispersion; therefore, this report will refrain from trying to generalise the results and define a 'less dispersed' and 'more conservative' configuration of modelling choices.

16. As mentioned above, the dispersion in sVaR figures is generally higher than the dispersion observed for regulatory VaR (see Table 21 and Table 22). The stressed period used was the one applied by the bank for capital purposes, so it was not harmonised in the sample. Different choices for the stressed period are permitted by the Capital Requirements Regulation (CRR), and these choices are considered and questioned as part of the regulatory approval process. While allowing banks to use their own individual stress periods reduces the comparability of the sVaR results across the sample, doing so facilitates the estimation of implied capital needs from the HPE. Nonetheless, banks in the exercise are asked to report the stressed period applied. As a result, the EBA selected a subset of homogeneous time windows applied and ran the benchmark for this subsample. It appears clear that when a homogeneous stress window is applied, the sVaR figures tend to be less dispersed (see Table 41: Stress VaR statistics (2008-2009 stress period only)).

17. Moreover, to carry out these analyses, the EBA conducted a comparison across banks of the ratio between sVaR and VaR for each of the hypothetical portfolios included in the benchmarking exercise (see Table 6: sVaR–VaR ratio by range (number of banks as a percentage of the total)). The ratio generally varies significantly between the portfolios (from 0.09 to 34.5), with values that cannot be explained except by errors. However, on average, the ratio comes in at around 2.25 (see Table 25: sVaR/VaR statistics).

18. As expected, for the larger banks with significant trading activities, the benchmarking portfolios are generally relevant to their actual trading book. For smaller banks, this is less the case, and this is why the EBA included simpler and more plain vanilla instruments starting from the 2019 exercise. The challenge remains to design a benchmarking exercise that can fit banks that have a specialised business model. Overall, the portfolios are, however, reflective of the risk factors experienced by most banks. In the 2024 exercise, it is noticeable a further decrease in the VaR dispersion (14% from the 16% of 2023), still that in some cases (16 over 77 single portfolios - see Table 21: VaR statistics). The aggregate portfolios also feature notably low levels of IQDs.

19. Regarding the IRC, the average variability (as measured by the average IQD for this category of portfolios) is higher than that observed for all other metrics considered in the report (44%). This high variability is slightly higher than in the previous exercise – the IQD was 42% on average in the 2023 exercise (45% in 2022, 43% in 2021) (see Table 14: IRC statistics and cluster analysis). The understanding of the IRC dispersion was further analysed by disaggregating various modelling choices (see Table 15, Table 43, Table 44, Table 45 and Table 46). While the number of risk factors and applying market conventions to the source of LGD seems to have a different impact, depending on the asset classes applied. These results are not consistent with what was observed in the previous exercises, so it looks like even for the IRC, the modelling choices influence the dispersion, but the effect cannot be generalised, and it looks very time dependent.
20. An additional metric considered as part of the analysis was the diversification benefits observed for VaR, sVaR and IRC in the aggregated portfolios (see Table 16: Diversification benefit statistics). As expected, there is evidence that larger aggregated portfolios exhibited greater diversification benefits than smaller ones. In general, the level of dispersion observed in diversification benefits tends to be lower than that in the corresponding metrics at the level of the individual portfolios.
21. As for previous exercises, an assessment was also carried out on the variability of the empirical estimates of the expected shortfall (ES) at a 97.5% confidence level. The results indicate that the dispersion in this metric across risk factors is like that found for VaR and P&L VaR (see Table 24).

Dispersion in the capital outcome

22. Alongside the variability analysis, the EBA also conducted the usual assessment regarding possible underestimations of capital requirements (see Table 17: Interquartile dispersion for capital proxy). As the analysis is based on hypothetical portfolios and the capital requirements were defined using a proxy, the results should be interpreted as approximations of potential capital underestimations. The proxy for the implied capital requirements was defined as the sum of VaR and sVaR across all portfolios. For purposes of comparison, the proxy was computed three times. In one case, the VaR and sVaR figures were multiplied by the banks' total multiplication factor and, in the other, by the regulatory minimum of three only, i.e., ignoring the banks' individual addend(s) set by the CAs. Finally, a subset of banks applying the same stress period was also considered for capital dispersion. This metric enables a comparison of banks and an assessment of their variability in this regard.
23. The average variability across the sample as measured by the IQD is significant (around 18%), especially for the most complex portfolios in the credit spread asset class. This dispersion very slightly decreases when considering a more homogenous capital proxy (15% applying three as the multiplier and 14% for banks with the same stress period).

Additional analysis of Risk measures

24. As introduced in the previous exercises, the EBA extended the analysis to other drivers of variation (see Section 4.2.5), such as the size of the bank, the business model of the bank, the

level of approval granted by the CAs and the already mentioned stressed period applied in the sVaR calibration. The size and business model analyses were further provided as they were run in the 2020-2023 reports.

25. In a nutshell, based on this additional analysis, we observe that the size (in terms of RWA for market risk) of the bank has an impact on the figures since small and medium-sized banks tend to produce slightly more dispersed results than larger banks (see Table 9: Asset class comparison for VaR in terms of banks' size). Consistently, when considering the size in terms of the trading book (as a ratio of total assets), the bigger a bank is in terms of its trading book, the (slightly) smaller the dispersion (on average).
26. Concerning the business model, the EBA applied the internal classification of banks as a criterion, under which many of them are classified as cross-border universal banks (see Table 10: Asset class comparison for VaR within the same business model (cross-border universal bank)). Applying this definition of the business model, a smaller decrease in the IQD was identified due to a more homogenous sample. The business model analysis was further extended by considering the 'Level 3' assets and liabilities in the bank's books as a proxy for a more sophisticated business model linked to more exotic products (see Table 34, Table 35 and Table 36). This further specification did not prove conclusive since the dispersion did not change substantially depending on the 'Level 3' assets and liabilities ratio in the bank's trading book.
27. The subsample analysis based on the level of approval delivered interesting results. A priori, it was expected that having banks with different levels of approval would have increased the dispersion of the results of the risk measures. In line with this assumption, the IQD results seem to fluctuate among the subsamples of different approval levels. This is because more homogeneous subsamples tend to produce slightly smaller dispersions, but this positive effect is counterbalanced by the smaller number of firms in the sample. Basically, the benchmark provided and the 25th and 75th quantiles of the distribution tend to be less dispersed with respect to the whole set of banks. This implies that the different level of approval does indeed have an impact on the dispersion of the benchmarking results (see Table 11: Asset class comparison for VaR in terms of level of approval).
28. Finally, as already mentioned above, and in line with previous findings, sVaR figures are less dispersed when the benchmark is computed for a homogeneous subsample of firms that applied a similar time period for the stress window used for calibrating the sVaR (see Table 12: Asset class comparison for sVaR in terms of the time window applied).
29. As introduced in the 2020 Report, PV statistics are reported (see Table 42). The PVs reported generally have quite low IQDs, and they were useful in distinguishing true outliers and outliers due to mispricing of the portfolios.

SBM and ASA OFR analysis

30. The 2024 benchmarking exercise is the third year of collecting SBM sensitivities and OFR data. It is also the first year of collecting DRC and RRAO data, as well as the application of ASA

Validation portfolios. The amount of data concerning solely the FRTB-ASA methodology has grown with time, and it is now more appropriate to separate this part of the exercise in an independent report.

1.2 CAs' assessments based on supervisory benchmarks

31. CAs shared the outcomes of their assessments at the bank level with the EBA (see Figure 16: CAs' own assessments of the levels of MR own funds requirements). The CAs' assessments confirmed the existence of some areas that require follow-up actions on the part of specific institutions whose internal models were flagged as outliers in this benchmarking exercise.
32. Overall, CAs' assessment of the over- and underestimation of RWA was encouraging in the sense that CAs were aware of and able to explain the causes of almost all deviations. Although most of the causes were identified and actions put in place in order to reduce the unwanted variability of the RWA, the effectiveness of these actions can be evaluated only by CAs via constant monitoring of the benchmarking results.
33. The CAs are expected to pay the utmost attention to the minority of cases in which the over- and underestimations were unexplained, to closely monitor these institutions and to put in place additional efforts to reduce these gaps in future exercises.

1.3 Past exercises and future expected changes

34. The 2019 exercise represented a significant change from the 2016-2018 exercises in terms of the simplification of the portfolios. This simplification had a positive effect in obtaining less dispersed results than with the previous portfolios. Furthermore, it improved the significant data quality issues relating to some portfolios while focusing on the model risk elements.
35. In the 2020 exercise, the data submitted further improved in quality thanks to the clarification of the legal text description of some instruments and to the further practice that the banks have gained in conducting the present exercise. This had a positive effect in terms of dispersion in the data provided. Improvements in terms of less dispersed results have also stemmed from the change in the methodology to detect outliers for the risk measures.
36. In the 2021 exercise, the data quality of the submissions was acceptable. That said, the variabilities of the risk measures (VaR, PL VaR and ES) were substantially higher than in the previous year. This seems to be linked to the increased volatility of the markets in 2021 due to the Covid outbreak, as captured by the market model, which generally provided higher figures for the risk measures. These higher figures, in absolute terms, seem to exacerbate the differences in modelling outputs, producing higher IQD metrics. As a result, this higher dispersion does not seem to be the outcome of a decrease in the quality of the market model.
37. For the 2022 exercise, the set of instruments remained mainly similar to the previous exercise, so the EBA reports a similar level in terms of the data quality of the submissions, aside from the mistake in the EQ instruction. The analysis that the EBA ran for the 2022 exercise was the first

in which banks reported sensitivities and OFR figures relating to the sensitivities-based method of the alternative standardised approach (ASA) introduced with the FRTB. The SBM submission was of good quality overall, especially considering the tendency to improve with time.

38. For the 2023 exercise the data collection was extended to allow the collection of new instruments and portfolios, in particular as regards the instruments and portfolios that have lately been applied by the industry. These new instruments are also accompanied by a rationalisation of the references of the instruments in Annex V. The result showed that the overall dispersion was significantly reduced by the adjustment to the instruction, while some new instruments present a quite significant dispersion, due of course to their novelty. The exercise did not change substantially, so the EBA and CAs focused on the analysis of the SBM data submitted. It is clear that there was an improvement in sensitivities submission, with respect to the previous exercise, but also during the exercise due to the many resubmissions and CAs control of the data submitted. While the analysis did not detect any major issues in the SBM data submission, it is clear that at the single-bank level and instrument, minor issues can be detected, and overall compliance with SBM requirements could be improved.
39. For 2024, the EBA extended the SBM data collection to the other ASA components (DRC and RRAO) to have a complete picture of the standardised approach and also adopted a series of validation instruments for the SBM approach, which was already applied by part of the industry, that should significantly enhance the compliance with the SBM requirements.
40. For 2025, the exercise was expected to be reshaped based on the AIMA-FRTB implementation. But during before the ITS 2025 finalisation the European Commission manifested the intention to postpone the FRTB implementation. Therefore, it was decided to maintain the data collection to the format applied in 2024 (for scope and content). The new of the delayed implementation of the FRTB had the indirect impact of postponing the usual timeline of the Market Risk exercise from the usual September-March to January-June, in order to give to banks time to react to the FRTB postponement and to prepare for the exercise.
41. At the moment this report is drafted, the exercise 2026 is under planning, i.e. the ITS is in its final phase before consultation. The new benchmarking ITS will see the introduction of the new templates for the FRTB Alternative Internal Model Approach, which were expected in 2025, but also the extension to the data collection of the ASA methodology to all the banks that apply it, subject a proportionality threshold of 500 million.
42. On a medium-term horizon, the EBA will consider reshaping the instruments and the portfolios in the exercise in a way that still keeps the instruments simple to ensure clarity regarding the instruments. Nonetheless, further enrichment of the variety of the instruments monitored could be beneficial. The effect of the AIMA and ASA implementation will have a significant impact on future design of the exercise.

2. Introduction of the 2024 market risk benchmarking exercise

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

2.1 Definition of the market risk hypothetical portfolios

44. The MR portfolios have been defined as hypothetical portfolios composed of both non-CTPs and CTPs, as set out in Annex V of the benchmarking ITS. The exercise includes 95 instruments recombined into 84 portfolios (77 individual and 7 aggregated), capitalised under the VaR, sVaR and IRC models, comprising mainly plain vanilla and some complex financial products in all major asset classes: EQ (21 instruments and 16 individual portfolios), IR (24 instruments and 23 individual portfolios), FX (11 instruments and seven individual portfolios), CO (five instruments and four individual portfolios) and CS (34 instruments and 27 individual portfolios). The EBA also designed aggregated portfolios, obtained by combining individual ones, to consider diversification effects. Each aggregated portfolio has a particular composition: the first (portfolio 10000) encompasses all asset classes; the second (portfolio 11000) is made up of only EQ portfolios; the third (portfolio 12000) is made up of only IR portfolios; the fourth (portfolio 13000) is made up of only FX portfolios; the fifth (portfolio 14000) is made up of only CO portfolios; and the sixth (portfolio 15000) is made up of only CS portfolios.

45. In addition, the set of portfolios includes ten instruments, and six portfolios (five individual and one aggregated) used for correlation trading activities, capitalised under the VaR, sVaR and APR models. These portfolios contain positions in index tranches referencing the iTraxx Europe index on-the-run series. The portfolios are constructed by hedging each index tranche with the iTraxx Europe index on-the-run 5-year series to achieve a zero-credit spread value of 1 basis point (CS01) as at the initial valuation date (spread hedged). No further re-hedging is required.

46. A more detailed explanation of the portfolios can be found in the benchmarking ITS on the EBA website.⁴

2.2 Data collection process

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

2.2.1 IMV

48. The reference date for IMV was 21 September 2023, 5.30 p.m. CET. Banks entered all positions on 14 September 2023 ('reset or booking date'), and, once positions had been entered, each instrument aged for the duration of the exercise. Furthermore, banks did not take any action to manage the instruments in any way during the entire exercise period.

49. The IMV figure to be reported by the banks for each hypothetical instrument was defined as the mark to market of the instrument on the booking date plus the profit and loss from the booking until the valuation date and time. Therefore, it was the mark to market of the instrument on 21 September 2022, 5:30 p.m. CET.

2.2.2 Risk measures

50. Pursuant to the common instructions provided, banks were required to calculate the risks of the positions without considering the funding costs associated with the portfolios (i.e., no assumptions were admitted with regard to the means of funding the portfolios). Moreover, banks were required to exclude, as far as possible, counterparty credit risk when valuing the risks of the portfolios.

51. Banks were required to calculate the regulatory 10-day 99% VaR on a daily basis. sVaR and IRC could be calculated on a weekly basis. In such cases, sVaR and IRC had to be based on end-of-day prices for each Friday in the time window of the exercise. For the six CTPs (6001-6005 and 16000), APR was also requested.

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

⁴[ITS package for benchmarking exercises | European Banking Authority \(europa.eu\)](#). Please also refer to Commission Implementing Regulation EU 2016/2070 of 14 September 2016 and Commission Implementing Regulation 2019/439 of 15 February 2019, laying down ITS in accordance with Article 78(2) of Directive 2013/36/EU ([Implementing regulation - 2024/348 - EN - EUR-Lex](#)).

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

2.3 Participating banks

54. A total of 43 banks representing 13 EU countries participated in the exercise (see Table 18 in the annex). All EU banks with MR internal models approved by CAs were asked to submit data at all levels where own funds requirements are calculated. The EBA collected the results only at the highest level of consolidation.

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

2.4 Data quality

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

57. IMV results reached the EBA in November/December 2023, after which the EBA carried out a preliminary IMV analysis and provided CAs with a tool to help them spot likely anomalies or misunderstandings regarding the interpretation of each portfolio. This was done to enhance the quality of all risk measures so that they would be provided in accordance with a correct interpretation of the portfolios. This step was conducted before the computation of the risk measures by the banks. Where the price of an instrument fell outside a certain range,⁵ more investigation had to be undertaken by the CA, which could – if necessary – ask the banks in its jurisdiction for a repricing and subsequent resubmission. The same process was carried out for the risk measure submission.

58. The issue experienced in the previous exercises linked to the aggregated portfolio figures no longer seems to be a major issue. It is worth noting that some banks reported the IMVs and risk measures for the aggregated portfolios without including all the relevant components.⁶ The reason was that the 2018 (and previous) ITS required banks to report the value of aggregated portfolios even if not all individual portfolios are modelled for the benchmarking exercise. As a result, the submissions were not comparable with those valued in full. This issue was addressed in the 2019 exercise, and since then banks have reported the results for the aggregated

⁵ The range means the interval between the first and third quartiles. These quartiles were considered and subsequently updated when resubmissions were received.

⁶ Some banks reported values for aggregated portfolios, considering only those components for which they had permission to use an internal model. This is clearly not a data quality issue, and it is correct that banks report results only where they have permission to do so for regulatory purposes.

portfolios only if the results of all components have been submitted.⁷ The structure of the 2019-2020 exercise, i.e. a plurality of instruments that are recombined into a plurality of individual portfolios, which are themselves the components of the aggregated portfolios, produced a similar error, i.e. the absence of some instrument components within some of the individual portfolios. Nonetheless, banks should not provide any (aggregated or individual) portfolios where any instrument is missing in order not to distort the risk measures analysis. This specification was further clarified in the ITS 2022, so the possibility that some individual portfolios could have been submitted even when some specific instruments were missing cannot be ruled out. On the other hand, the data submission seems compatible with the correct interpretation of the rule, at least for many submitters.

59. It should be recalled that the 2024 exercise is the third exercise where EBA is collection information concerning the sensitivities linked to the SBM and the OFR linked to the SBM from the banks participating in the benchmarking exercise. The complete representation of the sensitivities collected is provided at the moment due to the very granular nature of the data collected. Nonetheless, some issues were detected, mainly linked to the volatility reported (inconsistent representation). All in all, the quality of the submitted sensitivities was appropriate.

60. The 2024 exercise also marks the first year where the validation instruments/portfolio for the SBM methodology were introduced by the new Annex 10 of the benchmarking ITS. ITS should be noted that only a small number of banks complained with this new set of requirements.

61. In the data analysis, it looks like no major errors in the reporting of any asset class were present. A complete list of the errors in the submitted data is beyond the scope of this report, but the most common and easily avoided mistakes worth mentioning are as follows:

- Equity asset class: in the past it was usually detected cases of use of the wrong notional in the equity positions. In the 2023 Annex, the instruction was corrected, reporting now the exact amount of share (or point of index) that the option or the future should report. This has enhanced the quality of the submission of this asset class substantially. The only issue remained in the Equity Asset class seems to be linked to the instrument 121 (VIX option), where a noticeable dispersion in the IMV is still present.
- Interest rates: confirmed the very good results were obtained in the previous exercise, especially where the international securities identification number was available. The cross-currency swap (instrument 220, now included on IR instruments) finally present a very low IQD (1%) indicating a consistent booking practice of this instrument, with only a couple of exceptions. The 223 (inflation swap) exhibits some relevant dispersion (309% IQD) due to a low market value of the instrument, but also to some inconsistency in the booking practice.

⁷ Annex 5, Market risk 2024 BM, Section 1 (Common instructions), letter (ee)

- FX: this asset class shows generally low IQD, with a few of noticeable exceptions in instrument 301, 302 and instrument 310-311, all forward contracts. In this case, the dispersion is attributed to mix of error in booking, and some inconsistent interpretation of the instruction. Luckily this kind of error, does not impact negatively the risk measures provided in the exercise. Nonetheless, the instructions were amended in the 2025, which hopefully should provide additional clarity in the booking phase of the exercise.
- Commodity: high IQD for instruments 401 and 401. This is also not easily explained since the instruments should be well known by the banks.
- Credit spread: very good results in terms of CV and IQD, with very sporadic mistakes entailing possible wrong bookings, and no long position instead of a short, or vice versa.

62. Although these mistakes were detected thanks to the EBA and Competent Authorities data analysis and corrected by resubmission/cleansing of the data from the banks, unnoticed errors in data submissions could still be present in the dataset analysed, and this can potentially drive and pollute the results.

63. Nonetheless, data quality for the 2024 exercise has been generally good. Ensuring data quality is a fundamental step for the benchmarking exercise. However, reporting errors might still occur in future exercises, and the process will allow both regulators and participating banks to learn from it.

3. Market risk benchmarking framework

64. The benchmarking exercise aims to assess the variability in banks' MR models and to identify the drivers that account for it. Variability in banks' models can come from three types of drivers.
65. First, variability can stem from banks' modelling choices that are explicitly envisaged in the regulation. For example, when modelling VaR institutions can choose to use a lookback period longer than the minimum (i.e., the previous year), use a weighting scheme for the data series, calculate the 10-day VaR directly or, alternatively, obtain a 1-day VaR and rescale it using the square root of time approximation. Likewise, when modelling IRC, banks can choose from several sources of the probability of default (PD) and have a certain degree of freedom when choosing the transition matrices applied, or when deciding on the liquidity horizon applied to a particular instrument. It should be highlighted that all these possibilities are, in principle, acceptable under the current regulatory framework (the CRR), provided that they have been agreed on with the CA during the approval process. Therefore, given the wide range of approaches that each institution using internal models can choose to implement, some degree of variability is expected.
66. Second, there are other modelling choices that are not explicitly envisaged in the regulations, which may cause variability. Examples include differences in simulation engines; differences in pricing model assumptions; the modelling of returns, volatility, correlations and other indirect parameter estimates; additional risk factors considered in the models; different approaches to P&L computation and attribution; and a stochastic framework for the simulated shocks.
67. 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 information technology (IT) and organisational weaknesses, independent pricing valuations or detected flaws) and, quite significantly, the application of limits to the diversification benefits applied by banks (i.e. not allowing a single calculation at consolidated level and, instead, requesting an aggregation of the capital results at sub-consolidated and/or subsidiary levels) are likely to increase the observed variability in capital. In most cases, these supervisory actions have been established to address known flaws or model limitations, or to add an additional layer of prudence. Therefore, they typically result in higher capital requirements than would otherwise be the case. However, they can also increase the variation in market own funds requirements between banks, particularly across jurisdictions. Although the effects on capital levels of these supervisory actions can be substantial, a benchmarking portfolio exercise is not suitable for assessing some of these supervisory actions. In particular, any constraints on diversification benefits and direct capital add-ons cannot be properly assessed, since these effects are entirely portfolio dependent. To assess these effects, it would be necessary to use a much more realistic (hypothetical) portfolio,

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

68. Possible additional drivers of variation include:

- misunderstandings regarding the positions or risk factors involved that could not be resolved during the preliminary assessment (see Section 2.2);
- non-uniform market conventions and practices adopted in the hypothetical portfolio booking;
- incompletely implemented models (e.g., because a pricing module is being tested, or an additional risk factor is being taken into consideration);
- missing risk factors not incorporated into the model;
- differences in calibration or data series used in the modelling simulation;
- additional risk factors incorporated into the model;
- alternative model assumptions applied; and
- differences attributable to the methodology used (i.e. Monte Carlo (MC) versus HS or parametric).

3.1 Outlier analysis

69. After the data quality assurance process, the EBA performed an ‘extreme value’ analysis with the aim of excluding from the computation of the benchmarks those values for which the IMV and risk measures (RMs: VaR, sVaR, P&L VaR and ES) were found to lie outside a certain tolerance range due to misinterpretation of the trade or mistyping of bookings by the banks.

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

71. Extreme IMVs and RMs are defined as values outside the range of two truncated standard deviations⁸ from the median. Since some results exhibited empirical distributions that had fatter tails than expected, outliers were defined as values differing by twice the truncated standard deviation or more from the median.

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

72. If a bank’s IMV or RM are found to be an extreme value for a particular instrument, then this observation is removed from the computation of the final benchmark statistics. The empirical evidence indicates that excluding the RMs based solely on IMV submissions, as in the previous exercise, implied that some extreme RM submissions are wrongly reflected in the benchmarking computation, while some good observations are removed. Changing this methodology did not influence the benchmarking data point, i.e., the median result. In addition, the overall dispersion of the portfolio was only marginally affected (slightly improved). The significant enhancement is in the communication to the CAs of the significant outliers to be examined with the bank. This approach, which was first adopted for the 2020 market risk benchmarking exercise, increased the overall quality of the benchmark data, providing more consistency for the benchmarks of these metrics.

73. The dispersion across the contributions is summarised by the IQD coefficient, which is more robust than the coefficient of variation (CV) for data derived from fat-tailed distributions. The higher the IQD, the more dispersed the data. IQD is defined as:

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

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

74. Another metric used in the variability studies is the CV, which is defined as the ratio between the standard deviation⁹ and the mean (in absolute values):

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

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

⁹ The standard deviation was considered to gain a sense of the entire variability and a harmonised approach across the HPE. Obviously, a truncated standard deviation may appear more consistent for some highly dispersed trades.

Table 3: Average IMVs' interquartile dispersion by asset class

Average Interquartile dispersion by asset class - IMV

	Interquartile range 2024 exercise	Interquartile range 2023 exercise	Interquartile range 2022 exercise	Interquartile range 2021 exercise	Interquartile range 2020 exercise	Interquartile range 2019 exercise	Interquartile range 2018 exercise
Equity	4%	2%	21%	2%	1%	2%	2%
IR	4%	2%	16%	19%	2%	3%	8%
FX	19%	8%	3%	4%	16%	15%	6%
Commodity	16%	14%	24%	4%	10%	6%	8%
Credit spreads	5%	3%	1%	1%	1%	3%	6%
CTP	4%				5%	8%	103%

76. Table 2 and Table 3 show the results at the level of both each individual instrument and each risk type. As shown, the highest dispersion at the level of the individual instruments is detected for Fx instrument 301 (Fx forward) (IQD 1766%). It appears that the variety of interpretation of the instruction make it particularly difficult for banks to book it consistently. Same issue with the instruction could be the cause of the high IQD of instrument 302, 310 and 311 (all Fx forwards). Overall, excluding these four instruments with high dispersion, it would lead to an average IQD of 1% for the Fx asset class i.e., comparable or lower with respect the previous exercises.

77. On the IR asset class, it should be highlighted instrument 223, with 309% of IQD. This significant dispersion, beside probably some inconsistencies in the booking of the instrument, is also due to the 'low value' of the instruments. In terms of its construction the IQD is a ratio of two absolute measures (difference of the 25th and 75th quantiles, divided by the sum of the two). Therefore, a difference of a few hundred euros in the IMV generates very high IQD statistics, which is the case for some derivative instruments that exhibit an IMV of close to zero at inception, since they are entered at market rates. The same differences in the case of instruments that are much more valuable generate IQDs close to zero.

78. The Cmd instruments 401 and 402 also show moderately high IQDs (19% and 21%). This is likely due to a combination of the low IMVs value, which exacerbate the IQDs, and different market practise linked to these instruments, since the instruments are not changed with respect the previous exercise, so such worsening of the IMVs submission would not be explained otherwise.

79. The EQ instrument 121 is the only one with medium-high IQDs (40%). These high IQD is likely due to the underling (Vix) which makes the instruments slightly more exotic with respect to the rest of the EQ instruments.

80. Overall, the IQD of the IMVs by asset class for the instruments of the 2024 exercise is slightly decreased when comparable to the past exercises for all asset classes. The worsening of the dispersion is driven by specific instruments (e.g., instrument 121, 223, 301, 401 and 401). This

means that some specific clarification and amendment to the instructions could still be beneficial (this was done in the ITS 2025).

81. Comparing the 2024 instruments with the 2023 instruments purely on the basis of the IQD, once the few instruments with abnormal IQD have been excluded, it would appear that the quality of the data submission is acceptable, and comparable with the previous exercise.
82. From an aggregated risk-type perspective, as in the past, Fx and CO instruments show the highest dispersion.
83. A cluster analysis (see Table 4 and Figure 1, Figure 2, Figure 18) was performed to strengthen and deepen the aforementioned descriptive insights. It shows the dispersion of the IMVs by instrument and helps in identifying clusters in the instruments' pricing that could explain the scattering of IMVs for some trades. The results of this analysis suggest that the clusters are observable for instruments 121, 223, 301, 302, 310, 311 (i.e. also instruments with higher IQD).

Table 4: IMV cluster analysis – number of banks by range

2024 IMV cluster analysis by instrument: number of banks by range

(X = ratio with the median)

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

	Instr. ID	300% < X	300% ≥ X	200% < X	150% < X	100% < X	50% < X ≤ 50%	0 < X ≤ 100%	-100% < X	Num obs.
		>200%	>150%	>100%	>50%	>50%	>50%	>100%	>200%	
Equity	101				14	22				36
	102				11	22				33
	103				16	16				32
	104				16	16				32
	105				16	16				32
	106				14	16				30
	107				12	20				32
	108				16	16				32
	109				15	16				31
	110				15	16				31
	111				13	14				27
	112				13	14				27
	113				15	16				31
	114				15	16				31
	115		2		1	11	14			28
116		1			13	14			28	
117					15	16			31	
118					12	10		2	24	
119					17	17			34	
120					11	14			27	
121					4	5		2	13	
Interest Rate	201				21	21				43
	202				20	21				41
	203		1		20	20		1		42
	204				21	21		1		43
	205				9	9				18
	206				19	19				38
	207				21	21				42
	208				18	18				36
	209				21	21				42
	210				21	21				42
	211				21	21				42
	212				18	24				42
	213				20	21				41
	214				20	21				41
	215				20	20				40
216				14	15				29	
217				14	17				31	
218				21	21				43	
219				21	22				43	
220				19	17		2		38	
221		1	2	6	12	13	2	5	41	
222					18	18			36	
223		4	1	3	8	1	3	3	29	
224		3	1	1	15	21			41	
FX	301				19	14				19
	302				19	12		7		38
	303				17	20				37
	304				18	19				37
	305				18	18				37
	306				19	18				37
	307		1		17	19				37
	308				18	19				37
	309				18	19				37
	310			1	18	2	16		1	38
311		1		1	12	2	5	8	29	
Commodities	401			1	7	8				16
	402		1		8	8				16
	403			1	7	8				15
	404				6	8				15
	405			1	6	7				13
Credit Spread	501				13	13				28
	502		1		12	11		1	1	26
	503				13	13				26
	504				11	12				23
	505				11	12				23
	506				12	12			1	25
	507				12	15				27
	508				13	14				27
	509				13	14				27
	510				15	14				27
	511				13	14				27
	512				13	14				27
	513				12	13				25
	514				13	14				27
	515				12	15				27
	516				13	14				27
	517				13	13			1	26
	518				12	12				24
	519				15	15				30
	520				15	15				30
521				15	15				30	
522				15	15				30	
523				14	16				30	
524				13	13				26	
525				15	15				30	
526				12	12			1	25	
527				15	15				30	
528				12	12				24	
529				12	12				24	
530				7	7			1	15	
531				12	13				25	
532				12	12				24	
533				13	13				26	
534				13	13				26	
CFI	601				2	3				5
	602				2	3				5
	603				2	3				5
	604				2	3				5
	605				2	3				5
	606				2	3				5
	607				2	3				5
608				2	3				5	
609				2	3				5	
610				2	3				5	

84. In particular, as shown in Table 3 and Figure 2:

- Instrument 121 (EQ) reports few submissions (13) – with some extreme value, and two clusters (around 300k and 700K of IMV);
- 223 exhibits extreme outliers in terms IMVs and in its IQD, which imply some residual issue in term of correct booking from banks.
- Instruments 301, 302, 310 and 311 (FX): generally high IQD (47%), with substantial clustering – highlight issue in the interpretation of the instructions.

85. Some of these extreme outlier banks were classified as a high priority for the CAs (see also Chapter 5), so they were followed with greater attention during the exercise in order to specifically define the reason for the extreme result.

86. Despite many recommendations, some minor misalignments in the IMV have been detected due to the reporting of the 'clean price' (i.e., the price of a trade excluding the accrued interest) instead of the 'dirty price' (i.e., the price of a trade including any interest), which is what was intended for the mark to market valuation. This has been detected especially in the bond price, as in instruments 517-527. This problem was more frequent in the past, but it is evident that not all the banks follow the instructions in this regard. On the other hand, this mistake does not significantly prejudice the provision of the risk measures.

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

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

89. Figure 1 and Figure 2 report the clusters found in the IMV results for a sample of low IQD instruments (0% IQD or close to zero) and high IQD (the highest in the asset class) instruments. All the instruments' IMV distributions are available in the annex in Figure 18.

Figure 1: IMV scatter plots – low-IQD instruments

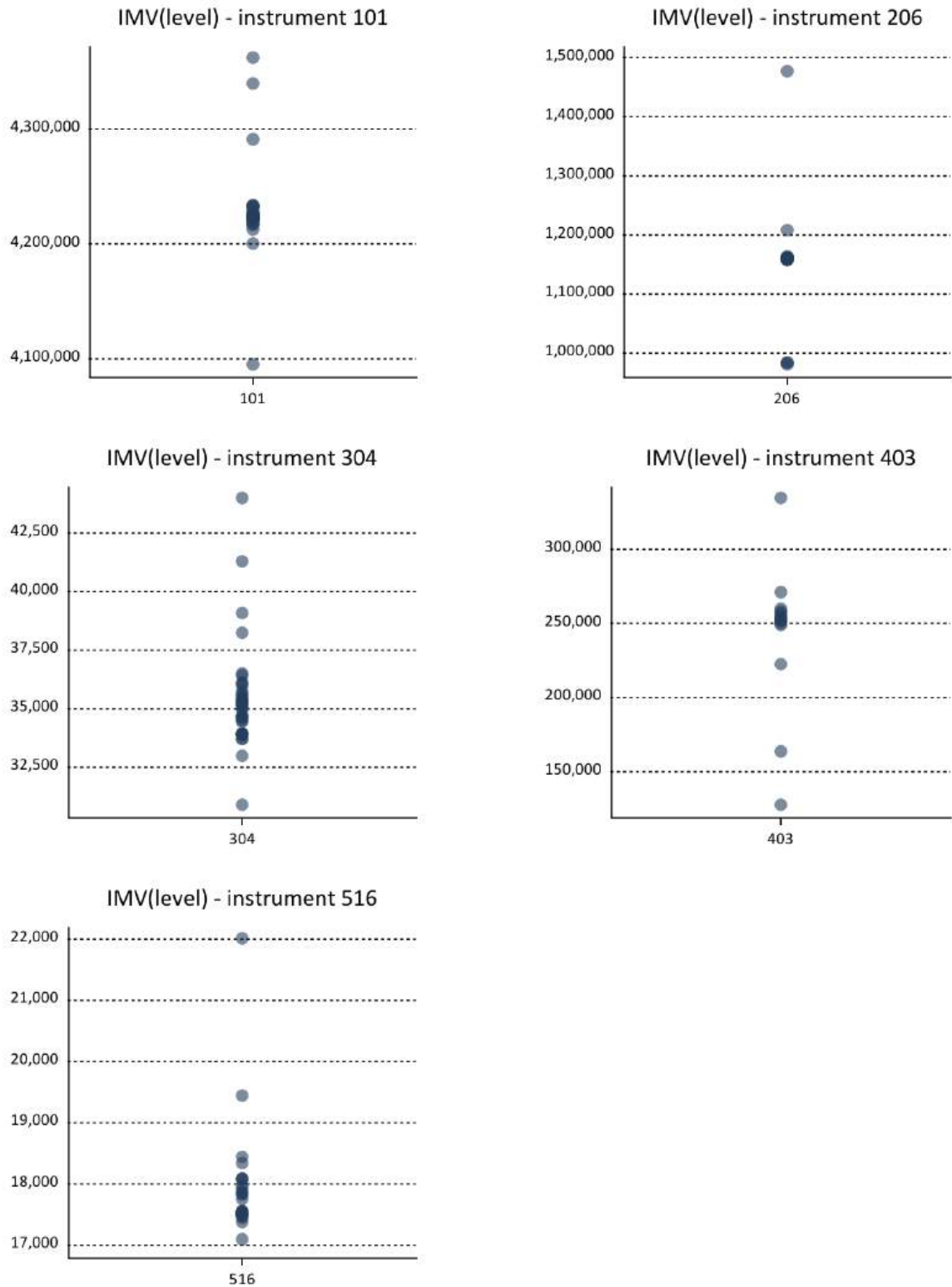
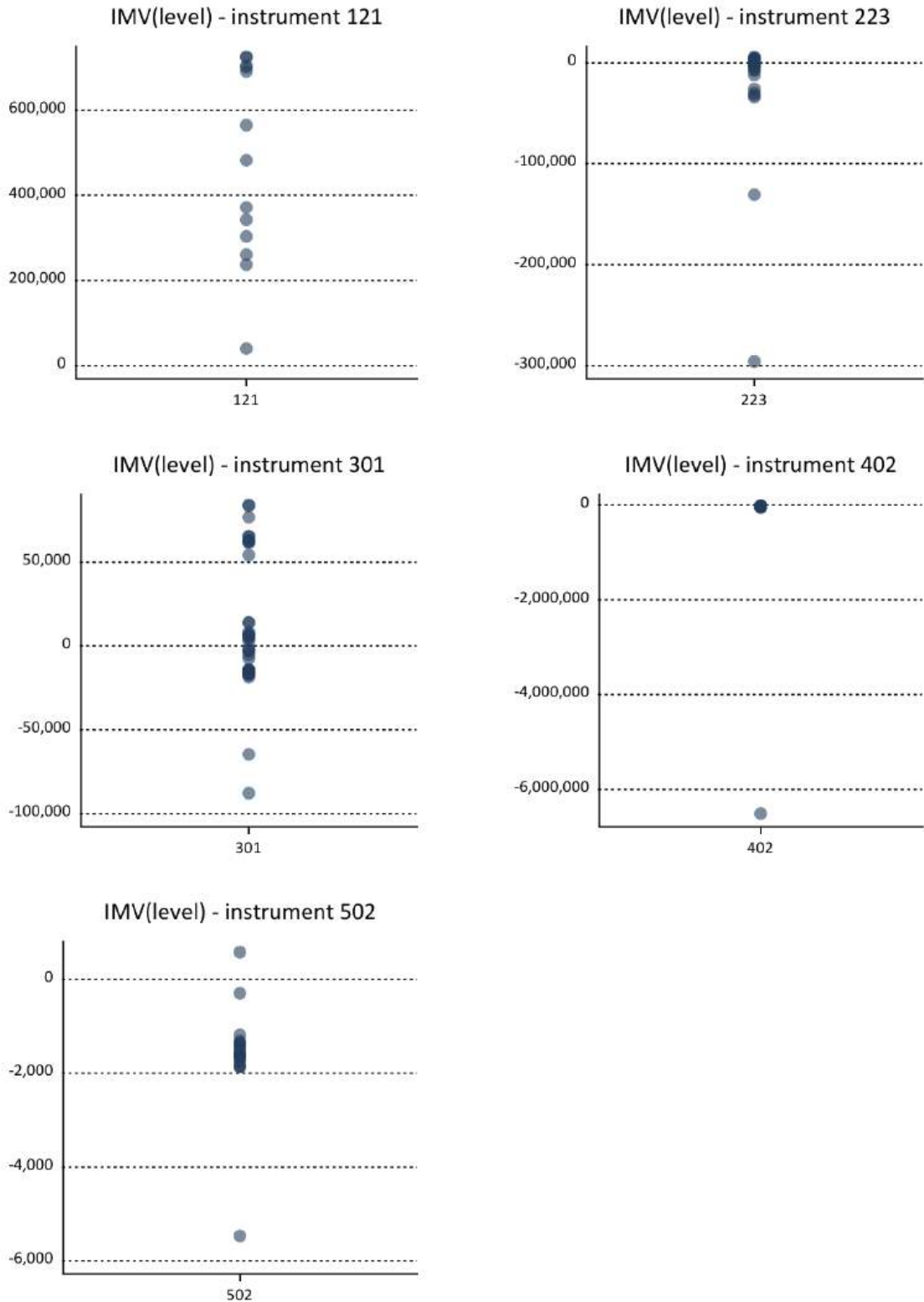


Figure 2: IMV scatter plots – high-IQD instruments



90. The 'concentration index' as per the percentage of values between 50% and 150% of the median value in Table 4 shows that, overall, 95% of the observations lie between those ranges.

91. This result is similar to what reported last year’s MR benchmarking exercise, demonstrating a consistent level in terms of submissions quality.
92. Given the EBA’s experience of past benchmarking exercises, values lying in this range might be considered acceptable on the basis of fine-tuning as successive benchmarking exercises are run.
93. For many hypothetical instruments, the IMV variability is explained by the divergence in terms of both fixings and market practice assumptions by the participating banks. Therefore, the interpretation of the deals and market practices substantially explains the observed variability.

3.2 Risk and stressed measures assessment

94. For VaR and sVaR, variability was assessed by using the banks’ reported VaR and sVaR over a 2-week period (from 15 January 2024 to 26 January 2024). Banks submitted weekly or daily observations, depending on their models, and the final risk measures by portfolio were obtained by averaging the observations over the 2 weeks.
95. In the sample, 14 out of 43 banks calculated weekly sVaR measures. The remaining 29 banks computed daily sVaR measures.
96. Moreover, a P&L VaR measure produced by the EBA using the P&L data provided by banks via an HS approach was analysed. The relevant banks delivered a yearly 1-day P&L vector for each of the individual and aggregated portfolios modelled. These were used to compute the P&L VaR.
97. The additional P&L information for non-APR portfolios allowed the EBA to compute the alternative measure for VaR previously defined, and to check the variability of the results across banks by calculating VaR using a 1-year lookback period.
98. Additional checks were carried out for the available P&L vectors, such as the 1-day P&L versus the 10-day P&L (either overlapped or not), where applicable. Furthermore, the time series with the wrong time window were dropped. P&L vectors provided by banks with no HS model were also dropped. A final consistency checks across the HS banks entailed computing the ratio between P&L VaR and the regulatory VaR provided, which can be expected to be close to 1.¹⁰
99. Clearly, the P&L VaR assessment is possible only for banks applying an HS approach, and with at least 185 days of results submitted. Accordingly, banks applying an MC or parametric approach, or another approach other than HS, cannot be subject to this assessment, and have been dropped from the sample (see also Section 2.4, ‘Data quality issues’).

¹⁰ It should be noted that this expectation depends on the lookback period for VaR.

100. The P&L VaR was computed as the absolute value of the empirical first percentile of the P&L vector rescaled to 10 days by applying the square root of time approximation, without applying any data-weighting scheme:¹¹

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

101. 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 provides useful insights into the degree of market consensus on the relevant risk factors in terms of both market dynamics and volatility levels. Obviously, this analysis, like most of those discussed here, relies on sufficient data points and portfolios being modelled by banks to ensure robustness and consistency.

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

103. In the sample, 15 out of 27 banks computed weekly IRC measures.

104. It is apparent that more complex risk measures, such as IRC, are computed at a less frequent pace (i.e., a weekly basis instead of a daily basis).

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

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

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

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

107. For the aggregated portfolios, diversification effects were checked with regard to the VaR, sVaR and IRC metrics, regardless of whether they were provided or estimated.

¹¹ Some banks apply data weightings at a risk factor level, and these will be present in the P&L vectors. This is an implicit source of variability that cannot be controlled.

108. For the most inclusive portfolios – i.e., the aggregate portfolios – the implied capital charges were also computed, and their variability analysed. Where possible, the idiosyncratic factors that drive variability and the impact of regulatory add-ons (e.g., multipliers) were analysed.
109. It is worth noting that, although the effects on capital levels of these supervisory actions can be substantial, an HPE is not suitable for assessing such differences. This is especially the case for diversification benefits since these effects are entirely portfolio dependent. More on this is included in the following subsection entitled ‘Limitations’.
110. Finally, to make the analysis more comprehensive, CAs were asked to complete a questionnaire about the takeaways from this benchmarking analysis and the actions they plan to take to overcome potential weaknesses in the banks’ MR models (see Section 5 of this report). Thanks to the interview process, the EBA had the opportunity to discuss directly some issues raised by CAs when challenging the models in the ongoing assessment process.

3.2.1 Limitations

111. The design of the benchmarking portfolio exercise described in the ITS aims to ensure the quality of the data used in the report to be produced by the EBA and, more importantly, to identify the banks and portfolios that need specific attention on the part of the responsible CAs. Nevertheless, any conclusions regarding the total levels of capital derived from the hypothetical data should be treated with due caution. The hypothetical portfolios are very different from real portfolios in terms of size and structure. What is more, the data cannot reflect all the actions taken by supervisors.
112. From a methodological perspective, the sVaR metric variability observed could originate either from differences in modelling or from the different data periods used for sVaR computation. Further variability stems from banks’ different stress periods because there is no common benchmarking stress period. To allow more specific analysis of this aspect, since the 2019-2020 benchmarking exercise more information about the stressed VaR time window has been requested from banks by expanding the relative template envisaged in Annex VI of the benchmarking ITS (in this regard, see subsection 4.2.5.d, ‘Common stress period considered’ below).
113. Another limitation that was tackled in this analysis is that of producing a segregated analysis for institutions with partial model approval (e.g., general risk only) in order to split the result for portfolios with specific risk to filter the additional unwarranted dispersion of VaR figures. The benchmark analysis was run by splitting banks with full approval for equity and IR from those with partial approval to filter out the variability of the risk measure introduced by the partially approved banks.
114. Banks with partial model approval provided insights into how they approached the benchmarking exercise. It has been found that the differences reported by the banks in respect of the EBA’s benchmark measure are almost entirely explained by considering the internal

measure of risk, which is not approved for capital purposes but is more complete in terms of risk factor coverage.

115. In summary, the reporting of partial use approval results should be continued for the purpose of the exercise. However, it should be considered within the specific sample in order to assess any bias these partial use approval results could introduce into the results for the rest of the sample observed.

4. Overview of the results obtained

4.1 Analysis of VaR and sVaR metrics

116. The dataset used to perform the assessment of risk measures for the 2024 exercise was determined based on the actual dispersion of the risk measures analysed. The outcome of the IMV extreme value analysis was used as an early indication of the potential problems to be reported to banks by their CAs. As explained in Section 3.1, banks' data were taken into account only for portfolios for which the RM is between the benchmark (50th percentile) +/- two times the truncated standard deviation in the portfolio analysed. The rest was classified as an outlier. As shown in Figure 27, we can see that this methodology, contrary to what was used until the 2019 exercise, does not exclude RMs that are clearly consistent with the benchmark.
117. To check if submissions (by portfolio) were at least approximately symmetrically distributed around the mean and/or the median, the EBA checked for any significant differences between the mean and median values for the truncated sample. Table 20 in the annex reports the banks' VaR results in relation to the median, aggregated into six buckets, to enable the detection of unexpected clusters.
118. As Table 20 and Table 21 show, the variability of the VaR (on average 15% in IQD vs an average variability of 17% in 2023 and 23% in 2022) has improved compared to the previous year, where basically all asset classes report some decrease in the IQDs. The analysis also identifies clusters for portfolios 1016 (EQ), portfolio 2008 and 2019 (IR), and 5009, 5012, 5014 and 5024 (credit spread). This improvement is likely due to a substantial amount of resubmission which improved the quality of Risk Measure dispersion, as long as the fixing and clarification of some instructions.
119. As in the previous exercise, the VaR values for CTPs (portfolios 6001 to 6005) are not reported because of insufficient numbers of these data submission to guarantee the significance of the statistics provided and the anonymity of the submissions.
120. The cluster analysis presented above is superior to a simple outlier analysis that flags submissions more than a designated number of standard deviations from the mean, as this method cannot easily be used for clustered or strongly asymmetric portfolios.

Interquartile dispersion

121. Figure 3 and Table 5 summarise the variability of the results, measured via the IQD and coefficient of variation, for the IMV as well as all three VaR measures (i.e. VaR, VaR for HS banks only and VaR calculated from the 1-year P&L series submitted by HS banks). IQD and CV for IMV, PV, VaR and stress VaR, divided by risk factors, are reported at the bottom of Figure 3. Table 5 also includes the VaR results for MC simulation banks and the expected shortfall.

122. In terms of risks across different assets classes, the IQDs for VaR for all asset classes are decreased, and they are all well below 20%. The asset class with the lower level of IQD is FX, with just 9% (it was 12% in 2023). The asset class with the highest IQD remain the CS (16%, it was 18% in 2023, 28% in 2022; and it was 37% in 2021) and EQ (16%). Overall, the IQD is lower (14%) than in the previous exercises (in 2021 exercise there was an average dispersion of the VaR of 25%, whereas this decrease to 21% in the 2022 exercise, and 16% in 2023), and it is now lower of the 17% before Covid pandemic in 2020. This decrease in the IQD of the VaR is likely to have stemmed from a stable decrease in the market volatility, but also to a good refinement of the instructions and submission of the data.

123. As expected, the IQD for sVaR is higher than for VaR (see the bottom panels of Figure 3), with an average IQD of 21% (22% in 2023, 28% in 2022, 29% in 2021 and 25% in 2020). The CS asset class features a higher dispersion once again (29% as it was in 2023, and 35% in 2022; in 2020 and in 2021 it was 34%). Higher sVaR dispersion is likely to be due to the differences between banks in their choice of the 1-year stress period used, which is chosen based on each participating bank's actual portfolio. It might therefore be the case that the sVaR is not calculated with respect to the 1-year period that maximises VaR for the given hypothetical portfolio.

Figure 3: Interquartile dispersion and coefficient of variation for IMV and risk metrics by portfolio

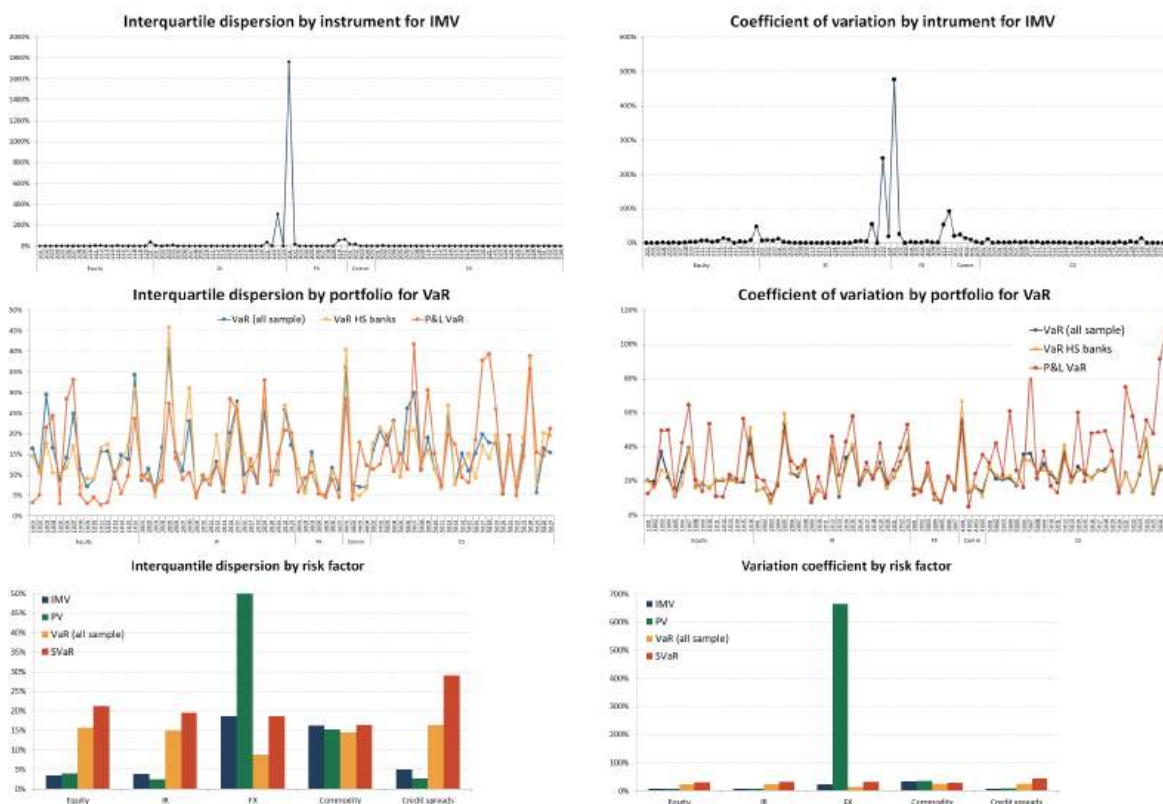


Table 5: Interquartile dispersion for IMV, risk metrics and SBM OFR by risk factor

Average Interquartile dispersion by risk factor

	<i>IMV</i>	<i>VaR (all sample)</i>	<i>SVaR</i>	<i>P&L VaR</i>	<i>VaR HS banks</i>	<i>VaR MC banks</i>	<i>Exp shortfall</i>	<i>SBM OFR</i>
Equity	4%	16%	21%	12%	12%	10%	11%	12%
IR	4%	15%	20%	14%	16%	8%	13%	8%
FX	19%	9%	19%	7%	8%	5%	8%	2%
Commodity	16%	14%	16%	16%	13%	5%	17%	20%
Credit spr.	5%	16%	29%	18%	14%	13%	18%	14%

124. Table 5 confirms that when a homogeneous subset of banks is considered (i.e., HS or MC banks), the VaR results show less dispersion than the total sample (average 13% vs. 14%). Regarding the P&L VaR, the dispersion is also 13% (on average among different asset classes) is slightly lower with respect to the all-sample VaR for almost all the asset classes (not for CS). This is consistent with the assumption that fewer differences in the methodology would imply less dispersion among the risk measures.

125. When comparing variability for HS VaR and MC VaR, also this year’s result tells us that the MC VaR values are less dispersed than those of the HS VaR, as it was in the past exercise. Nonetheless, the analysis needs to take account of the fact that the sample of MC banks is quite small compared with that of HS banks (i.e., 7 MC banks versus 30 HS banks). As far as parametric banks are concerned, a similar analysis is not informative as the total number of parametric banks is very small (i.e., two banks in the sample – the remaining three apply a combination of methods, and one failed to report).

126. The ratio between sVaR and VaR was also analysed across the sample (see Table 25 in the annex). Some banks have ratios below 1 for many portfolios, while other banks have extremely high ratios for some portfolios. While it is generally expected that the sVaR is greater than the VaR, the clear disparity between these values is usually a natural indication that something is wrong with the data submitted, and the EBA and CAs must pay attention to these observations.

127. Table 6 shows the distribution of the sVaR–VaR ratio classified into three buckets (i.e., below 1, between 1 and 3, and above 3) for each portfolio. It is worth noting that a significant number of portfolios for EQ, and IR have a significant proportion of ratios below 1.

Table 6: 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)

	Port. ID	X > 3	1 < X ≤ 3	X ≤ 1
Equity	1001	17.9%	78.6%	3.6%
	1002	86.4%	13.6%	0.0%
	1003	17.4%	78.3%	4.3%
	1004	19.0%	71.4%	9.5%
	1005	33.3%	66.7%	0.0%
	1006	12.5%	83.3%	4.2%
	1007	55.0%	40.0%	5.0%
	1008	9.1%	86.4%	4.5%
	1009	8.0%	92.0%	0.0%
	1010	88.0%	12.0%	0.0%
	1011	11.1%	88.9%	0.0%
	1012	14.8%	85.2%	0.0%
	1013	10.3%	62.1%	27.6%
	1014	14.3%	85.7%	0.0%
	1015	10.5%	89.5%	0.0%
	1016	27.3%	63.6%	9.1%
Interest Rate	2001	0.0%	82.4%	17.6%
	2002	0.0%	52.6%	47.4%
	2003	0.0%	75.8%	24.2%
	2004	2.8%	36.1%	61.1%
	2005	21.4%	64.3%	14.3%
	2006	0.0%	88.9%	11.1%
	2007	0.0%	76.7%	23.3%
	2008	3.7%	85.2%	11.1%
	2009	0.0%	89.2%	10.8%
	2010	0.0%	72.7%	27.3%
	2011	0.0%	68.4%	31.6%
	2012	0.0%	78.8%	21.2%
	2013	2.7%	59.5%	37.8%
	2014	40.0%	52.0%	8.0%
	2015	28.6%	60.0%	11.4%
	2016	0.0%	57.1%	42.9%
	2017	86.2%	10.3%	3.4%
	2018	0.0%	68.6%	31.4%
2019	14.7%	73.5%	11.8%	
2020	50.0%	39.5%	10.5%	
2021	3.2%	71.0%	25.8%	
2022	0.0%	82.8%	17.2%	
2023	0.0%	81.1%	18.9%	
FX	3001	6.3%	90.6%	3.1%
	3002	0.0%	93.3%	6.7%
	3003	10.7%	89.3%	0.0%
	3004	6.7%	90.0%	3.3%
	3005	54.5%	45.5%	0.0%
	3006	19.4%	66.7%	13.9%
	3007	35.7%	64.3%	0.0%
Commodities	4001	20.0%	71.3%	6.7%
	4002	7.7%	92.3%	0.0%
	4003	18.2%	81.8%	0.0%
	4004	0.0%	100.0%	0.0%
Credit Spread	5001	18.2%	81.8%	0.0%
	5002	62.5%	37.5%	0.0%
	5003	30.4%	69.6%	0.0%
	5004	52.6%	47.4%	0.0%
	5005	68.2%	31.8%	0.0%
	5006	47.8%	52.2%	0.0%
	5007	18.2%	68.2%	13.6%
	5008	4.2%	70.8%	25.0%
	5009	3.8%	80.8%	15.4%
	5010	4.3%	78.3%	17.4%
	5011	8.3%	70.8%	20.8%
	5012	57.1%	33.3%	9.5%
	5013	22.7%	77.3%	0.0%
	5014	50.0%	40.9%	9.1%
	5015	0.0%	90.9%	9.1%
	5016	21.1%	78.9%	0.0%
	5017	26.3%	73.7%	0.0%
	5018	21.1%	78.9%	0.0%
	5019	13.6%	81.8%	4.5%
	5020	0.0%	77.8%	22.2%
5021	52.4%	47.6%	0.0%	
5022	0.0%	89.5%	10.5%	
5023	15.4%	84.6%	0.0%	
5024	15.8%	84.2%	0.0%	
5025	8.7%	91.3%	0.0%	
5026	0.0%	92.0%	8.0%	
5027	0.0%	84.0%	16.0%	
CTP	6001	75.0%	25.0%	0.0%
	6002	50.0%	50.0%	0.0%
	6003	0.0%	100.0%	0.0%
	6004	0.0%	100.0%	0.0%
	6005	50.0%	50.0%	0.0%
ALL-IN no-CTP	10000	9.1%	90.9%	0.0%
Equity Cumulative	11000	31.8%	68.2%	0.0%
IR Cumulative	12000	0.0%	77.4%	22.6%
FX Cumulative	13000	8.8%	91.2%	0.0%
Commodity Cumulative	14000	15.4%	84.6%	0.0%
CS Cumulative	15000	0.0%	95.7%	4.3%
CTP Cumulative	16000	0.0%	50.0%	50.0%

4.2 A closer look at the VaR and sVaR results

128. Figure 4 and Figure 5 give an overview of the VaR and sVaR results for portfolios 1001 to 6005, i.e. they do not include the aggregated portfolios, where fewer observations were available for the reasons explained above (see Section 2.4).
129. Broken down by portfolio, the figures show the average VaR and sVaR over the 10-day submission period for each bank, normalised by the median¹² of the given portfolio.¹³
130. Comparing Figure 4 and Figure 5, it shows the dispersion for sVaR than for VaR (sVaR 21% IQD versus 14% VaR IQD on average). Differences in dispersion between VaR and sVaR seem steady but are more marked for the CS portfolios, in which sVaR shows a higher level of dispersion than in the other asset classes (29%).
131. FX and CO are the asset classes with the lowest levels of dispersion for VaR (9% and 14%), as they are for sVaR (19% and 16%).

¹² The portfolio median is the median of the average VaR and sVaR over the submission period.

¹³ Note that the figures are restricted to VaR–median and sVaR–median ratios below 450%.

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

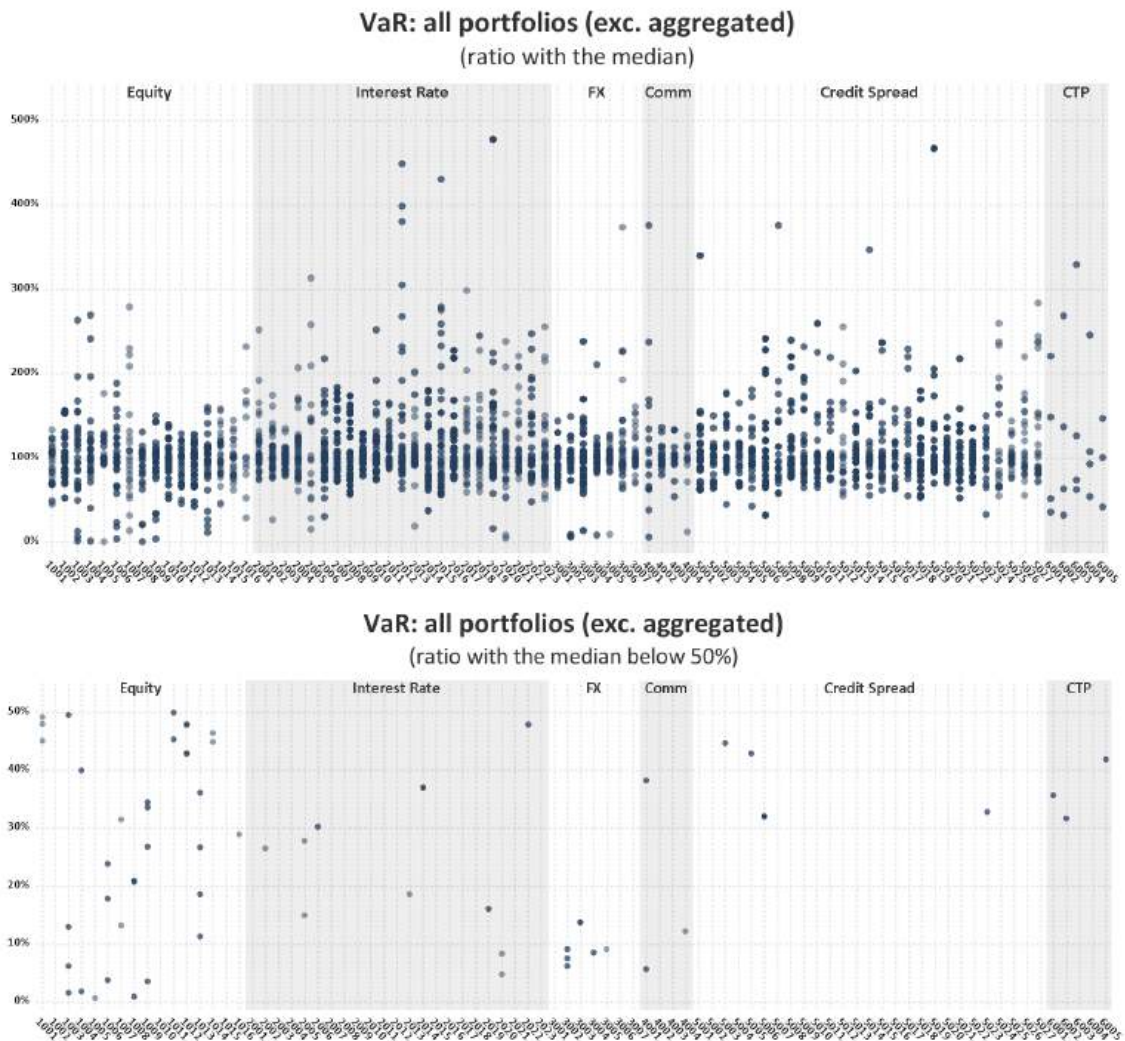
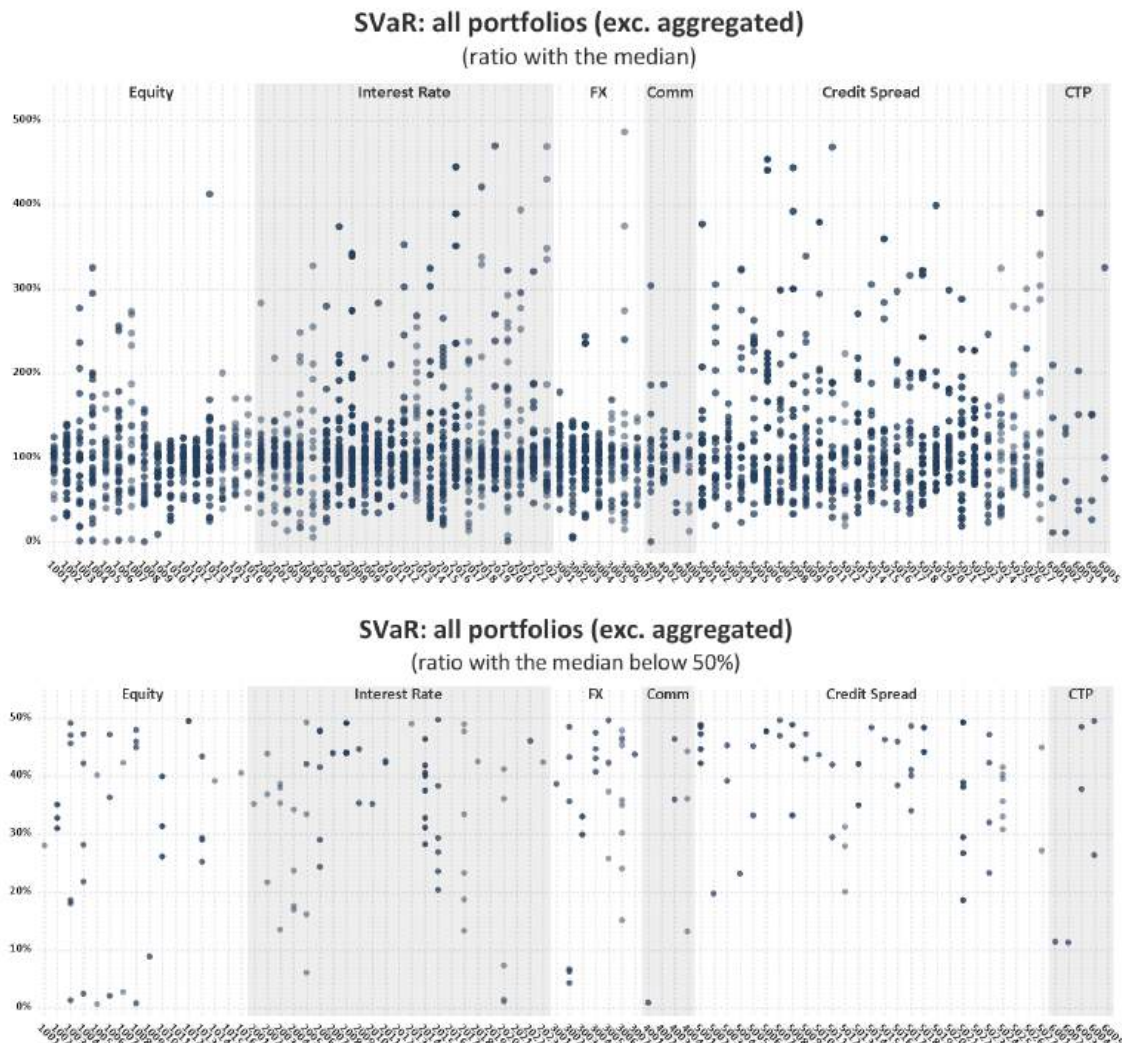


Figure 5: sVaR submissions normalised by the median of each portfolio



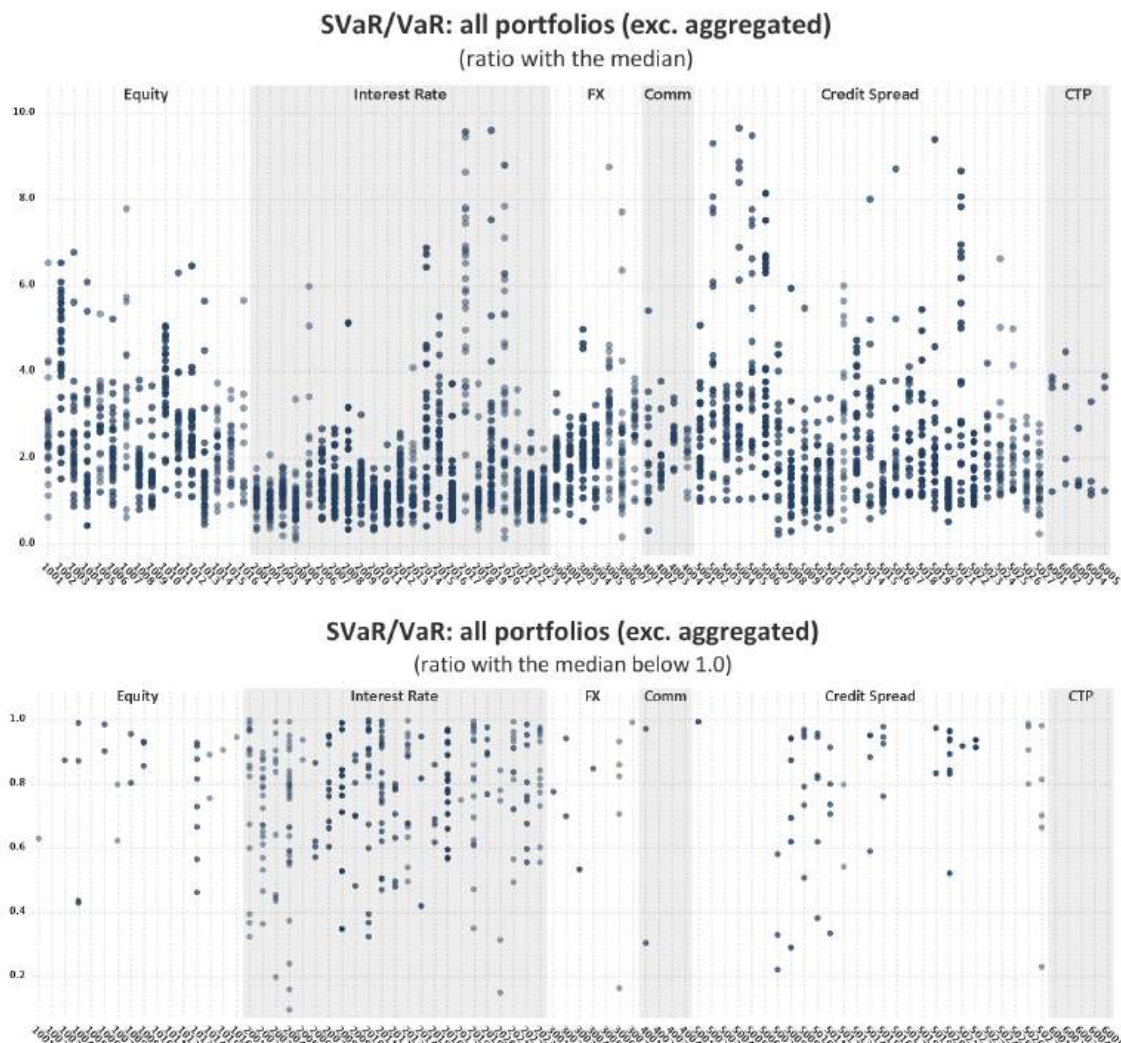
132. Table 21 and Table 22 in the annex report all the VaR and sVaR statistics along with EU benchmarks for all HPE portfolios.

4.2.1 Comparison of sVaR and VaR ratios

133. Banks were assessed in relation to the full sample not only by their VaR and sVaR values, but also by their sVaR–VaR ratios (Table 25). In general, it should be expected that sVaR would be at least as high as VaR, as sVaR is calibrated to a 1-year period of significant stress. This is verified in 88% of cases. This was 71% in 2023, 89% in 2022 and 73% in 2021.

134. Figure 6 shows the ratio of the average sVaR to the average VaR for each bank. The sVaR–VaR ratio varies significantly across the portfolios. Excluding outliers, the average sVaR–VaR ratio per portfolio varies between 0.09 and 34.50 and averages 2.25.

Figure 6: sVaR–VaR ratio for the average VaR and sVaR by portfolio



135. A few banks have a high sVaR–VaR ratio for portfolios in certain asset classes only. This suggests that these asset classes dominate the banks’ real trading portfolios and, for that reason, drive the calibration of the sVaR window.

4.2.2 Drivers of variation

136. Based on the qualitative information provided by banks (Figure 7 to Figure 11), the most common methodological approach used by banks to model MR is HS (71%). Although most banks use the same methodological approach, the dispersion of VaR remains substantial because other modelling choices play a key role in producing variability of the risk measures (e.g., differences in time scaling and/or weighting scheme choices, absolute versus relative returns for different asset classes).

Figure 7: Qualitative data: VaR methodological approaches

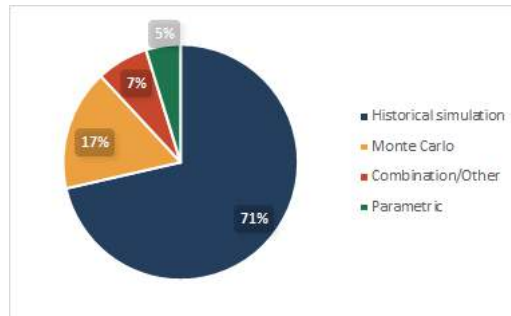
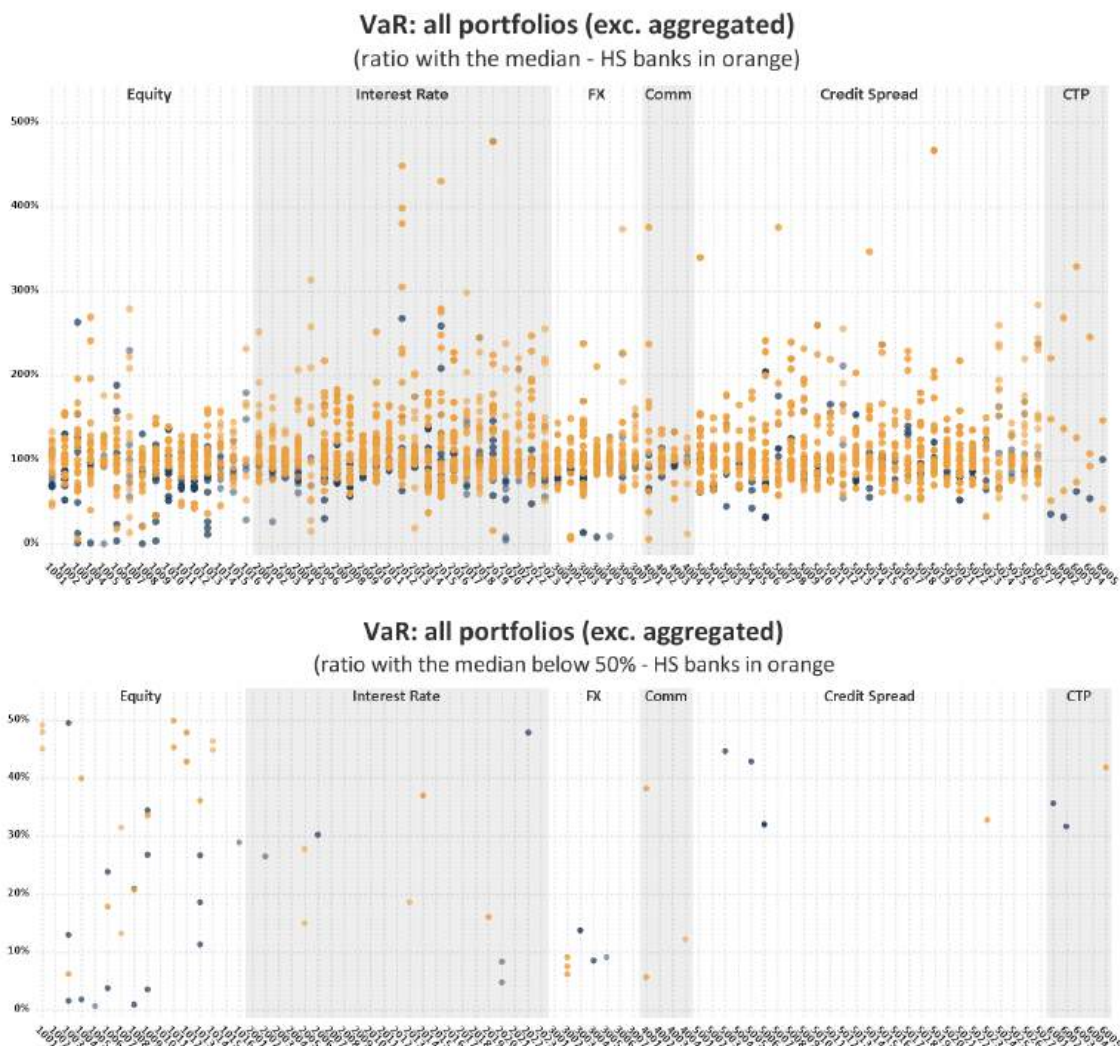
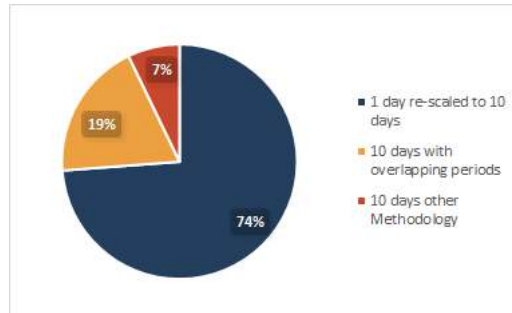


Figure 8: VaR submissions normalised by the median of each portfolio (by methodological approach)



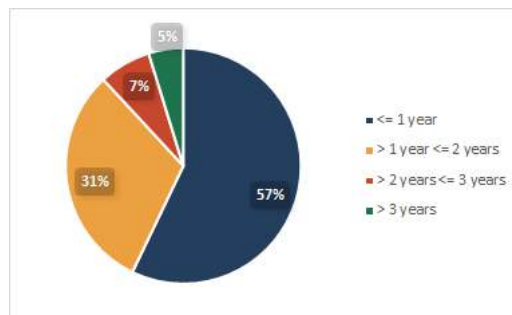
137. Regarding the regulatory 10-day VaR computation, by far the preferred method is rescaling the 1-day VaR to the 10-day VaR using the square root of time approximation.

Figure 9: Qualitative data: VaR time-scaling techniques



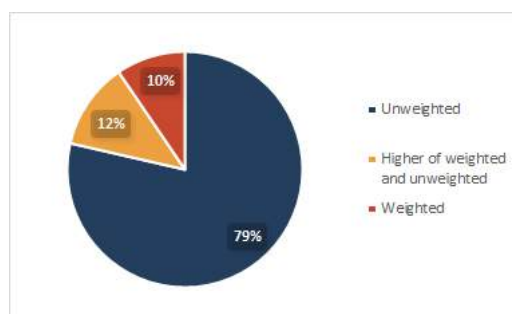
138. Regarding the historical lookback period used to calibrate banks' VaR models, 57% of the banks use the minimum period of one year and applying a period longer than 2 years is very unusual.

Figure 10: Qualitative data – length of VaR lookback period



139. As for the possible use of a data-weighting scheme, the great majority of banks' models use unweighted data in the regulatory VaR computation (79% of respondents).

Figure 11: Qualitative data – VaR weighting choices



140. Finally, regarding supervisory actions on regulatory add-ons, 72% of the banks in the sample have a total multiplication factor greater than the minimum of 3, which includes the addend resulting from the number of over-shootings (Table 1 in Article 366 of the CRR) and any supervisory extra charge(s). The average total multiplication factor in this sample is equal to 3.56, with a maximum of 5.63. As a result, quite a few banks either must correct for excessive over-shootings or are subject to supervisory measures. In addition, some banks have been assigned other kinds of added penalties that encompass risk ‘not in VaR’ and additional charges for IRC and APR. This was apparent from the additional and related information provided by some CAs about their supervised banks, and from discussions with some banks during the interviews.

141. These responses suggest that the observed variation may be due to a few different drivers. The EBA chooses to present the analysis using the following broad headings:

- supervisory actions;
- modelling differences; and
- other drivers of variation.

4.2.3 Supervisory actions

142. Supervisory actions can take different forms and are therefore difficult to capture fully in the analysis. However, the effects of some types of supervisory charges can be approximated. The effect of a higher VaR or sVaR multiplier imposed by a CA because of model weaknesses, for example, can be studied using the following proxy:

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

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

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

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

4.2.4 Modelling differences

145. As outlined in Chapter 3, the CRR permits banks to tailor their VaR models to their specific requirements by making different modelling choices. To test the impact of different modelling choices in a controlled manner, four portfolios were selected based on low IQD. Obviously, the average sample size in this analysis is limited.
146. The portfolios – portfolios 1010, 2010, 3004 and 5020 – cover the main asset classes (i.e., EQ, IR, FX and CS) and were chosen due to the relative low variability of the submissions received for them. Six subsets of banks were defined within (and hence controlling for) the sample of banks using historical simulation, distinguishing the following modelling choices:
- 1-day scaled versus 10-day overlapping returns¹⁴;
 - the length of the historical lookback period (1 year versus > 1 year)¹⁵; and
 - keeping constant the 1-day and unweighted modelling choices and varying the length of the lookback period (1 year versus > 1 year).¹⁶
147. As shown in Table 7 and Table 8, there seems to be evidence that the modelling choices have an impact on dispersion and the conservativeness of the VaR. For instance, for the EQ portfolio the 1-day calibration, more than 1 year and unweighted choices produce less dispersed results. On the contrary, for IR, FX and CS portfolios, 10-days calibration produces less dispersion.
148. In terms of conservativeness, for all portfolios selected, 1-day and ‘more than 1 year’ calibration produces more conservative results.
149. Columns 5 and 6 of Table 7 and Table 8 illustrate the effect of increasing the lookback period (1-year compared to ‘more than 1 year’) when we keep the other factors (1-day & unweighted shocks) the same. No clear path appears on the modelling choice that would produce less dispersed and more conservative results across assets classes.
150. Considering the evolution of the evidence in the years, these results depend on the portfolios’ selection but also on the period applied for this analysis. Therefore, based on this analysis, it is difficult to conclude that one specific model choice will lead to consistently more conservative and less dispersed risk measures, at least on a stable basis.

¹⁴ 31 banks adopted 1-day returns, while 10 banks adopted 10-day returns.

¹⁵ 24 banks adopted 1-year, while 17 banks adopted > 1 year.

¹⁶ 16 banks adopted 1-day, unweighted & 1-year, while 9 banks adopted 1-day, unweighted & >1 year.

Table 7: Coefficient of variation for regulatory VaR (controlling for HS) by modelling choice (%)

Coefficient of Variation for regulatory VaR (controlling for HS)						
Port.	1-day	10-day	1y	>1y	1d, 1y, unw	1d, >1y, unw
EQ 1010	15.6%	17.7%	16.5%	12.8%	18.9%	8.5%
IR 2010	15.8%	11.3%	14.5%	14.7%	15.8%	18.8%
FX 3004	9.5%	9.1%	9.2%	9.7%	10.0%	10.7%
CS 5020	14.2%	8.3%	12.2%	14.9%	13.6%	18.7%
mean	13.8%	11.6%	13.1%	13.0%	14.6%	14.2%

Table 8: Average regulatory VaR by modelling choice

Average VaR subsamples						
	1-day	10-day	1y	>1y	1d, 1y, unw	1d, >1y, unw
EQ 1010	33,126	32,314	31,028	35,280	31,386	36,523
IR 2010	181,120	172,366	174,304	183,361	179,953	186,906
FX 3004	454,580	451,234	451,244	456,798	448,837	459,960
CS 5020	168,137	157,925	165,041	165,861	165,279	170,110

4.2.5 Other drivers of variation

151. In addition to the drivers of variation discussed in the preceding two subsections, there may be other drivers of variation. In the section 4.2.4 ‘Modelling differences’, for instance, only results obtained with HS VaR were discussed, although the methodological aspects considered are expected to be important for other model types (e.g., MC simulation) as well.

152. Another driver of variation are the risks not captured in a model. Due to the simplification of the exercise compared to initial benchmarking exercises (2016-2018), most of the most exotic instruments were deleted, so most of the possible risk factors not in the models are no longer present in the exercise. Moreover, banks that are not able to model specific trades are allowed by the Benchmarking RTS not to submit the risk measure. This is shown, for example, in instrument 205 (IR ‘Cap and Floor’ on 10-year note), where only 13 observations (across 43 banks, where the average number of submissions is 33 for IR asset class) are available. Nonetheless, for this non-vanilla product the IQD is 41% for the VaR (portfolio 2005, it was only 2% the IQD of the 205 IMV), which is considerably higher with respect to other IR portfolios (average IQD for the asset class is 16%), therefore it is likely that few risks not in VaR were present.

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

154. As in the previous exercise, four additional drivers of variation will therefore be tested in the following areas: (a) size of the bank, (b) business model, (c) level of approval of model (e.g., general interest risk versus general and specific interest risk approval, or general equity risk versus general and specific equity risk approval) and (d) time window selected for the calibration of the stressed VaR. As for the previous exercise (2020-2023), the EBA also tested different definitions of size and business models.

a. Size of the bank

155. The size of the bank could influence the internal model. Larger banks could have more resources to invest into internal modelling, and this could have an impact on the quality of the model and the results submitted. The same can be said of banks that invest more in market activities in terms of their whole bank activity. The composition of the bank's trading portfolio could also have some influence on the design and performance of the internal model. Nonetheless, size is not a uniquely definable variable.

156. For the scope of the analysis, the size of the banks was selected based on banks' common reporting results concerning the RWA for market risk. The market risk RWA was preferred in selecting the size because a bigger bank in terms of total RWA can have a smaller market risk trading book in relative terms. The market risk RWA variable was therefore preferred. It should be noted that market risk RWA also incorporates the standardised measure but classifying the bank by the internal model market risk RWA did not change the composition of the sample substantially.

157. The banks were divided into three subsamples: large (above the 75th quantile), medium (between the 75th and 25th quantiles) and small (lower than the 25th quantile). Detailed VaR tables are presented in the annex (see Table 27, Table 28 and Table 29).

158. Table 9 summarises the effect of the bank's size. Because of the decreased number of submitters, the 'small banks' sample lost a little of its significance. Fewer banks imply fewer submissions, and the smaller banks usually report less information. Therefore, it is more interesting to look at the difference in dispersion among medium and large banks. Almost for all asset classes, it seems that dispersion slightly decreases with the size of the banks. This implies that the banks' size has some influence and that variability in size increases the dispersion of the general results submitted.

159. Further analysis of this aspect can be carried out in terms of the factors selected to define the size. If we run the same analysis using the size of the trading book¹⁷ instead of the size of the bank (defined by RWA for market risk), we can see that dispersion varies again across different asset classes and different sizes of banks. The results are reported in Table 30, Table

¹⁷ The size of the trading book was defined as: (assets held for trading + liabilities held for trading) / (total assets × 2).
Data source: FINREP data)

31 and Table 32. Looking solely at the trading book size, we obtain different results. The average IQD ratio decrease with the size of the trading book. The average IQD is 13% for small TB banks (very few portfolios submission need to be considered as a factor here), 12% for medium TB and 11% for large TB banks.

Table 9: Asset class comparison for VaR in terms of banks' size

	VaR - Avg. Interquartile Range			
	All Banks	Small Banks	Medium Banks	Large Banks
Equity	16%	11%	13%	12%
Interest Rate	15%	14%	13%	14%
FX	9%	8%	10%	7%
Commodities	14%	21%	10%	10%
Credit Spread	16%	11%	14%	13%
CTP				33%
All-in	10%	5%	11%	11%

b. Business model

160. The business model of the banks in the sample was selected based on a previous analysis run by the EBA (EBA – LCR Report¹⁸). In the sample of 43 banks, 23 were classified as cross-border universal banks, which is by far the most numerous business model in the sample. The remaining banks were either not classified or had different business models (e.g., local universal banks), but they were too few to use as a subsample for this kind of analysis. As a result, the cross-border universal bank business model was selected.

161. Specific VaR results for banks classified as cross-border universal banks are shown in Table 33 of the annex. Table 10 summarises the impact of the business model on different asset classes. The business model selected is so predominant in the sample that it does not allow for proper discrimination among the whole sample; therefore, the dispersion of the banks belonging to the same business model is very close to the dispersion of the whole sample for the banks. Judging from the results, there is some weak evidence that the variety business model has some effect in increasing the dispersion of the VaR submission.

162. Further analysis of the business model can be carried out in terms of factors selected to define the business model. If we run the analysis based on the amount of 'Level 3 assets and liabilities' in relation to the size of the trading book¹⁹ (FINREP data), the results are reported in Table 34, Table 35 and Table 36. The average IQD is 10% for the low level of Level 3 A&L banks, 13% for the medium level and 12% for the high level of Level 3 A&L banks. Therefore, it seems

¹⁸ <https://www.eba.europa.eu/regulation-and-policy/liquidity-risk>

¹⁹ (Level 3 assets held for trading + level 3 liabilities held for trading) / (assets held for trading+ liabilities held for trading)

that a more exotic composition of the bank’s trading book does not affect the variability of the results.

Table 10: Asset class comparison for VaR within the same business model (cross-border universal bank)

	VaR - Avg. Interquartile Range	
	All Banks	Cross-border Universal bank
Equity	16%	14%
Interest Rate	15%	13%
FX	9%	8%
Commodities	14%	12%
Credit Spread	16%	13%
CTP		30%
All-in	10%	12%

c. Level of approval

163. Banks have different levels of approval for equity and interest rate risks. To be more specific, banks can apply to obtain approval for the general equity or interest rate risk or they can apply for approval of the specific equity or interest rate risk as well. See also the discussion in Section 3.2 on this point. In general, having approval for both the general and the specific parts of the equity and interest rate risks allows banks to fully model the instruments in the equity and credit spread sections of the exercise. Nonetheless, banks with only general approval are required to report these instruments as well, but this has been known to generate additional dispersion in the risk measures submitted. For this reason, in this exercise the EBA filtered all the results submitted and produced IQD statistics for the banks belonging to the sample of banks with different levels of approval.

164. Among the banks that submitted results for interest rate risk, 23 banks in the report have general and specific approval (see Table 37) and 17 banks have only general approval (see Table 38). Among the banks that submitted results for equity asset risk, 26 banks in the report have general and specific approval (see Table 39) and 8 banks have only general approval (see Table 40).

165. Table 11 summarises the result of the analysis when the filter for the level of approval is applied. The presence of banks with different levels of approval tends to moderately impact the benchmarking results.

166. Looking at Table 11, we see that the EQ asset class IQD is marginally smaller when considering only the subsample of firms with the full level of approval with respect to the full sample. The CS asset class also decreases, if only general risk is considered, but it should be considered that almost no banks without specific IR approval submitted any CS results. Finally, for the IR asset class splitting the sample between banks with general and specific approval and banks with only general approval produces some marginal changes in the benchmark for this asset class, confirming that the submissions from banks with partial approval tends to increase the IQD of the submissions.

Table 11: Asset class comparison for VaR in terms of level of approval

	VaR - Avg. Interquartile Range			
	<i>All Banks</i>	<i>IR Gen + Specific</i>	<i>IR Gen only</i>	<i>Eq Gen + Specific</i>
<i>Equity</i>	16%			15%
<i>Interest Rate</i>	15%	15%	13%	
<i>Credit Spread</i>	16%	16%	9%	

d. Common stress period considered

167. The stress window applied by the participating banks has always been understood as one of the main sources of the greater dispersion of the sVaR compared to the VaR, but this hypothesis was tested only from the 2019 exercise onwards due to a lack of information regarding the time window applied by the banks to calibrate the sVaR. This information was collected for the 2020-2023 exercises as well and applied to test the impact of the stress time window selected to calibrate the sVaR.

168. In their time window for the sVaR the banks select periods that include either 2008-2009 or 2011 in order to calibrate their sVaR, with a preference for 2008-2009. Because of the higher number of banks selecting 2008-2009, the EBA filtered the sample of the banks that applied a 2008–2009-time window for sVaR calibration, obtaining a subsample of 26 banks. The benchmark and the related statistics for this subsample of banks are available in Table 41 in the annex, and they are easily comparable with the full sample sVaR statistics in Table 22.

169. Table 12 summarises this stress period filtering analysis. It seems clear that the different time window selected for the bank has a significant impact on sVaR statistics. This means that the subsample with the same stress period generally exhibits smaller dispersion results for sVaR than the whole sample.

Table 12: Asset class comparison for sVaR in terms of the time window applied

	SVaR - Avg. Interquartile Range	
	<i>All Banks</i>	<i>Stressed Period</i>
<i>Equity</i>	21%	17%
<i>Interest Rate</i>	20%	17%
<i>FX</i>	19%	13%
<i>Commodities</i>	16%	10%
<i>Credit Spread</i>	29%	26%
<i>CTP</i>		50%
<i>All-in</i>	17%	15%

4.2.6 Portfolio comparison

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

171. This hypothesis can be tested with several portfolios in the 2024 exercise. Use of the following portfolios is suggested:

- portfolio 2006, which is composed of instruments 206 (long 1 million German bond – 10 years) and 207 (short 1 million German bond – 5 years);
- portfolio 2007, which is composed of instruments 206 (long 1 million German bond – 10 years), 207 (short 1 million German bond – 5 years) and 208 (long 1 million Italian bond – 10 years), so it is equal to portfolio 2006 plus instrument 208.

172. Both portfolios comprise sovereign bond instruments, yet portfolio 2006 is concentrated on only one issuer and is partially hedged (long and short positions). Portfolio 2007 adds a second issuer to this portfolio without any hedge. Against this backdrop and in view of the specific portfolio definitions, we would expect the following result:

$$VaR_{Portfolio\ 2007} > 200\% \times VaR_{Portfolio\ 2006}$$

173. Table 13 reports when this hypothesis holds true.

Table 13: Portfolio comparison for VaR, sVaR and IRC

	$VaR(P2007) > VaR(P2006)$	$sVaR(P2007) > sVaR(P2006)$	$IRC(P2007) > IRC(P2006)$
Num of banks	35 out of 35	35 out of 35	26 out of 26
	$VaR(P2007) > 1.5 * VaR(P2006)$	$sVaR(P2007) > 1.5 * sVaR(P2006)$	$IRC(P2007) > 1.5 * IRC(P2006)$
Num of banks	35 out of 35	35 out of 35	26 out of 26
	$VaR(P2007) > 1.75 * VaR(P2006)$	$sVaR(P2007) > 1.75 * sVaR(P2006)$	$IRC(P2007) > 1.75 * IRC(P2006)$
Num of banks	35 out of 35	34 out of 35	26 out of 26
	$VaR(P2007) > 2 * VaR(P2006)$	$sVaR(P2007) > 2 * sVaR(P2006)$	$IRC(P2007) > 2 * IRC(P2006)$
Num of banks	34 out of 35	32 out of 35	26 out of 26

174. The comparison between the two portfolios with respect to regulatory VaR shows that only 1 out of 35 banks do not meet the initial expectation. The same comparison based on sVaR yields 3 banks that are not in line with this expectation. Regarding the IRC model, no bank does not meet the a priori expectation.

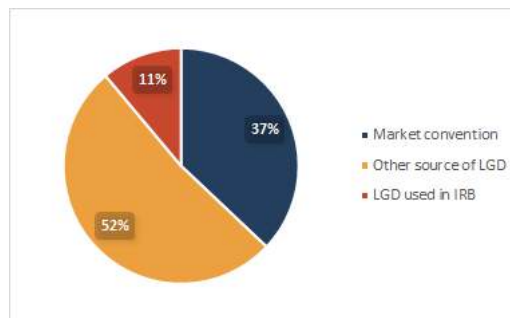
4.3 Analysis of IRC and APR

175. Banks with an approved IRC model constitute a subsample of those with an approved VaR model; only banks using internal models for specific risks of debt instruments are permitted to use IRC models (Article 372 of the CRR).
176. The full set of submissions for IRC results for each trade, after the data-cleaning process has been run as previously described, is reported in Table 14.
177. In the context of the HP exercise, only a subset of banks made submissions for IRC, and a number of those banks submitted very low figures. This suggests that important risk factors (in the context of the HPE) have not been modelled. While the submission of low figures may be linked to risk factors not modelled, this should not be taken to mean that banks with higher IRC figures included all risk factors from a given portfolio in their model.
178. The number of submissions is limited for some of the all-in portfolios. Statistical inferences for these portfolios are thus not appropriate. A prerequisite for consideration of banks' submissions for the all-in portfolios is that a bank needs to be able to model all the corresponding underlying portfolios.
179. As in the case of VaR, a selective comparison of IRC results across portfolios can be informative in instances where the riskiness of those portfolios may be ranked in a model-independent way. As shown in subsection 4.2.6, the expected diversification relationship holds true for all but one of the banks that submitted such results.
180. It is recommended that CAs assess the extent to which these missing risk factors are important in the context of banks' overall risk, and whether they need to be added to the model.
181. CAs should give particular attention to portfolios 2006, 2018-2019, 5001, 5004, 5010, 5014-5017, 5019-5020, 5022 and 5027, i.e., where IRC shows a higher level of dispersion (above 50%) above the average.
182. As is the case for VaR and sVaR, banks can choose from a range of permitted modelling approaches for IRC. For example, banks need to choose:
- a source of credit risk estimates such as PD and loss given default (LGD).
 - the number of systemic factors used to model the co-movement among obligors in their portfolios.
 - the size and granularity of credit spread shocks to apply to positions with an obligor following a rating transition; and
 - the liquidity horizons to assign to positions with a particular obligor.
183. The responses to the qualitative questionnaire relating to the IRC methodological aspects suggest that the use of market LGD is highly applied among respondents (Figure 12), with 10 out of 27 banks using market convention as the source of LGD. A minority of banks – 3 out of 27 –

use their own IRB models as the source of LGD. The majority – 14 banks – use various other sources to obtain the LGD.

184. The PDs are provided by rating agencies in 64% of cases, by the IRB in 21% and by other sources in %. The transition matrices are mostly taken from rating agencies (20 respondents out of 26), and the rest of the banks use their IRB, 'market implied transition matrices and various other sources.

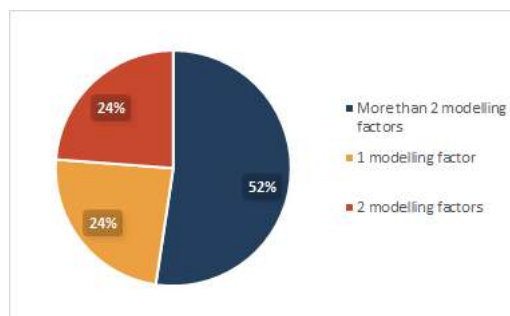
Figure 12: Qualitative data: source of LGD for IRC modelling



185. Moreover, many respondents stated that they use more than two systemic modelling factors at the overall IRC model level (Figure 13).

186. The liquidity horizon applied at the portfolio level for the IRC model is predominantly between nine and 12 months (70% of the responses).

Figure 13: Qualitative data – number of modelling factors for IRC



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

Table 14: IRC statistics and cluster analysis

EU Statistics for IRC

Part. ID	Main statistics							Percentiles					
	Min	Max	Avg.	STDev	STDev, trunc ¹	MAD (million absolute deviation)	Coefficient of variation (STDev/Mean)	Num obs. ²	25th	50th	75th	IQR	
Interest Rate	3005	20,889	425,631	232,008	332,131	145,052	91,152	62%	34	126,035	182,208	271,298	37%
	3006	2,085	56,173	25,410	17,065	18,847	12,633	67%	21	10,392	25,794	43,314	61%
	3007	98,981	874,866	490,358	250,168	234,388	102,517	51%	26	333,440	524,463	642,674	34%
	3008	147,137	1,579,283	872,641	457,334	427,464	330,773	52%	26	460,881	971,364	1,259,739	46%
	3011	9,762	197,073	59,243	50,823	84,353	25,474	86%	21	24,790	53,964	64,031	44%
	3014	197,368	983,179	672,235	231,013	282,084	184,811	34%	19	515,857	751,801	854,905	25%
	3016	152,347	1,761,730	950,131	487,809	449,663	374,697	51%	26	602,957	1,004,202	1,376,721	39%
	3018	35,999	717,199	354,984	230,908	239,209	211,936	65%	27	96,489	376,004	572,887	73%
	3019	35,999	717,199	334,877	227,998	214,454	202,774	68%	25	96,489	343,209	490,296	67%
	3022												
	Credit Spread	3009	10,359	392,390	96,624	116,827	174,514	15,517	121%	21	26,144	58,248	109,359
3032		40,542	146,646	69,775	34,519	30,015	17,900	35%	19	40,921	67,279	82,764	25%
3033		22,335	115,485	67,822	24,758	27,083	15,822	37%	21	52,239	68,146	80,465	23%
3034		16,266	411,563	116,727	127,261	180,245	37,741	109%	18	26,999	68,584	207,585	78%
3035		12	93,569	42,699	24,025	48,752	14,311	56%	24	34,627	43,524	58,312	25%
3036		350,193	853,886	632,211	140,281	184,571	95,671	22%	12	554,810	620,034	791,178	18%
3037		34,720	256,434	120,062	51,594	89,646	25,414	45%	21	99,509	120,295	143,814	18%
3038		387,435	856,002	599,729	133,112	142,206	111,848	22%	24	505,297	586,232	728,160	18%
3039		2,052	24,074	8,726	6,033	16,802	1,371	79%	25	4,095	7,026	8,801	36%
3040		3,559	143,840	55,628	47,928	57,573	28,529	86%	23	32,695	41,265	51,590	76%
3041		18,369	252,246	110,032	65,311	76,688	36,556	59%	24	65,074	104,170	132,817	33%
3042		20,231	185,315	103,328	38,501	67,934	31,262	37%	21	76,964	102,381	132,817	27%
3043		3,329	47,523	19,759	11,549	13,636	7,508	58%	24	9,584	21,885	25,907	46%
3044		11,070	447,899	115,263	133,047	181,374	38,844	115%	20	21,843	92,157	167,352	77%
3045		115	119,015	36,224	35,400	59,511	16,043	98%	23	7,768	28,230	67,256	79%
3046		24,107	263,065	116,961	78,972	92,544	42,991	68%	19	51,419	106,668	196,140	58%
3047		199	74,886	29,113	26,028	59,017	15,153	89%	19	10,302	70,139	44,399	62%
3048		40,591	266,616	99,001	65,739	106,926	23,417	66%	18	60,298	82,677	116,814	32%
3049	115	85,803	28,997	27,258	45,156	15,388	94%	21	7,768	25,609	39,021	67%	
3049	35,883	580,264	241,279	160,658	205,810	138,306	67%	24	133,704	233,586	367,375	53%	
3051	15,774	106,754	46,744	25,709	43,848	11,900	55%	18	29,838	48,256	55,838	39%	
3052	2,563	336,530	90,994	91,108	128,458	48,809	101%	21	32,996	79,509	115,262	65%	
3053	9,109	93,772	42,702	24,319	43,882	8,613	57%	15	25,929	34,346	49,175	45%	
3054	82,452	571,097	276,802	160,408	183,395	104,026	58%	21	158,671	238,399	383,024	42%	
3025	459,874	676,401	559,804	62,333	88,961	36,869	11%	18	522,002	567,587	574,934	3%	
3026	276,989	694,547	432,951	81,054	88,453	45,129	19%	21	405,493	445,631	454,857	6%	
3027	26,788	780,429	349,920	207,835	187,423	129,033	59%	24	194,926	381,505	516,273	54%	
ALL-Inv on CTP **	30000	645,623	1,435,718	981,547	174,750	378,427	268,502	28%	14	695,228	1,045,730	1,144,995	24%
CV Cumulative **	30000	492,813	1,021,210	754,603	151,343	135,786	116,951	20%	24	641,570	761,851	869,511	15%

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

² Refers to the number of banks included in the computation of the statistics

** For the aggregated portfolios (50 to 66), banks that reported at least a missing portfolio IRV among the ones composing the aggregate are not included in the computation of the benchmarks for that particular aggregate portfolio.

188. Table 14 shows that the average variability of IRC is higher than that observed for VaR. This table presents a summary of the descriptive statistics concerning the IRC values submitted, along with the median, first and third quartiles used to select out-of-range values to be discussed with the banks during the interviews. EBA received on average 21 submissions for IRC in relation to the IR and CS hypothetical trades. We can observe that, even if the IQD for the single portfolios is sometimes quite significant, at least at the aggregate level, the IQD is approximately 20%.

189. The EBA also provided a disaggregated analysis of sources of LGD and numbers of modelling factors. It is possible to split the sample between market convention and non-market convention (IRB and other sources) and the number of modelling factors (1-2 vs. more than 2). In Table 15 below, the average interquartile is reported. The full set of results is also reported in Table 43, Table 44, Table 45 and Table 46.

190. The IQD dispersion of the subsample is very stable for IR and CS portfolios among different model choices.

Table 15: Coefficient of variation for regulatory IRC by modelling choice (%)

	VaR - Avg. Interquartile Range				
	All Banks	Source of LGDss		No. modelling factors	
		Market Convention	Non-market Convention	1-2 factors	>2 factors
Interest Rate	49%	58%	41%	49%	49%
Credit Spread	43%	35%	42%	39%	40%
All-in	13%	17%	10%	18%	17%

191. This report is no longer reporting the summary of the responses to the qualitative questionnaire relating to the APR methodological aspects, since only 4 responses are available at the overall CTP model level, so no disclosure is possible without disclosing some specific information on the submitters.

192. The average variability of the APR charge is also no longer reported, since the limited data available do not allow a meaningful computation of the IQD of each CTP.

4.4 P&L analysis

193. The P&L analysis is complementary to the outcome of the assessment of variability based on VaR modelling. For each individual portfolio, the P&L vectors provided by banks using HS were compared, and a benchmark analysis is provided in the annex (see Table 23).

194. A graphic exemplification of low and high IQD portfolios is presented below in Figure 14 and Figure 15. Even though the P&L vectors available are much longer, only 3 months (1 November 2023 to 1 February 2024) are reported to simplify the representation. Additional examples of low and high IQD portfolios can be found in the annex in Figure 25 and Figure 26. P&L vector series that perform better tend to be closer to the benchmark. On the other hand, the low absolute value of the P&L, as per the risk measures, tends to provide misleading information if we consider the IQD figures alone.

Figure 14: P&L chart example of low IQD

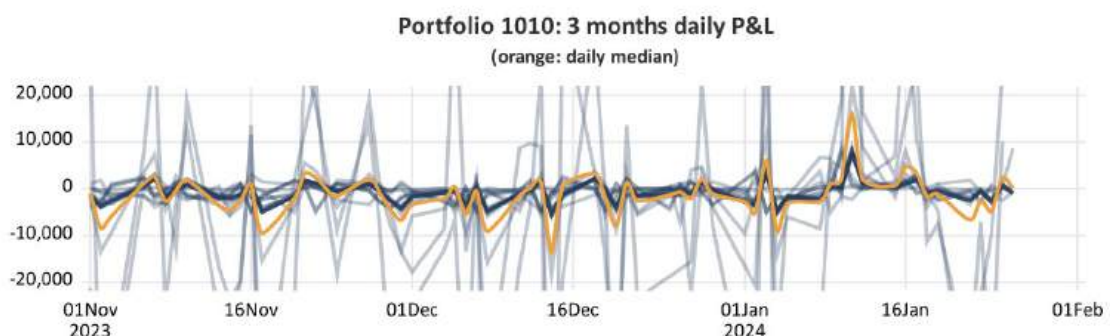
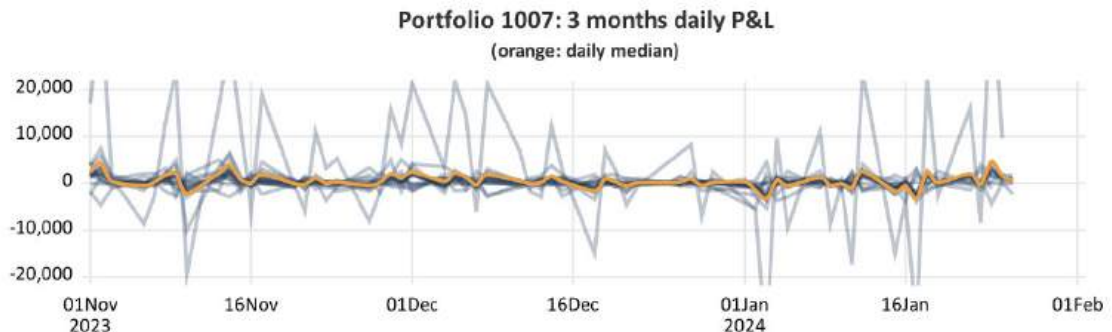


Figure 15: P&L chart example of high IQD



195. Another useful check for the P&L results submitted was a comparison of the ratio between the P&L VaR computed by the EBA (see Section 3.2 and Table 26) and the regulatory VaR submitted by the participating banks. A significant deviation of this ratio from 1 indicates an incoherent submission by the bank (see Table 26 in the annex). Moreover, it allows the tightness or the width of the realised P&L distribution for each bank to be checked at each hypothetical trade position. This can be done by referring to the standard deviation of the P&L series.
196. Another metric computed by the EBA from the P&L series provided by HS banks is the empirical ES (see Table 24 in the annex). The empirical ES results have approximately the same level of dispersion as the P&L VaR (see Table 5 in Section 5.1).

4.5 Diversification benefit

197. An additional metric considered as part of the analysis was the diversification benefit observed for VaR, sVaR and IRC in the aggregated portfolios.
198. The diversification benefit of a given metric (e.g., VaR) is computed as the absolute benefit, i.e., the difference between the sum of the single results for each individual position and the result for the aggregated portfolio, divided by the sum of the single results from each individual portfolio. Table 16 summarises the results of the analysis.
199. As expected, there is evidence that larger aggregated portfolios exhibited greater diversification benefits than smaller ones. The diversification benefit for all-in portfolio 10000 (all-in no-CTP portfolio), for instance, clearly exceeds the benefit for the other risk types, whose all-in portfolios are based on fewer individual instruments. Regarding the dispersion shown by the diversification benefits, it is possible to observe a significantly higher IQD for some portfolios than for others, and – in some cases – a quite comparable dispersion across VaR, sVaR and IRC (e.g., interest rate and commodity risk categories).

Table 16: Diversification benefit statistics

Diversification benefit statistics

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

VaR

	Port.	Other statistics			Percentiles			Interquartile dispersion
		Ave.	STDev	Num obs. ³	25th	50th	75th	
ALL-IN no-CTP	10000	77%	3%	9	75%	76%	78%	2%
Equity Cumulative	11000	67%	6%	23	63%	67%	72%	7%
IR Cumulative	12000	61%	7%	34	57%	59%	61%	4%
FX Cumulative	13000	41%	9%	33	36%	43%	47%	12%
Commodity Cumulative	14000	7%	4%	13	5%	6%	9%	30%
Credit spread Cumulative	15000	9%	4%	22	7%	9%	12%	27%

sVaR

	Port.	Other statistics			Percentiles			Interquartile dispersion
		Ave.	STDev	Num obs. ³	25th	50th	75th	
ALL-IN no-CTP	10000	36%	5%	9	35%	35%	37%	3%
Equity Cumulative	11000	23%	10%	23	18%	21%	24%	14%
IR Cumulative	12000	59%	17%	34	49%	53%	65%	14%
FX Cumulative	13000	22%	9%	33	17%	20%	26%	20%
Commodity Cumulative	14000	4%	3%	13	2%	3%	4%	25%
Credit spread Cumulative	15000	6%	3%	22	4%	5%	9%	36%

IRC

	Port.	Other statistics			Percentiles			Interquartile dispersion
		Ave.	STDev	Num obs. ³	25th	50th	75th	
Credit spread (36 to 53)**	27	2%	1%	22	1%	2%	3%	39%

4.6 Dispersion in capital outcome

200. As a final means of comparison, for each individual position a variable equating to the sum of the regulatory VaR and sVaR was computed. This variable was used in two ways: using the banks' total multiplication factor, and using only the regulatory multiplication factor, i.e., ignoring the banks' individual addend(s) set by the CAs. The results were averaged across a given risk type, thus arriving at a proxy for the implied capital outcome.
201. Moreover, the exercise also attempted to isolate the effect of the time windows selected as the stress period. Therefore, the same statistics were reported for banks applying the 2008-9 stress period.

Table 17: Interquartile dispersion for capital proxy

Interquartile dispersion for capital proxy

	<i>Capital proxy (banks own mult)</i>	<i>Capital proxy (fixed mult, =3)</i>	<i>Capital proxy Stressed period (fixed mult, =3)</i>
Equity	17%	15%	13%
IR	18%	15%	14%
FX	16%	13%	10%
Commodity	16%	13%	12%
Credit spreads	23%	20%	18%
CTP			

202. Table 17 suggests that variability is slightly exacerbated by regulatory add-ons. The ranges of capital value dispersion remain broadly aligned whether the banks' actual multiplication factors are used. On the other side, filtering for banks with the same stress window seems to have a marginal impact in decreasing the variability. However, we need to take into consideration the fact that the sample of banks decreases in number when analysing the subsample of banks with the same stress period, which – other things being equal – tends to increase the IQD.

4.7 Present value

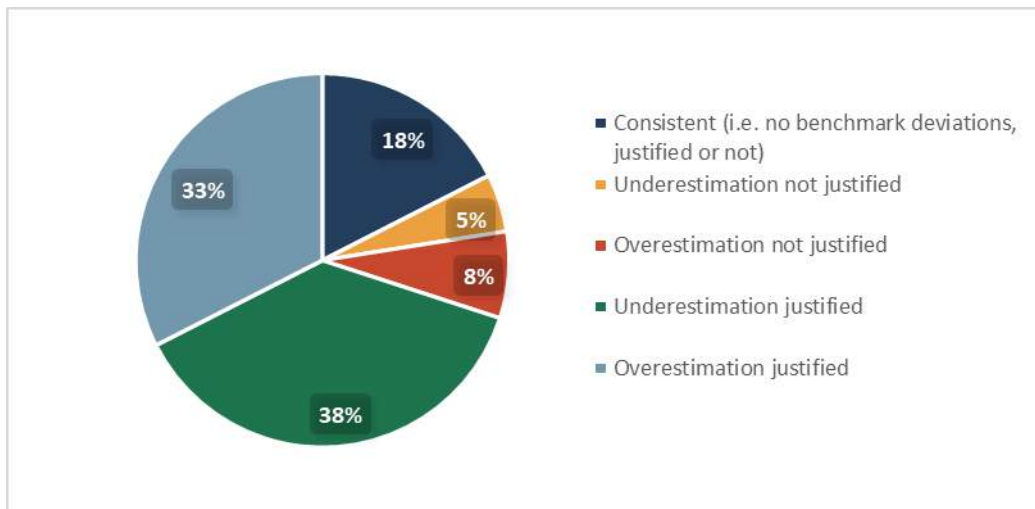
203. The 2020 exercise introduced the PV as a statistic to be provided by the banks. The full set of statistics is provided in Table 42 for this year's exercise as well.

204. The average IQD of the PV among the single portfolios is quite significant and not comparable to the low IQD of the previous years (it was 5% in 2023, it was 4% in 2022 and 11% in 2021). This IQD would be much comparable (3%) with the past if portfolios with a relatively high IQD (Portfolios 1016, 3006, and 3007) were excluded. By asset class, the IQD is distributed as follows: EQ (4%- or 2% if portfolio 1016 is excluded), IR (4%), FX (1% when 3006 and 3007 are excluded), CO (15%) and CS (3%).
205. PV measures are useful to CAs to verify the RM values. The ratio of RM over PV helps the CAs to quickly verify if the RM outlier comes from a simple mispricing of the portfolio or if it is indeed a true outlier with respect to the RM benchmark.

5. Competent authorities' assessment

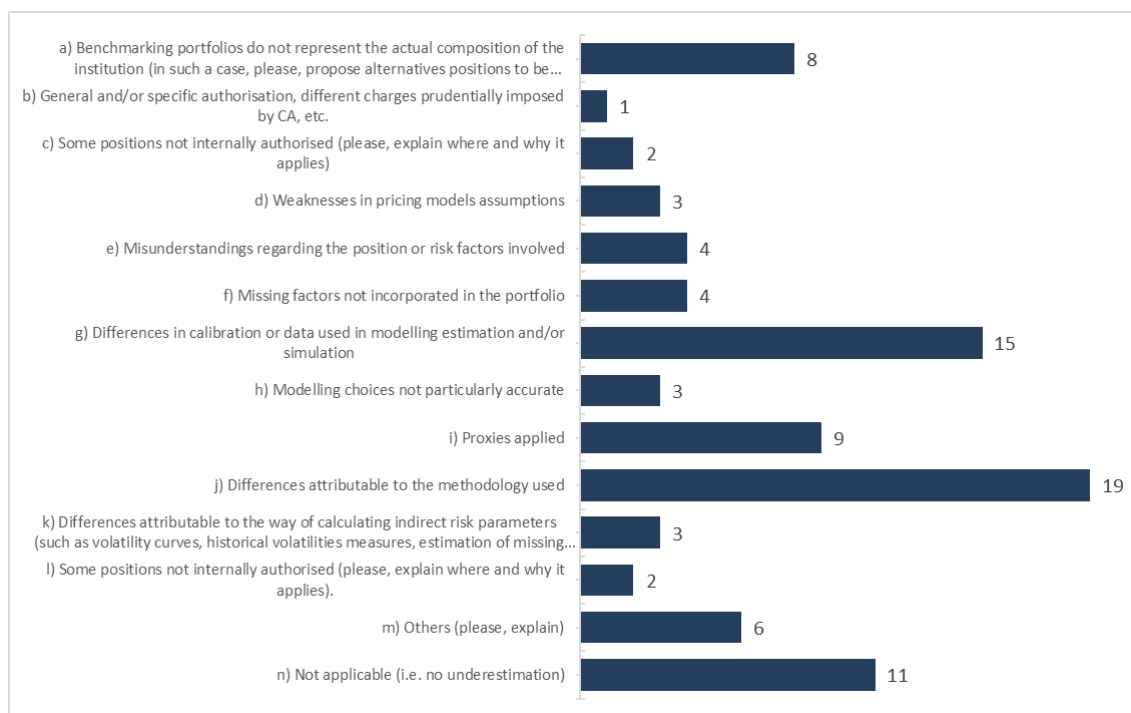
206. For each participating institution, the CAs provided individual assessments of any potential underestimation of the capital requirement as required by Article 78(4) of the CRD and Articles 9 and 10 of the draft RTS on supervisory benchmarking. This chapter highlights some key information derived from these assessments.
207. The EBA designed a questionnaire about this assessment, which asked CAs to provide detailed information concerning the level of priority, based on both judgemental and qualitative/quantitative examination results, the overall assessment concerning the MR capital requirements of the internal models and, finally, the CAs' ongoing monitoring activities.
208. A total of 40 questionnaires from 12 jurisdictions, provided by the CAs, have been considered in this assessment of the MR benchmarking exercise.
209. Regarding the level of priority of the assessments, 4 banks were reported to be a high priority for intervention by CAs. The CAs gave high priority because of the valuable comparison coming from the benchmarking exercise for that jurisdiction and for specific focus given to the SBM implementation.
210. Figure 16 reports the CAs' own overall assessments of the levels of own funds requirements. When it comes to benchmark deviations, justified or not, 33 banks were reported by CAs as under or overestimating MR own funds requirements, of which 28 provided justifications for this. Obviously, 'not justified' implies that further and targeted CA investigation is required. Finally, 7 banks had consistent results (i.e., no benchmark deviations).
211. CAs' assessments acknowledge two cases out of 40 of unjustified underestimation and 3 of 40 of overestimation of internal model market capital requirements that require further in-depth analysis. Obviously, CAs – and the joint supervisory teams, where applicable – pay close attention to the potential cases of underestimation and overestimation, both across the portfolio and across the risk categories. 4 out of 5 of these cases were classified as low priority by their supervisors.

Figure 16: CAS' own assessments of the levels of MR own funds requirements (BM exercise 2023)



212. The main (see Figure 17) factors and reasons that may explain possible underestimations are as follows: benchmarking portfolios that do not represent the actual composition of the real trading portfolios of the institutions (8/90); differences in calibration or data used in modelling estimation and/or simulation (15/90); proxies applied (9/90); and differences attributable to the methodology used (19/90). These explanations, and very often a combination of these explanations, were offered by a large majority of the applicable respondents.

Figure 17: CAS' reported reasons for over-underestimation of MR own funds requirements (BM exercise 2023)



213. One bank identified as underestimating without justification partially motivated the underestimation to its CAs with issues on the input data which are at the base of the modelling computation. The second bank identified as underestimating without justification assessed that the waiting scheme of the model, the limited scope of approval, and some additional simplification could have generated the differences reported. Nonetheless no full explanation was provided for these cases found by the bank of the competent authority.
214. Overall, CAs planned or reported action in respect of 8 banks, such as:
- a. reviewing the banks' internal VaR and IRC models;
 - b. extra supervisory charges;
 - c. additional resubmission, not included in the EBA benchmarking;
 - d. continue to monitor the data quality and pricing model modules in the annual validation;
 - e. further internal model investigations.
215. Currently, three banks have a due date for making improvements to their MR internal models, as already requested by CAs.
216. EBA reported 8 cases of substantial presence of outliers to CAs (5 on VaR, 2 on SVAR and one on IRC). CAs, together with banks, assigned "low priority" to the cases highlighted, based on a plurality of explanations: low impact of portfolios highlighted as outliers, overestimation justified by the methodology applied for VaR (e.g. 500 days in place of 250, which would have had a closer result to the benchmarking) and SVaR methodology, and based on the facts overestimation are caused by model limitation known by the supervisor and on model that are on their way to be decommissioned.

6. Conclusion

217. 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.
218. It must be remembered and emphasised that, as the quantitative analysis is based on hypothetical portfolios, this report focuses solely on potential rather than actual variations. The analysis shows the extent of the variability in these hypothetical portfolios, but this cannot automatically lead to conclusions regarding real under- or overestimations for the MR capital charge.
219. However, the analysis should help in determining possible supervisory activities to address uniformity and harmonisation across the Member States and in promoting in-depth future cross-investigations of this matter.
220. The objective of the benchmarking exercise was not to reach a definitive assessment of all 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 between banks that is attributable to non-risk-driven behaviours.
221. In particular, the report provides inputs for CAs on areas that may require further investigation, such as IMV variability for some credit spread products. Supervisors should pay attention to the materiality of risk factors not in VaR and not encompassed in the IRC models.
222. Moreover, the conclusions reached in regular supervisory model monitoring activities will consider the outcome of the supervisory benchmarking exercises to achieve greater alignment between CAs' targeted internal model reviews and the EU's benchmarking analysis.
223. Overall, this exercise exhibits a slight increase in the IMV variability for IR and EQ asset class. CO IQDs remain subtidal, and marginally higher than 2023; for FX a significant increase of IQD in IMV may be due to a misunderstanding in the instruction that was not uniformly interpreted by the institutions; it should be highlighted that a high IQD is limited to a few instruments, slightly less vanilla compared to the average instruments required, had the effect to increase the average IQD. All considered, with the exception of a few cases, the booking of the instruments for the 2024 exercise was good in general.
224. The variability of risk measures, especially the VaR, is marginally lower than the previous exercise and overall, this exercise mark the lowest level of dispersion of the risk measures since the exercise has started. This reduction of the risk measure is due to a combination of factors, such as the improvement of the instruction, the relative stability of the set of portfolios, the good job done by competent authorities and banks in terms of resubmission during the exercise. The variability of the VaR aggregated portfolios is limited: the 'all-in portfolio' IQD is 10% (it was

18% in 2023, 11% in 2022, and 16% in 2021). Aggregated by asset class, the portfolio IQD of the others is 9% (vs 12% in 2023, 9% in 2022 and 15% in 2021) on average and never above 12%. The standard analysis carried out in the 2019-2023 exercise – relating to the considerations of the level of approval, size of banks, business model adopted and stress period – was repeated in the 2024 exercise as consolidated sample of information in the benchmarking report. The 2024 Market Risk benchmarking report also provides an analysis of the ASA OFR. The SBM OFRs see an improvement overall in terms of data quality and exhibit, as expected, a lower level of dispersion with respect to the IMA Risk measures (Table 5). The granularity of the sensitivities data submitted, and their representation shed some light on where potential problems of ASA implementation could be at the bank-specific level, with focus on some problematic to treat the FX component of the ASA.

225. Hopefully, this report provides a framework that can be useful for the purpose of future benchmarking exercises under Article 78 of the CRD. The type of analysis conducted (i.e., the statistical tools provided to CAs, the graphs and tables created, and the methodology defined, etc.) offers a clear direction for future investigations into and activities relating to the benchmarking exercise.

7. Annex 1 – Additional tables

Table 18: Banks participating in the 2024 EBA MR benchmarking exercise

Country	Bank name
AT	Erste Group Bank AG
AT	Raiffeisen Bank International AG
BE	Belfius Bank
BE	KBC Groep
DE	COMMERZBANK Aktiengesellschaft
DE	Citigroup Global Markets Europe AG
DE	DEUTSCHE BANK AKTIENGESELLSCHAFT
DE	DZ BANK AG Deutsche Zentral-Genossenschaftsbank, Frankfurt am Main
DE	DekaBank Deutsche Girozentrale
DE	Goldman Sachs Bank Europe SE
DE	Landesbank Baden-Württemberg
DE	Landesbank Hessen-Thüringen Girozentrale
DE	Morgan Stanley Europe Holding SE
DE	Nomura Financial Products Europe GmbH
DE	Norddeutsche Landesbank - Girozentrale -
DK	Danske Bank A/S
DK	Nykredit Realkredit A/S
ES	Banco Bilbao Vizcaya Argentaria, S.A.
ES	Banco Santander, S.A.
ES	CaixaBank, S.A.
FI	Nordea Bank Abp
FR	BNP Paribas
FR	BofA Securities Europe SA
FR	Groupe BPCE
FR	Groupe Crédit Agricole
FR	HSBC Continental Europe
FR	Société générale S.A.
GR	ALPHA SERVICES AND HOLDINGS S.A.
GR	Eurobank Ergasias Services and Holdings S.A.
GR	National Bank of Greece, S.A.
IE	Barclays Bank Ireland plc
IE	Citibank Europe plc
IT	BANCO BPM SOCIETA' PER AZIONI
IT	Intesa Sanpaolo S.p.A.
IT	UNICREDIT, SOCIETA' PER AZIONI
NL	ABN AMRO Bank N.V.
NL	Coöperatieve Rabobank U.A.
NL	ING Groep N.V.
NL	NIBC Holding N.V.
NL	RBS Holdings N.V.
PT	Banco Comercial Português, SA
SE	Skandinaviska Enskilda Banken - gruppen
SE	Swedbank - Grupp

Country	AT	BE	DE	DK	ES	FI	FR	GR	IE	IT	NL	PT	SE
N.banks	2	2	11	2	3	1	6	3	2	3	5	1	2

Table 19: Instruments/portfolios underlying the HPE

Section 2: Instruments

EQUITY

101. Long EURO STOXX 50 index (Ticker: SX5E) Futures.

Notional: equivalent to the value of the index times 1 000 EUR

Exchange: Eurex

Expiry date: June Year T

Base currency: EUR

102. Long 10 000 BAYER (Ticker: BAYN GR) shares.

Exchange: Xetra

Base currency: EUR

103. Short Futures BAYER (Ticker: BAYN GR).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Exchange: Eurex

Expiry date: June Year T

Base currency: EUR

104. Short Futures, STELLANTIS (Ticker: STLA FP).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Exchange: Euronext

Expiry date: June Year T

Base currency: EUR

105. Short Futures, ALLIANZ (Ticker: ALV GR).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Exchange: Eurex

Expiry date: June Year T

Base currency: EUR

106. Short Futures BARCLAYS (Ticker: BARC LN).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Exchange: Eurex

Expiry date: June Year T

Base currency: GBP

107. Short Futures DEUTSCHE BANK (Ticker: DBK GR).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Exchange: Eurex

Expiry date: June Year T

Base currency: EUR

108. Short Futures CRÉDIT AGRICOLE (Ticker: ACA FP).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Exchange: Euronext

Expiry date: June Year T

Base currency: EUR

109. Long Call Options. Underlying BAYER (Ticker: BAYN GR), ATM (1 contract = 100 shares).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Expiry date: June Year T

Base currency: EUR

110. Short Call Options. Underlying BAYER (Ticker: BAYN GR), ATM (1 contract = 100 shares).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Expiry date: December Year T

Base currency: EUR

111. Long Call Options. Underlying PFIZER (Ticker PFE US) 10% OTM, (1 contract = 100 shares).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Expiry date: June Year T

Base currency: USD

112. Long Put Options. Underlying PFIZER (Ticker PFE US) 10% OTM, (1 contract = 100 shares).

Notional: equivalent to value of 10 000 shares of the underlying asset

Expiry date: June Year T

Base currency: USD

113. Long Call Options. Underlying BAYER (Ticker: BAYN GR), 10% OTM (1 contract = 100 shares).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Expiry date: December Year T

Base currency: EUR

114. Short Call Options. Underlying BAYER (Ticker: BAYN GR), 10% OTM (1 contract = 100 shares).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Expiry date: June Year T

Base currency: EUR

115. Long Call Options. Underlying AVIVA (Ticker: AV/LN), 10% OTM (1 contract = 100 shares).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Expiry date: December Year T

Base currency: GBP

116. Long Put Options. Underlying AVIVA (Ticker: AV/LN), 10% OTM (1 contract = 100 shares).

Notional: equivalent to the value of 10 000 shares of the underlying asset

Expiry date: December Year T

Base currency: GBP

117. Short Futures NIKKEI 225 (Ticker NKY).

Notional: equivalent to the value of the index times 20 000 JPY

Exchange: CME

Expiry date: 8 June Year T

Base currency: JPY

118. Auto-callable Equity product.

Long position

Booking on 'Booking date'

Notional amount ('Capital'): EUR 1 000 000

Underlying: Index EURO STOXX 50 (Ticker: SX5E)

Base currency: EUR

Maturity: 5 years

Annual Pay-out and annual observation ('Booking date + 1 year', 'Booking date + 2 years', 'Booking date + 3 years', 'Booking date + 4 years', 'Booking date + 5 years'). Pay-out occurs 10 days after reference date.

Coupon: 6%

Autocall level ('Initial value'): End of day Booking date + 1 month

Barrier coupon payment 60% of autocall level

Protection barrier: 55% of autocall level

additional details in the original ITS 2023)

119. Long Call Options. Underlying EURO STOXX 50 index (Ticker: SX5E), ATM.

Notional: equivalent to the value of the index times 1 000 EUR

Expiry date: June Year T

Base currency: EUR

120. Long Call Options. Underlying EURO STOXX 600 index (Ticker: SXXP), ATM.

Notional: equivalent to the value of the index times 10 000 EUR

Expiry date: June Year T

Base currency: EUR

121. Long Call Options. Underlying VIX (CBOE), ATM.

Notional: equivalent to the value of the index times 100 000 USD

Expiry date: June Year T

Base currency: USD

IR

201. 5-year IRS EUR – Receive fixed rate and pay floating rate.

Fixed leg: receive annually

Floating rate: 3-month EURIBOR, pay quarterly

Notional: EUR 10 000 000

Roll convention and calendar: standard

Effective date as booking date (i.e. the rates to be used shall be those at the market close as of the booking date)

Maturity: September Year T+4.

Base currency: EUR

202. Two-year EUR swaption on 5-year IRS EUR – pay fixed rate and receive floating rate.

Notional: EUR 10 000 000.

The institution is the seller of the option on the swap. The counterparty of the institution buys the right to enter a swap with the institution; if the counterparty exercises its right, the counterparty shall receive the fixed rate while the institution shall receive the floating rate.

Swaption with maturity of two years (Booking date + 2 years) on IRS defined as follow:

Fixed leg - pay annually; Floating rate: 3-month EURIBOR, receive quarterly;

Notional: EUR 10 000 000; Roll convention and calendar: standard;

Effective date as booking date (i.e. the rates to be used shall be those at the market close as of the booking date)

Maturity of the underlying swap: Booking date + 7 years

Premium paid at the booking date (Booking date). Cash settled

The strike price is based on the IRS defined within this instrument

Base currency: EUR

203. 5-year IRS USD. Receive fixed rate and pay floating rate.

Fixed rate: receive annually

Floating rate: 3-month USD LIBOR rate, pay quarterly

Notional: USD 1 000 000

Roll convention and calendar: standard

Effective date as booking date (i.e. the rates to be used shall be those at the market close as of the booking date)

Maturity date: September Year T+4.

Base currency: USD

204. 2-year IRS GBP. Receive fixed rate and pay floating rate.

Fixed rate: receive annually

Floating rate: 3-month SONIA rate compounded and paid annually

Notional: GBP 10 000 000

Roll convention and calendar: standard

Effective date as booking date (i.e. the rates to be used shall be those at the market close as of the booking date)

Maturity: Booking date + 2 years

Base currency GBP

205. Collared 10y floating rate note sold by UBS.

Notional (Principal) Amount: USD 1 000 000.

Floating Rate Notes (the 'Notes') are senior unsecured obligations of UBS AG ('UBS').

Base currency USD

Interest Payment Amount

Trade and Settlement Date

Interest Payment Dates

Maturity Date

Currency

Daycount Basis

Business Day Convention

Coupon Determination

Date

206. Long GERMANY GOVT EUR 1 000 000 (ISIN DE0001030583).

Maturity: 15 April 2033

Base currency: EUR

207. Short GERMANY GOVT EUR 1 000 000 (ISIN DE0001135044).

Maturity: 4 July 2027

Base currency: EUR

208. Long ITALY GOVT EUR 1 000 000 (ISIN IT0005138828).

Maturity: 15 September 2032

Base currency: EUR

209. Long ITALY GOVT EUR 1 000 000 (ISIN IT0005210650).

Maturity: 1 December 2026

Base currency: EUR

210. Long SPAIN GOVT EUR 1 000 000 (ISIN ES00000127A2).

Maturity: 30 July 2030

Base currency: EUR

211. Short FRANCE GOVT EUR 1 000 000 (ISIN FR0012993103).

Maturity: 25 May 2031

Base currency: EUR

212. Short GERMANY GOVT EUR 1 000 000 (ISIN DE0001135176).

Maturity: 4 January 2031

Base currency: EUR

213. Long UNITED KINGDOM GOVT GBP 1 000 000 (ISIN GB0004893086).

Maturity: 7 June 2032

Base currency: GBP

214. Long PORTUGAL GOVT EUR 1 000 000 (ISIN PTOTEXOE0024).

Maturity: 15 June 2029

Base currency: EUR

215. Short UNITED STATES GOVT USD 1 000 000 (ISIN US9128283F58).

Maturity: 15 November 2027

Base currency: USD

216. Long BRAZIL GOVT 1 000 000 USD (ISIN US105756BZ27).

Maturity: 13 January 2028

Base currency: USD

217. Long MEXICO GOVT 1 000 000 USD (ISIN US91087BAC46).

Maturity: 28 March 2027

Base currency USD

218. 10-year IRS EURO – Receive floating rate and pay fixed rate.

Fixed leg: pay annually

Floating rate: 3-month EURIBOR, receive quarterly

Notional: EUR 10 000 000

Roll convention and calendar: standard

Effective date as the booking date (i.e. rates to be used are those at the market close on booking date)

Maturity: Booking date + 10 years

Base currency: EUR

219. 5-year IRS EURO – Receive floating rate and pay fixed rate.

Fixed leg: pay annually

Floating rate: 6-month EURIBOR, receive every 6 months

Notional: EUR 1 000 000

Roll convention and calendar: standard

Effective date as the booking date (i.e. rates to be used are those at the market close on booking date)

Maturity: Booking date + 5 years

Base currency: EUR

220. 5-year Mark to Market (MtM) Cross Currency EUR/USD SWAP. Receive USD and pay EUR.

EUR: 3-month ESTER, pay quarterly compounded with a payment lag of 2 days

USD: 3-month SOFR, receive quarterly compounded with a payment lag of 2 days

Leg 1 – USD: Notional EUR 10 000 000 equivalent adjusted on a quarterly basis

Leg 2 – EUR: Notional EUR 10 000 000

Roll convention and calendar: standard

Effective date as booking date + 6 months

Maturity: Booking date + 5,5 years

Base currency: EUR

See also Section 5 of this Annex – Instrument additional specifications

221. 10-year IRS EURO – Receive ESTER and pay EURIBOR.

ESTER leg: receive annually

EURIBOR leg: 3-month EURIBOR + Basis, pay quarterly

Notional: EUR 10 000 000

Roll convention and calendar: standard

Effective date as booking date (i.e. the rates to be used shall be those at the market close as of the booking date)

Maturity: September Year T + 9 years

Base currency: EUR

222. Long ITALY GOVT EUR 1 000 000 (ISIN IT0005387052).

Maturity: 15 May 2030

Base currency: EUR

223. 5-year Zero Coupon Inflation swap EUR – Receive Inflation indexed return and pay fixed rate (r).

Inflation Index: CPI (HICPxT)

Fixed leg (Pay fixed): $[(1 + r)^5 - 1]$

Rec Inflation indexed return: $[\frac{CPI \text{ at the end (maturity) date}}{CPI \text{ at the start date}} - 1]$

Notional: EUR 10 000 000

Base fixing date: August Year T

Final Fixing: August Year T+4

Maturity: September Year T+4

Base currency: EUR

224. Two-year EUR swaption on 5-year IRS EUR – receive fixed rate and pay floating rate.

Notional: EUR 10 000 000.

The institution is the seller of the option on the swap. The counterparty of the institution buys the right to enter a swap with the institution; if the counterparty exercises its right, the counterparty shall receive the fixed rate while the institution shall receive the floating rate.

Swaption with maturity of two years (Booking date + 2 years) on IRS defined as follow: Fixed leg- receive annually;

Floating rate: 6-month EURIBOR, pay every 6 months; Notional: EUR 10 000 000; Roll convention and calendar: standard;

Effective date as the booking date (i.e. rates to be used are those at the market close on booking date)

Maturity of the underlying swap: Booking date + 7 years

Premium paid at the booking date (Booking date). Cash settled

The strike price is based on the IRS defined within this instrument+ 100 bps

Base currency: EUR

FX

301. 6-month USD/EUR forward contract. Cash settled. Long USD – Short EUR; Notional USD 10 000 000; EUR/USD ECB reference spot rate as of end of the booking date.

Base currency: EUR

302. 6-month EUR/GBP forward contract. Cash settled. Long EUR – Short GBP; Notional 10 000 000 GBP; EUR/GBP ECB reference spot rate as of end of the booking date.

Base currency: EUR

303. Long 10 000 000 USD Cash.

Cash position

Base currency: EUR

304. Long Call option. EUR 10 000 000. Equivalent amount based on EUR/USD ECB reference spot rate as of end of the booking date.

Strike price: 110% of EUR/USD ECB reference rate as of end of the booking date

Expiry date: Booking date + 1 year

Base currency: EUR

305. Long Call option. EUR 10 000 000. Equivalent amount based on EUR/USD ECB reference spot rate as of end of the booking date.

Strike price: 90% of EUR/USD ECB reference rate as of end of the booking date

Expiry date: Booking date + 1 year

Base currency: EUR

306. Short Call option. EUR 10 000 000. Equivalent amount based on EUR/USD ECB reference spot rate as of end of the booking date.

Strike price: 100% of EUR/USD ECB reference rate as of end of the booking date

Expiry date: Booking date + 1 year

Base currency: EUR

307. Short Call option. EUR 10 000 000. Equivalent amount based on EUR/GBP ECB reference spot rate as of end of the booking date.

Strike price: 110% of EUR/GBP ECB reference rate as of end of the booking date

Expiry date: Booking date + 1 year

Base currency: EUR

308. Long Put option. EUR 10 000 000. Equivalent amount based on EUR/JPY ECB reference spot rate as of end of the booking date.

Strike price: 110% of EUR/JPY ECB reference rate as of end of the booking date

Expiry date: Booking date + 1 year

Base currency: EUR

309. Short Put option. EUR 10 000 000. Equivalent amount based on EUR/AUD ECB reference spot rate as of end of the booking date.

Strike price: 110% of EUR/AUD ECB reference rate as of end of the booking date

Expiry date: Booking date + 1 year

Base currency: EUR

310. 6-month EUR/DKK forward contract. Cash settled. Long EUR – Short DKK; Notional EUR 10 000 000; EUR/DKK ECB reference spot rate as of end of the booking date.

Base currency: EUR

311. 6-month EUR/BRL Non deliverable forward contract. Long EUR – Short BRL; Notional EUR 10 000 000; EUR/BRL ECB reference spot rate as of end of the booking date.

Base currency: EUR

COMMODITIES

401. Long 3 500 000 6-month ATM London Gold Forwards contracts (1 contract = 0.001 troy ounces, notional: 3 500 troy ounces).

Cash Settlement

Base currency: USD

402. Short 3 500 000 12-month ATM London Gold Forwards contracts (1 contract = 0.001 troy ounces, notional: 3 500 troy ounces).

Cash Settlement

Base currency: USD

403. Long 30 contracts of 6-month WTI Crude Oil Call option with strike equals 12-month end-of-day forward price on the booking date (1 contract = 1 000 barrels. Total notional 30 000 barrels).

Cash Settlement

Base currency USD

404. Short 30 contracts of 6-month WTI Crude Oil Put option with strike equals 12-month end-of-day forward price on the booking date (1 contract = 1 000 barrels. Total notional 30 000 barrels).

Cash Settlement

Base currency USD

405. Long Call option. 5 000 0zt of London Gold.

Strike price: ATM as of end of the booking date

Expiry date: Booking date + 18 months

Cash Settlement

Base currency: USD

CREDIT SPREAD

501. Long (i.e. Buy protection) USD 1 000 000 CDS on PORTUGAL.

Restructuring clause: FULL

Base currency: USD

502. Long (i.e. Buy protection) USD 1 000 000 CDS on ITALY.

Restructuring clause: FULL

Base currency: USD

503. Short (i.e. Sell protection) USD 1 000 000 CDS on SPAIN.

Restructuring clause: FULL

Base currency: USD

504. Long (i.e. Buy protection) USD 1 000 000 CDS on MEXICO.

Restructuring clause: FULL

Base currency: USD

505. Long (i.e. Buy protection) USD 1 000 000 CDS on BRAZIL.

Restructuring clause: FULL

Base currency: USD

506. Long (i.e. Buy protection) USD 1 000 000 CDS on UK.

Restructuring clause: FULL

Base currency: USD

507. Short (i.e. Sell protection) EUR 1 000 000 CDS on Telefonica (Ticker TEF SM).

Base currency: EUR

508. Long (i.e. Buy protection) EUR 1 000 000 CDS on Telefonica (Ticker TEF SM).

Maturity: December Year T+2

Base currency: EUR

509. Short (i.e. Sell protection) EUR 1 000 000 CDS on Aviva (Ticker AV LN).

ISDA Definitions year 2003

Base currency: EUR

510. Long (i.e. Buy protection) EUR 1 000 000 CDS on Aviva (Ticker AV LN).

ISDA Definitions year 2003

Maturity: December Year T+2

Base currency: EUR

511. Short (i.e. Sell protection) EUR 1 000 000 CDS on Vodafone (Ticker VOD LN).

Base currency: EUR

512. Short (i.e. Sell protection) EUR 1 000 000 CDS on ENI SpA (Ticker ENI IM).

Base currency: EUR

513. Short (i.e. Sell protection) USD 1 000 000 CDS on Eli Lilly (Ticker LLY US).

Restructuring clause: No restructuring (XR14)

Base currency: USD

514. Short (i.e. Sell protection) EUR 1 000 000 CDS on Unilever (Ticker UNA NA).

Base currency: EUR

515. Long (i.e. Buy protection) EUR 1 000 000 CDS on Total SA (Ticker FP FP).

Base currency: EUR

516. Long (i.e. Buy protection) EUR 1 000 000 CDS on Volkswagen Group (Ticker VOW GR).

Base currency: EUR

517. Long position on TURKEY Govt. notes USD 1 000 000 (ISIN US900123CT57).

Maturity: 26 April 2029

Base currency: USD

518. Long (i.e. Buy protection) USD 1 000 000 CDS on TURKEY. Effective date as booking date.

Restructuring clause: FULL

Base currency: USD

519. Long position on Telefonica notes EUR 1 000 000 (ISIN XS1681521081).

Maturity: 12 January 2028

Base currency: EUR

520. Long position on Volkswagen Group notes EUR 1 000 000 (ISIN XS1944390597).

Maturity: 31 July 2026

Base currency: EUR

521. Short position Volkswagen Group notes EUR 1 000 000 (ISIN XS1944390241).

Maturity: 31 January 2024

Base currency: EUR

522. Long position on Total SA notes EUR 1 000 000 (ISIN XS1048519679).

Maturity: 25 March 2026

Base currency: EUR

523. Long AUSTRIA GOVT EUR 1 000 000 (ISIN AT0000A04967).

Maturity: 15 March 2037

Base currency: EUR

524. Long (i.e. Buy protection) USD 1 000 000 CDS on AUSTRIA.

Maturity: June Year T+15

Base currency: USD

525. Long NETHERLANDS GOVT EUR 1 000 000 (ISIN NL0013552060).

Maturity: 15 January 2040

Base currency: EUR

526. Long (i.e. Buy protection) USD 1 000 000 CDS on NETHERLANDS.

Maturity: June Year T+20

Base currency: USD

527. Long BELGIUM GOVT EUR 1 000 000 (ISIN BE0000348574).

Maturity: 22 June 2050

Base currency: EUR

528. Long (i.e. Buy protection) USD 1 000 000 CDS on BELGIUM.

Maturity: June Year T+30

Base currency: USD

529. Long (Buy protection) EUR 10 000 000 CDS on iTraxx Europe index on-the-run series.

Maturity: June Year T+5

Base currency: EUR

530. Short Put option. EUR 10 000 000. Underlying iTraxx Europe index on-the-run series (same instrument of 529).

Strike price: ATM

Expiry date: Booking date + 1 year

Base currency: EUR

531. Long AXA SA (callable) EUR 1 000 000 (ISIN XS1799611642).

Maturity: 28 May 2049

Base currency: EUR

532. Long AT&T Bond (callable) USD 1 000 000 (ISIN US00206RFW79).

Maturity: 15 August 2037

Base currency: USD

533. Long BAYER AG (callable) EUR 1 000 000 (ISIN XS2199266268).

Maturity: 06 January 2030

Base currency: EUR

534. Long AT&T Bond (callable) EUR 1 000 000 (ISIN XS0993148856).

Maturity: 17 December 2025

Base currency: EUR

CTP

601. Short (i.e. Sell protection) position in iTraxx Europe index on-the-run series.

Attachment point: 3%

Detachment point: 6%

Notional: EUR 5 000 000

Maturity: 5 years

Base currency: EUR

602. Long (i.e. Buy protection) EUR 5 000 000 CDS on iTraxx Europe index most recent on-the-run series.

Maturity: June Year T+5

Base currency: EUR

Notional adj. to fully hedge CS01 of 601 with no re-hedging required

603. Long (i.e. Buy protection) position in iTraxx Europe index on-the-run series.

Attachment point: 3%

Detachment point: 6%

Notional: EUR 5 000 000

Maturity: 5 years

Base currency: EUR

604. Short (i.e. Sell protection) EUR 5 000 000 CDS on iTraxx Europe index most recent on-the-run series.

Maturity: June Year T+5

Base currency: EUR

Notional adj. to fully hedge CS01 of 603 with no re-hedging required

605. Short (i.e. Sell protection) position in iTraxx Europe index on-the-run series.

Attachment point: 12%

Detachment point: 100%

Notional: EUR 5 000 000

Maturity: 5 years

Base currency: EUR

606. Long (i.e. Buy protection) EUR 5 000 000 CDS on iTraxx Europe index most recent on-the-run series.

Maturity: June Year T+5

Base currency: EUR

Notional adj. to fully hedge CS01 of 605 with no re-hedging required

607. Long (i.e. Buy protection) position in iTraxx Europe index on-the-run series.

Attachment point: 12%

Detachment point: 100%

Notional: EUR 5 000 000

Maturity: 5 years

Base currency: EUR

608. Short (i.e. Sell protection) EUR 5 000 000 CDS on iTraxx Europe index most recent on-the-run series.

Maturity: June Year T+5

Base currency: EUR

Notional adj. to fully hedge CS01 of 607 with no re-hedging required

609. Short (i.e. Sell protection) position in iTraxx Europe index on-the-run series.

Attachment point: 3%

Detachment point: 6%

Notional: EUR 5 000 000

Maturity: 5 years

Base currency: EUR

Recovery rate: 40% fixed.

610. Long (i.e. Buy protection) EUR 5 000 000 CDS on iTraxx Europe index most recent on-the-run series.

Maturity: June Year T+5

Base currency: EUR

Notional adj. to fully hedge CS01 of 609 with no re-hedging required

Portfolio	Combination of instruments:	Currency	Portfolio	Combination of instruments:	Currency
1001	101 – 1 instrument	EUR	4001	401 – 1 instrument	USD
1002	103 – 1 instrument	EUR		402 – 1 instrument	
	104 – 1 instrument		4002	403 – 1 instrument	USD
	105 – 1 instrument			404 – 1 instrument	
1003	113 – 1 instrument	EUR	4003	401 – 1 instrument	USD
	110 – 1 instrument			404 – 1 instrument	
1004	115 – 1 instrument	GBP	4004	405 – 1 instrument	EUR
	116 – 1 instrument		5001	501 – 1 instrument	USD
1005	117 – 1 instrument	JPY		502 – 1 instrument	
1006	109 – 1 instrument	EUR		503 – 1 instrument	
	110 – 1 instrument		5002	504 – 1 instrument	USD
1007	118 – 1 instrument	EUR		505 – 1 instrument	
1008	111 – 1 instrument	USD	5003	507 – 1 instrument	EUR

	112 – 1 instrument			508 – 1 instrument	
1009	102 – 1 instrument	EUR	5004	503 – 1 instrument	USD
	114 – 1 instrument			504 – 1 instrument	
1010	106 – 1 instrument	EUR	5005	509 – 1 instrument	EUR
	107 – 1 instrument			510 – 1 instrument	
	108 – 1 instrument		5006	511 – 1 instrument	EUR
1011	101 – 1 instrument	EUR		512 – 1 instrument	
	103 – 1 instrument			514 – 1 instrument	
1012	101 – 1 instrument	EUR		515 – 1 instrument	
	103 – 1 instrument			516 – 1 instrument	
	104 – 1 instrument		5007	517 – 1 instrument	USD
1013	102 – 1 instrument	EUR		518 – 1 instrument	
	104 – 1 instrument		5008	519 – 1 instrument	EUR
1014	119 – 1 instrument	EUR		520 – 1 instrument	
1015	120 – 1 instrument	EUR		522 – 1 instrument	
1016	121 – 1 instrument	EUR	5009	520 – 1 instrument	EUR
2001	201 – 1 instrument	EUR		521 – 1 instrument	
2002	202 – 1 instrument	EUR	5010	519 – 1 instrument	EUR
2003	203 – 1 instrument	USD		508 – 1 instrument	
2004	204 – 1 instrument	GBP	5011	515 – 1 instrument	EUR
2005	205 – 1 instrument	USD		522 – 1 instrument	
2006	206 – 1 instrument	EUR	5012	513 – 1 instrument	USD
	207 – 1 instrument		5013	520 – 1 instrument	EUR
2007	206 – 1 instrument	EUR		521 – 1 instrument	
	207 – 1 instrument			516 – 1 instrument	
	208 – 1 instrument		5014	506 – 1 instrument	USD
2008	206 – 1 instrument	EUR		503 – 1 instrument	
	207 – 1 instrument		5015	502 – 1 instrument	EUR
	208 – 1 instrument			209 – 1 instrument	
	209 – 1 instrument		5016	504 – 1 instrument	USD
	210 – 1 instrument			217 – 1 instrument	
	211 – 1 instrument		5017	505 – 1 instrument	USD
	212 – 1 instrument			216 – 1 instrument	
2009	201 – 1 instrument	EUR	5018	504 – 1 instrument	USD
	218 – 1 instrument			217 – 1 instrument	
2010	201 – 1 instrument	EUR		505 – 1 instrument	
	219 – 1 instrument			216 – 1 instrument	
2011	218 – 1 instrument	EUR	5019	502 – 1 instrument	EUR
	219 – 1 instrument			209 – 1 instrument	
2012	201 – 1 instrument	EUR		219 – 1 instrument	
	202 – 1 instrument		5020	523 – 1 instrument	EUR
2013	213 – 1 instrument	GBP		525 – 1 instrument	
2014	215 – 1 instrument	USD		527 – 1 instrument	
	216 – 1 instrument		5021	524 – 1 instrument	USD

	217 – 1 instrument			526 – 1 instrument	
2015	203 – 1 instrument	USD		528 – 1 instrument	
	215 – 1 instrument		5022	523 – 1 instrument	EUR
2016	208 – 1 instrument	EUR		524 – 1 instrument	
	209 – 1 instrument			525 – 1 instrument	
	210 – 1 instrument			526 – 1 instrument	
	214 – 1 instrument			527 – 1 instrument	
2017	220 – 1 instrument	EUR		528 – 1 instrument	
2018	209 – 1 instrument	EUR	5023	529 – 1 instrument	EUR
				530 – 1 instrument	
2019	209 – 1 instrument	EUR	5024	531 – 1 instrument	EUR
	219 – 1 instrument		5025	532 – 1 instrument	USD
2020	221 – 1 instrument	EUR	5026	533 – 1 instrument	EUR
2021	222 – 1 instrument	EUR	5027	534 – 1 instrument	EUR
2022	201 – 1 instrument	EUR	6001	601 – 1 instrument	EUR
	223 – 1 instrument			602 – 1 instrument	
2023	224 – 1 instrument	EUR	6002	603 – 1 instrument	EUR
3001	301 – 1 instrument	EUR		604 – 1 instrument	
	302 – 1 instrument		6003	605 – 1 instrument	EUR
3002	303 – 1 instrument	EUR		606 – 1 instrument	
	304 – 1 instrument		6004	607 – 1 instrument	EUR
3003	304 – 1 instrument	EUR		608 – 1 instrument	
	305 – 1 instrument		6005	609 – 1 instrument	EUR
	306 – 1 instrument			610 – 1 instrument	
3004	307 – 1 instrument	EUR			
	308 – 1 instrument				
3005	309 – 1 instrument	EUR			
3006	310 – 1 instrument	EUR			
3007	311 – 1 instrument	EUR			

Aggreg. Portfolio	Description	Combination of Individual Portfolios (individual portfolios as stated by their numbers as referred to in Section 3 of this Annex)	Base Currency
10000	ALL-IN no-CTP	1001, 1002, 1006, 1007, 1009, 2001, 2002, 2008, 2011, 3001, 3002, 3003, 3004, 4001, 4002, 5003, 5006, 5008, 5022	EUR
11000	EQUITY Cumulative	1001, 1002, 1006, 1007, 1009	EUR
12000	IR Cumulative	2001, 2002, 2008, 2011	EUR

13000	FX Cumulative	3001, 3002, 3003, 3004	EUR
14000	Commodity Cumulative	4001, 4002	USD
15000	Credit Spread cumulative	5003, 5006, 5008, 5022	EUR
16000	CTP cumulative EUR	6001, 6002	EUR

For a detailed description of the portfolios, please refer to the EBA website:

<https://www.eba.europa.eu/activities/single-rulebook/regulatory-activities/supervisory-benchmarking-exercises/its-package-benchmarking-exercises>

Adopted as consolidated text: 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 of the European Parliament and of the Council (Text with EEA relevance)Text with EEA relevance

<https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02016R2070-20240328>

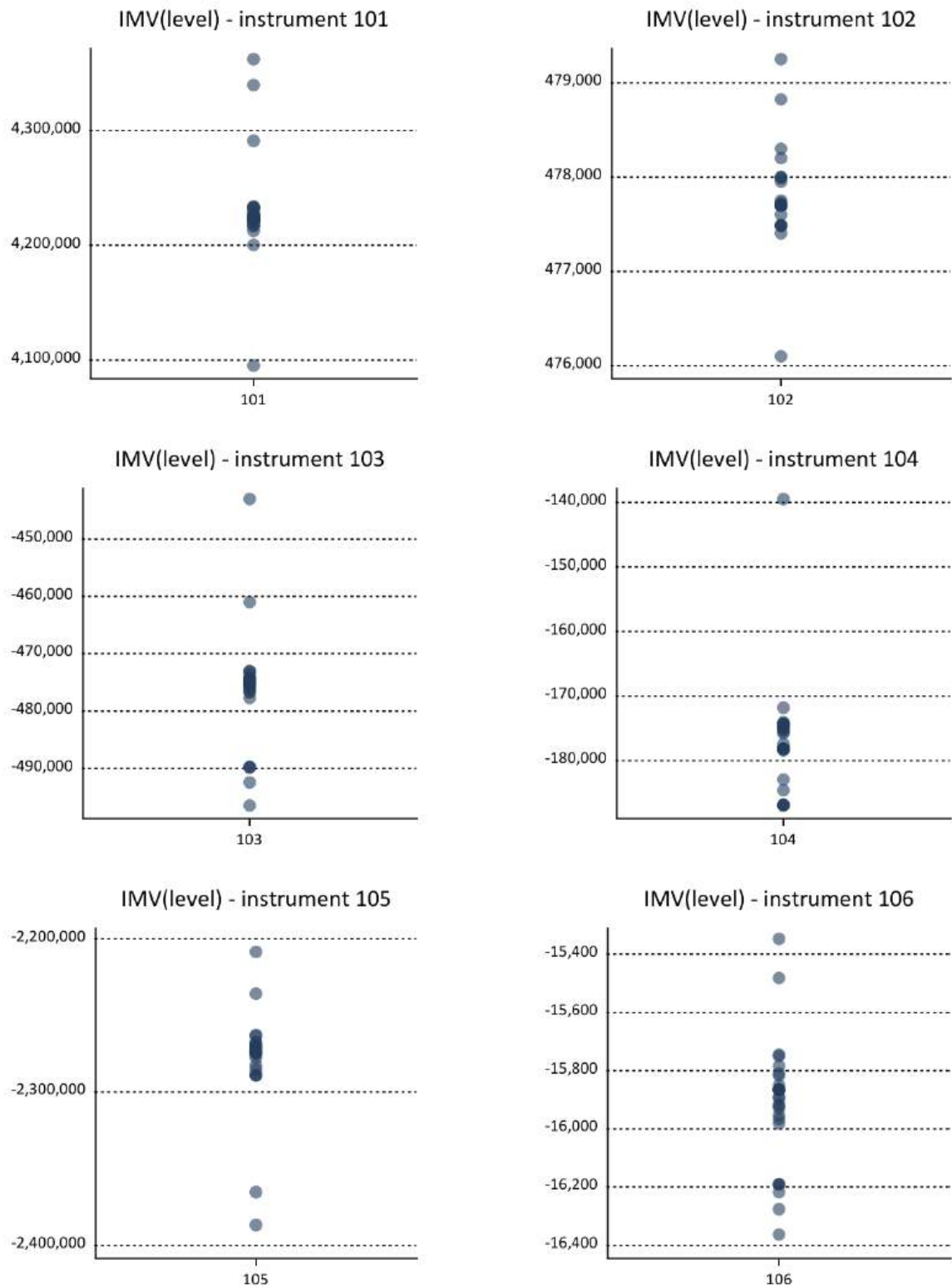
Table 20: VaR cluster analysis – number of banks by range

2024 VaR cluster analysis: number of banks by range

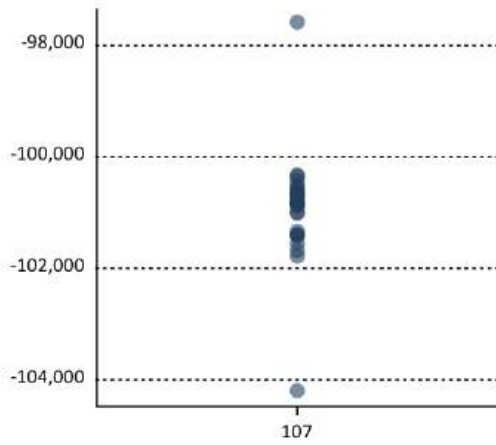
(X = ratio with the median)

		100					
Port. ID	300% < X	300% ≥ X >200%	200% ≥ X >150%	150% ≥ X >100%	100% ≥ X >50%	50% ≥ X >0	Num obs.
Equity	1001				17	13	30
	1002				10	15	25
	1003			3	9	11	25
	1004				10	12	23
	1005				11	14	25
	1006			1	11	12	24
	1007			1	6	10	19
	1008				13	10	23
	1009				14	11	25
	1010				12	13	25
	1011				15	13	28
	1012				15	13	28
	1013			2	13	11	26
	1014				13	14	27
	1015				10	12	22
	1016			3	2	5	11
Interest Rate	2001				16	21	37
	2002				16	19	35
	2003				19	16	35
	2004				16	21	37
	2005		1	1	5	7	16
	2006			2	11	18	31
	2007			2	10	18	30
	2008			6	9	18	33
	2009				16	20	36
	2010				16	21	37
	2011				16	21	37
	2012		2	4	9	20	35
	2013				14	19	33
	2014			2	9	14	26
	2015		1	4	8	19	32
	2016				13	18	31
	2017			3	11	18	32
2018			1	13	21	35	
2019			8	8	19	35	
2020				18	16	34	
2021			2	11	18	31	
2022			3	9	16	29	
2023		3		14	20	37	
FX	3001				18	16	34
	3002				17	14	31
	3003				14	17	31
	3004				16	16	32
	3005				12	17	29
	3006				14	18	32
	3007				10	15	25
Commodities	4001		1	2	4	6	25
	4002				6	7	13
	4003				6	6	12
	4004				6	6	12
Credit Spread	5001			2	10	13	25
	5002				10	12	22
	5003			1	10	13	24
	5004				10	12	22
	5005				10	13	23
	5006		1		8	13	23
	5007			3	6	12	21
	5008			3	7	15	25
	5009			4	6	15	25
	5010			1	9	14	24
	5011				9	14	23
	5012			4	5	13	22
	5013				11	14	25
	5014			4	6	13	23
	5015			1	8	14	23
	5016				9	11	20
	5017			2	6	11	19
5018				9	11	20	
5019			1	7	14	24	
5020			2	11	15	26	
5021				10	12	22	
5022				9	13	22	
5023				8	8	16	
5024			7	2	12	21	
5025				8	12	20	
5026			2	6	13	21	
5027			2	5	13	20	
CTP	6001						0
	6002						0
	6003						0
	6004						0
	6005						0
All-in/No-CTP	10000				6	7	13
Equity Cumulative	11000				8	12	20
IR Cumulative	12000				15	15	30
FX Cumulative	13000				14	17	31
Commodity Cumulative	14000				6	7	13
CS Cumulative	15000			1	7	12	20
CTP Cumulative	16000						0

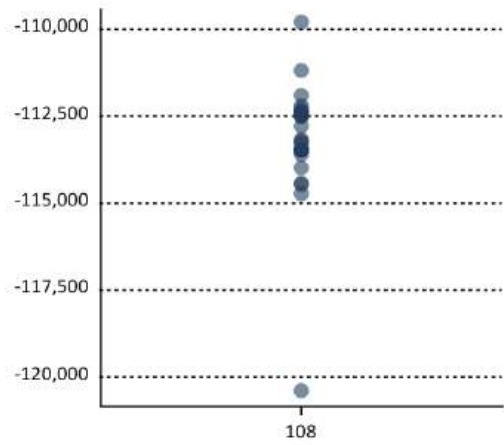
Figure 18: IMV scatter plots (all)



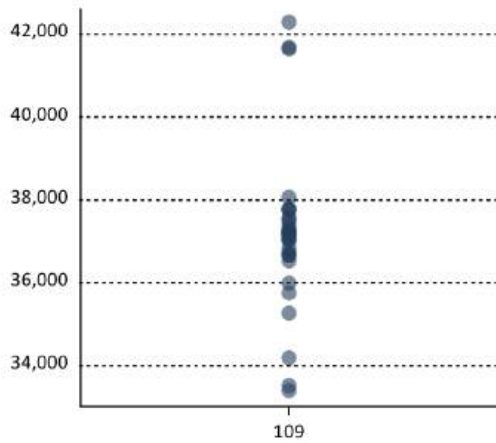
IMV(level) - instrument 107



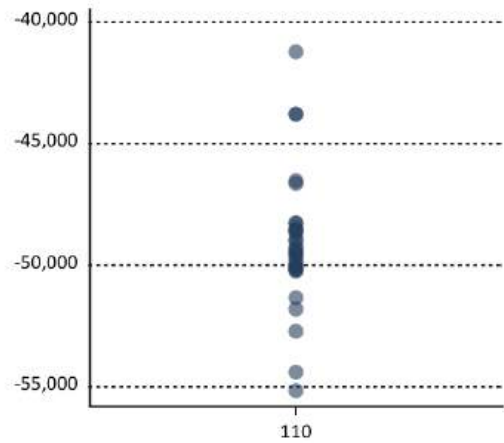
IMV(level) - instrument 108



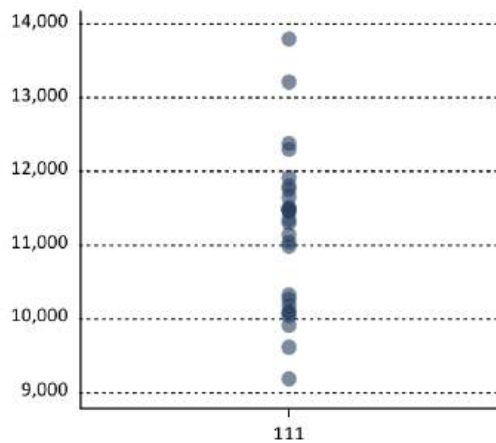
IMV(level) - instrument 109



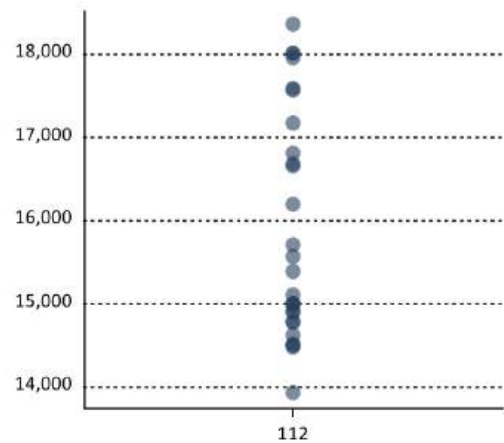
IMV(level) - instrument 110

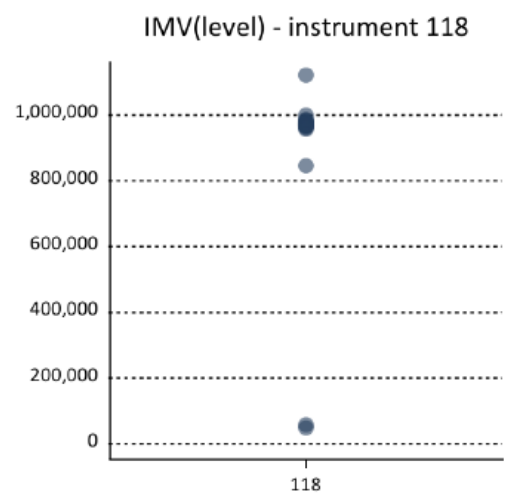
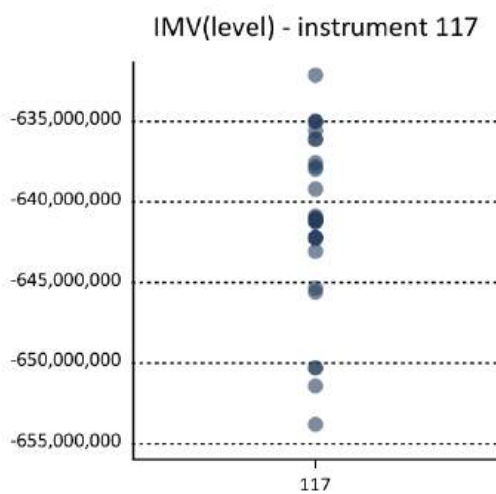
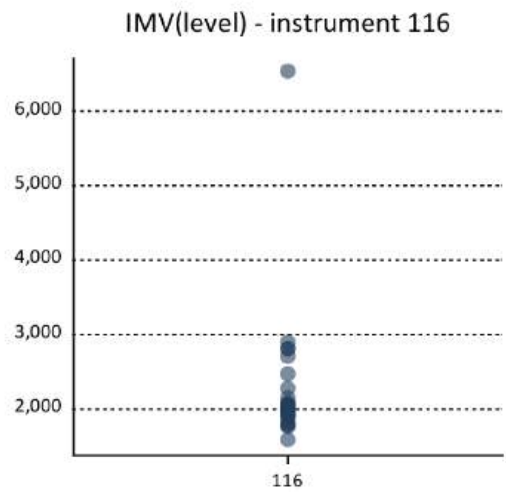
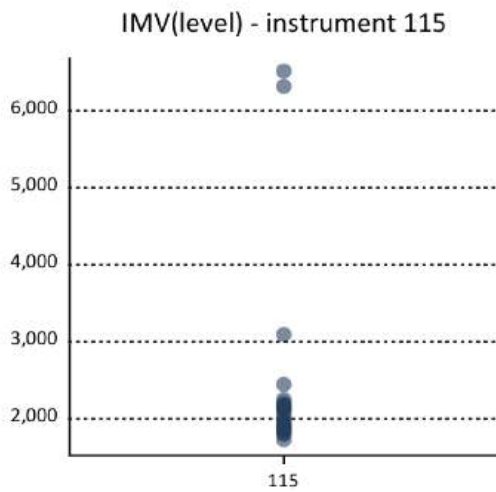
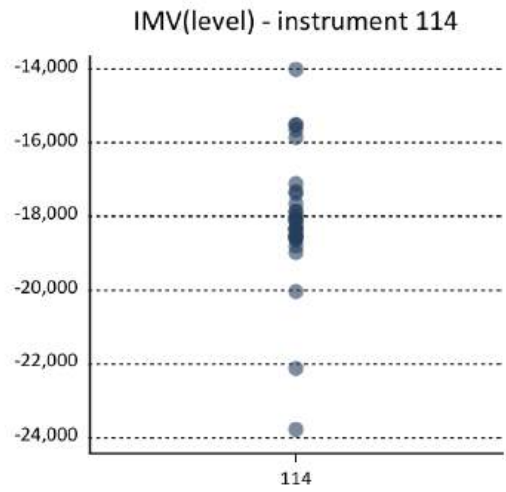
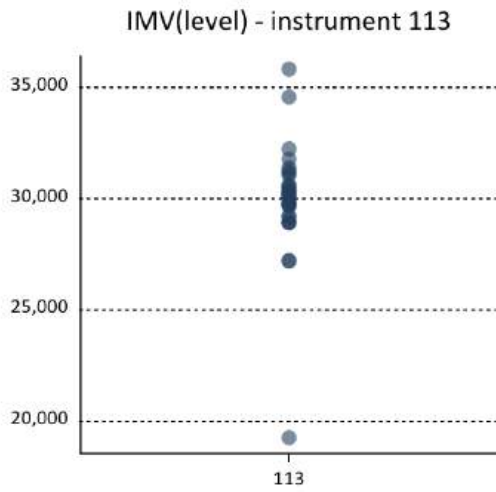


IMV(level) - instrument 111

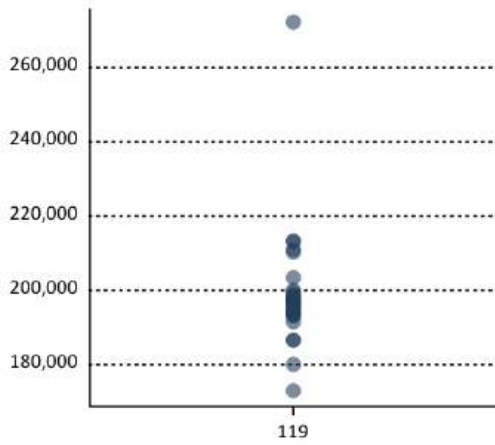


IMV(level) - instrument 112

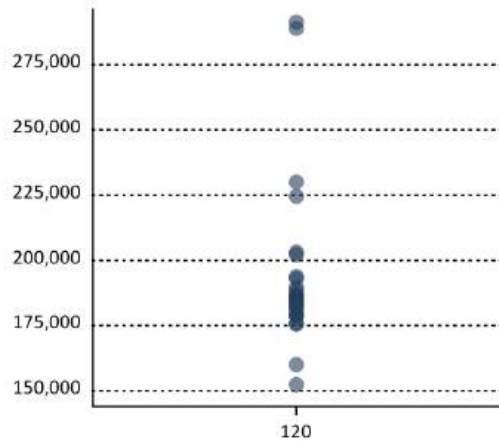




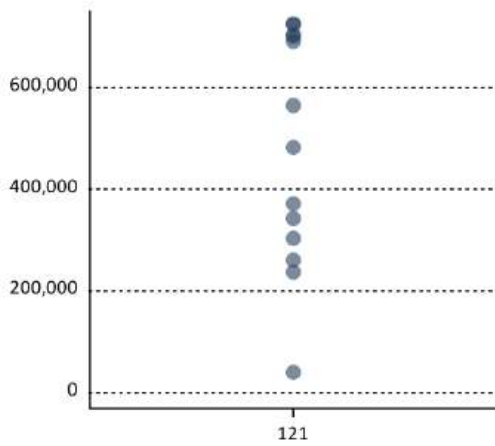
IMV(level) - instrument 119



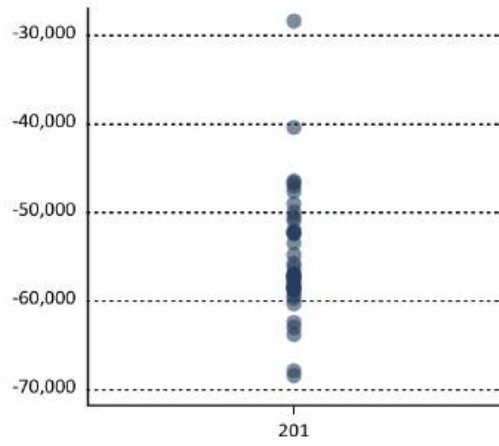
IMV(level) - instrument 120



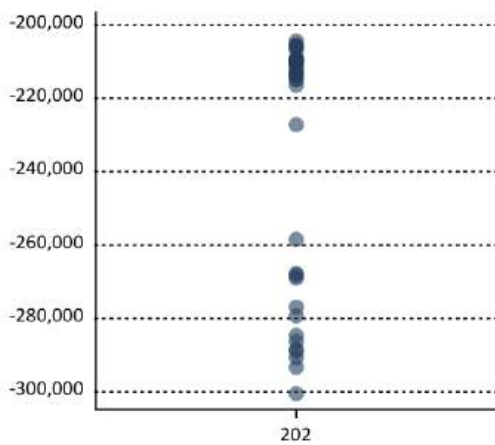
IMV(level) - instrument 121



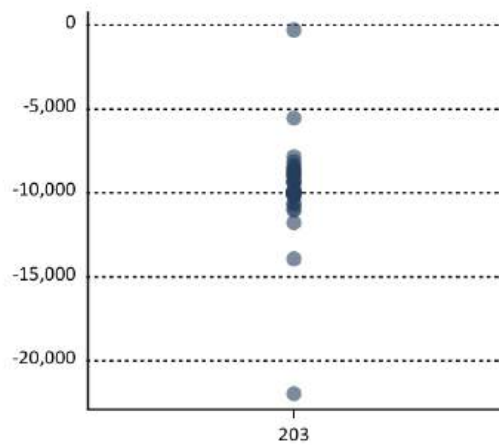
IMV(level) - instrument 201



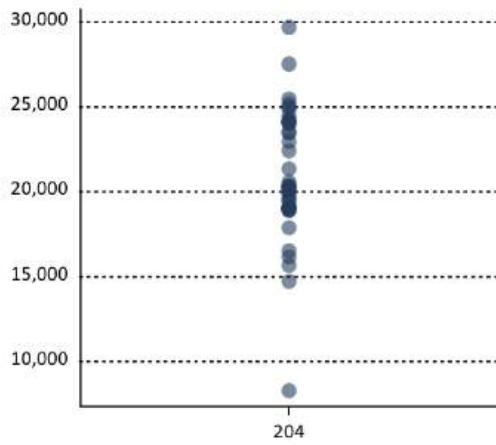
IMV(level) - instrument 202



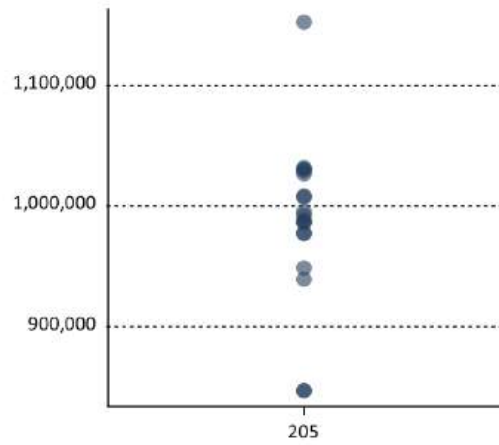
IMV(level) - instrument 203



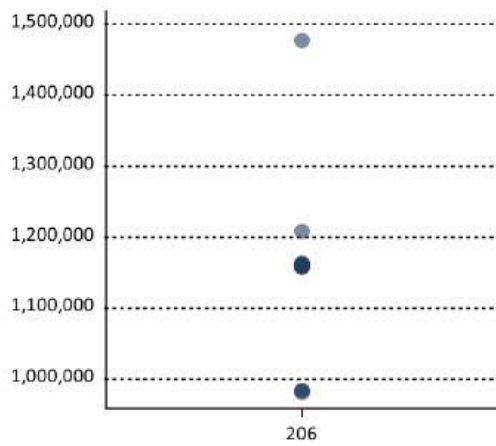
IMV(level) - instrument 204



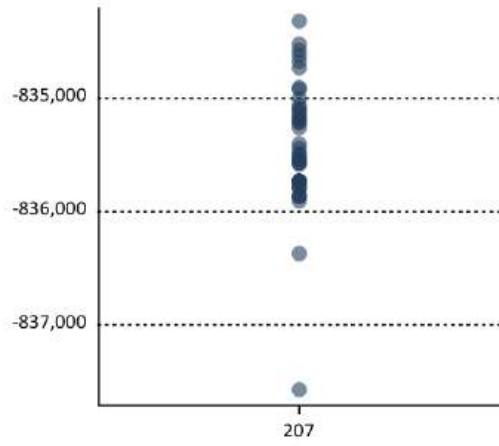
IMV(level) - instrument 205



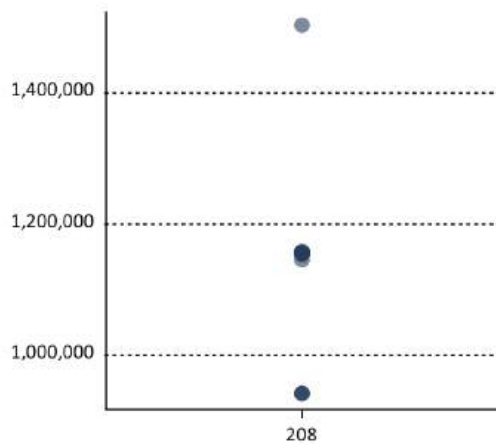
IMV(level) - instrument 206



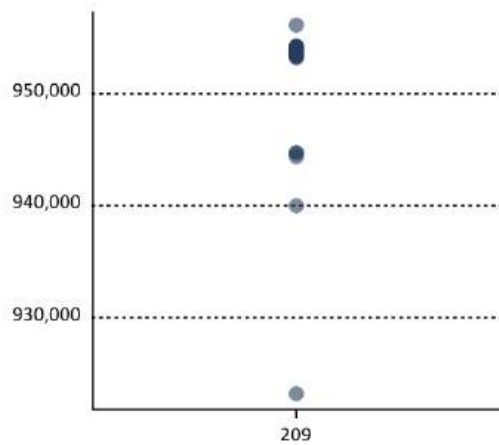
IMV(level) - instrument 207



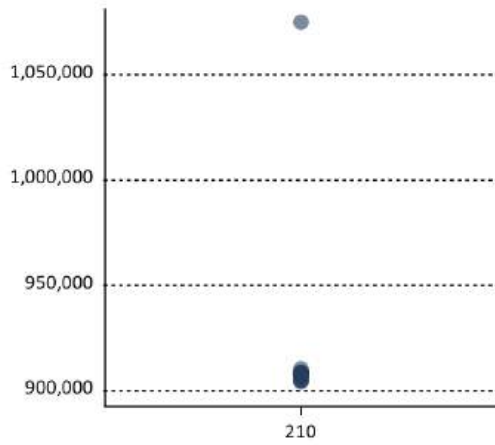
IMV(level) - instrument 208



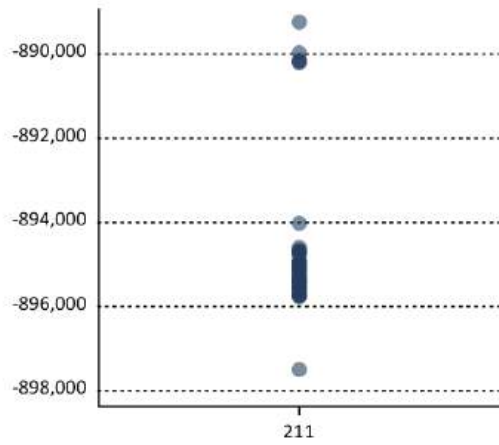
IMV(level) - instrument 209



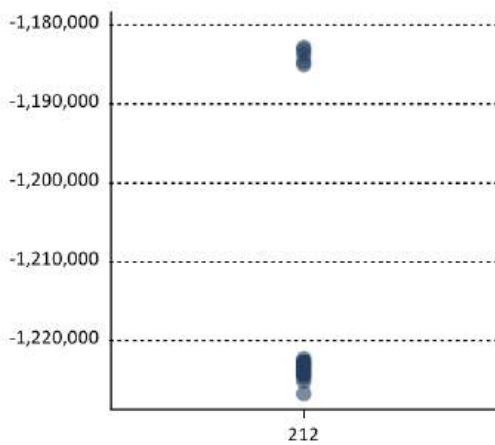
IMV(level) - instrument 210



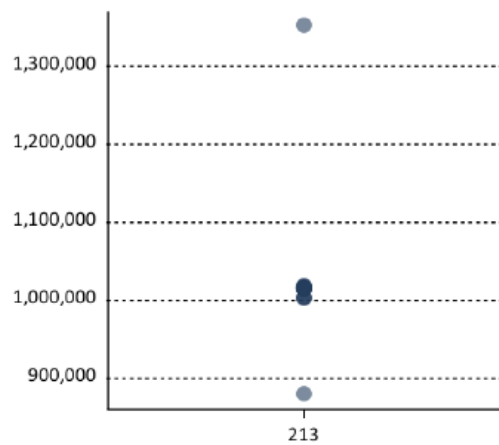
IMV(level) - instrument 211



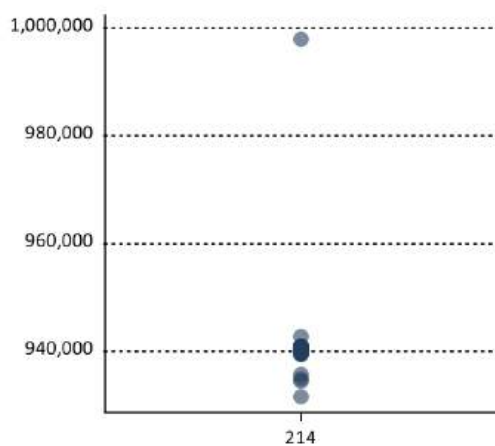
IMV(level) - instrument 212



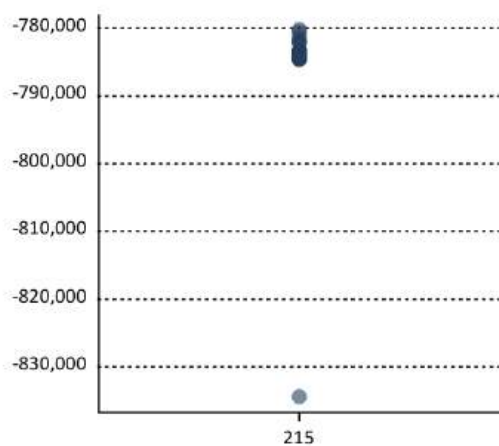
IMV(level) - instrument 213



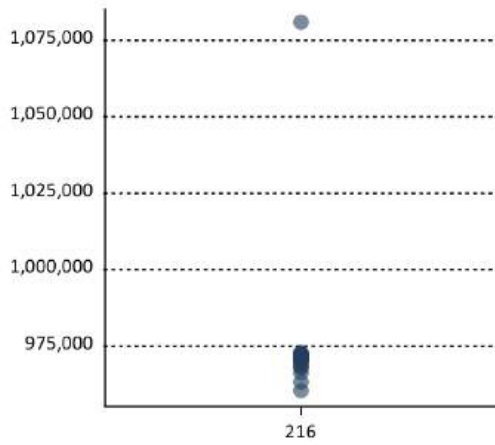
IMV(level) - instrument 214



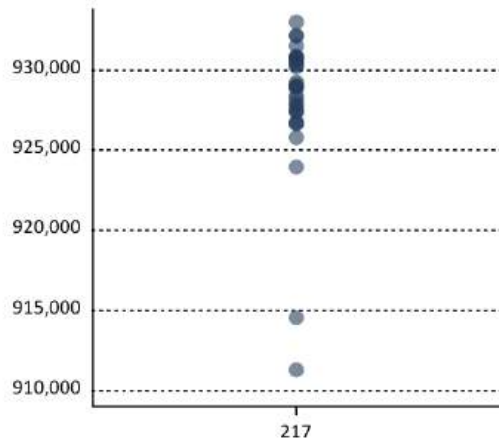
IMV(level) - instrument 215



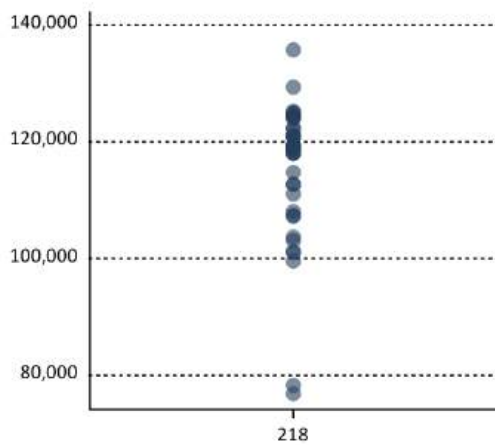
IMV(level) - instrument 216



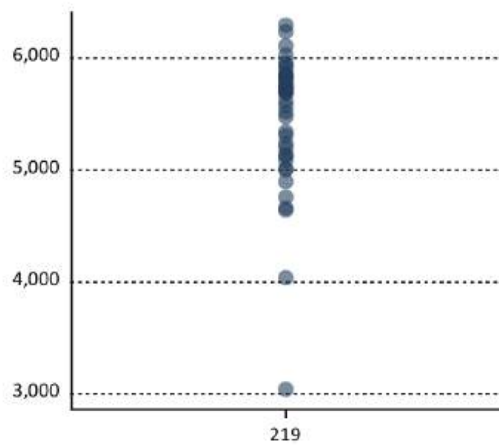
IMV(level) - instrument 217



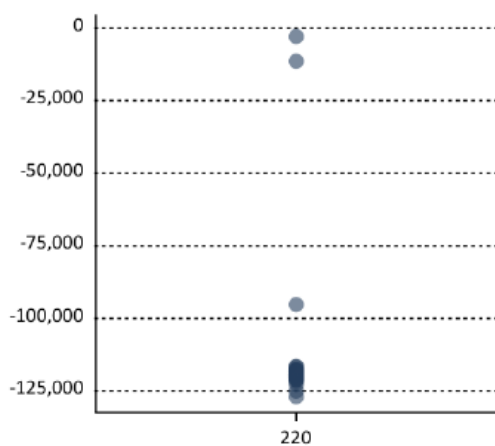
IMV(level) - instrument 218



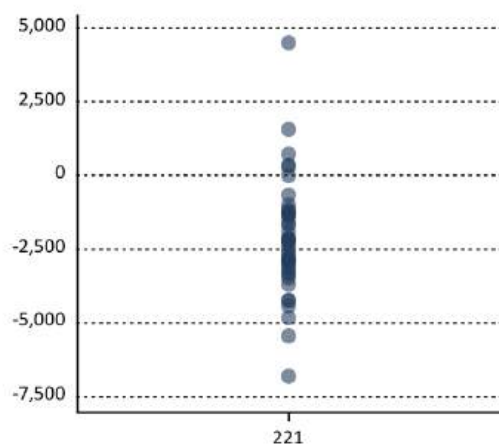
IMV(level) - instrument 219

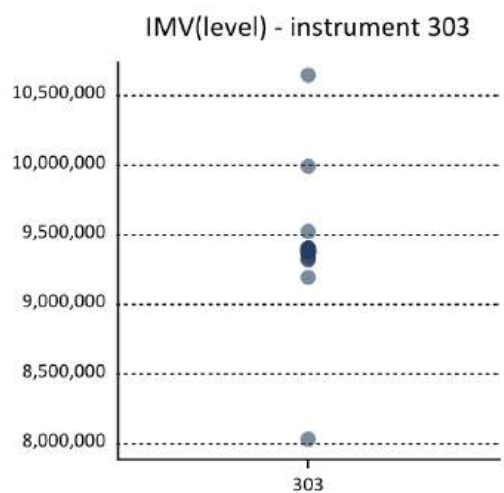
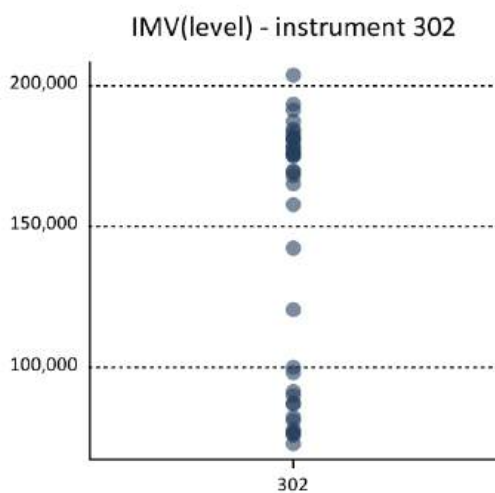
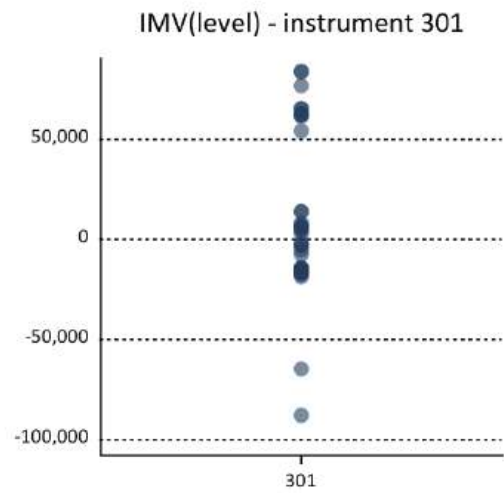
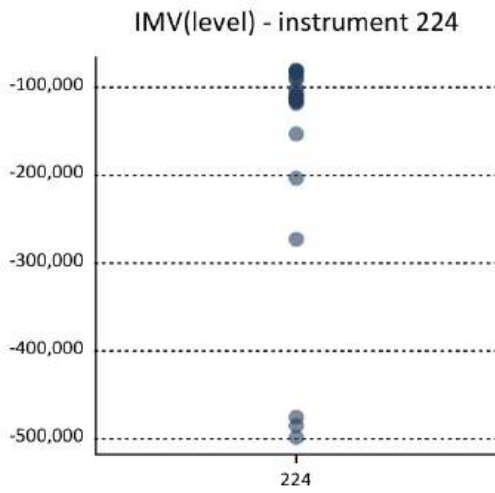
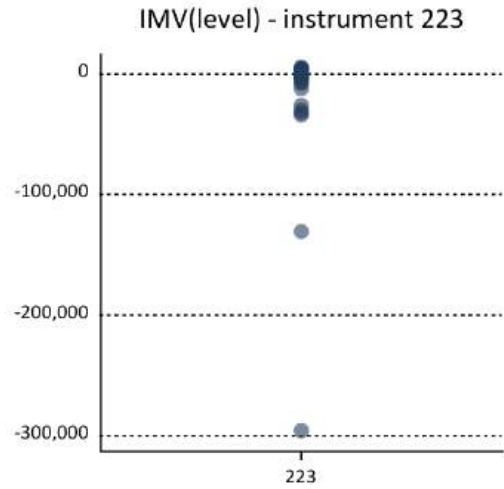
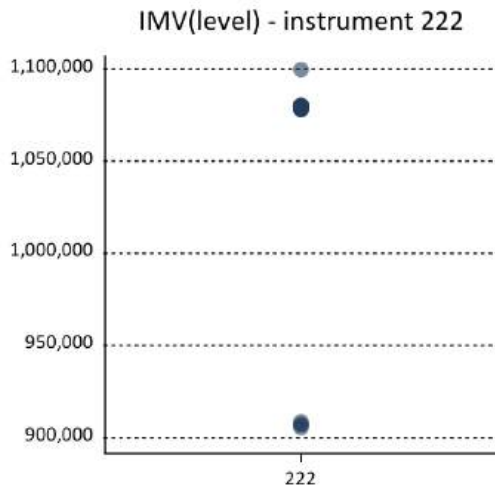


IMV(level) - instrument 220

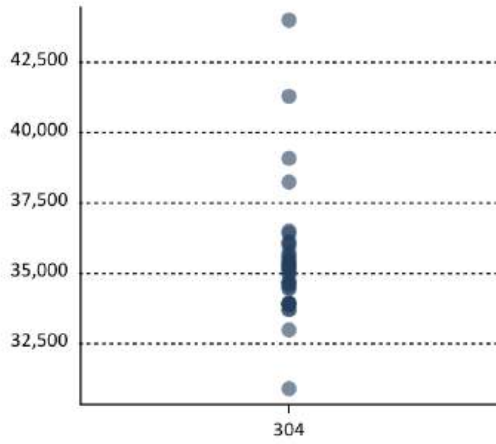


IMV(level) - instrument 221

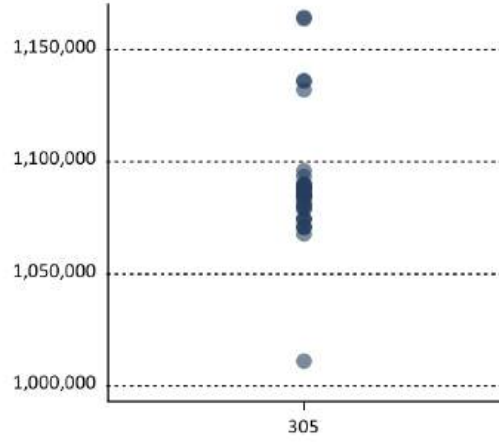




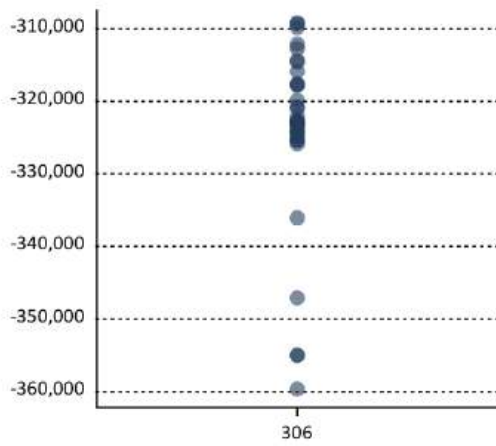
IMV(level) - instrument 304



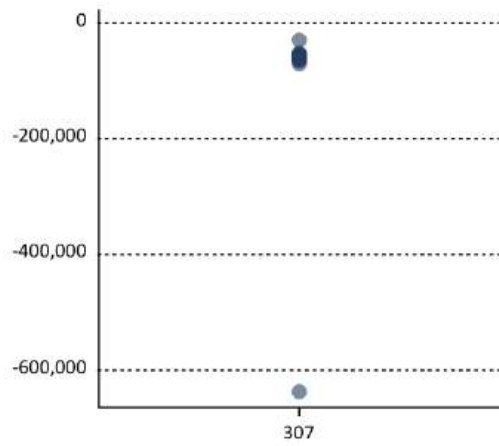
IMV(level) - instrument 305



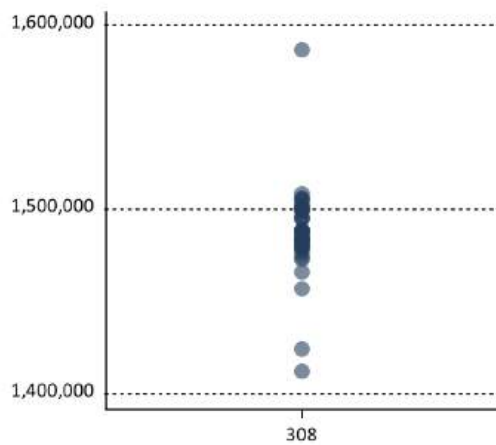
IMV(level) - instrument 306



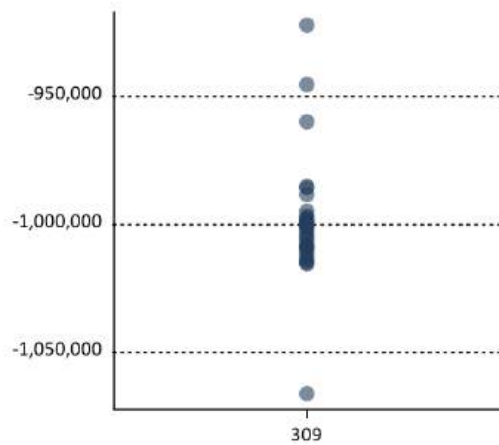
IMV(level) - instrument 307



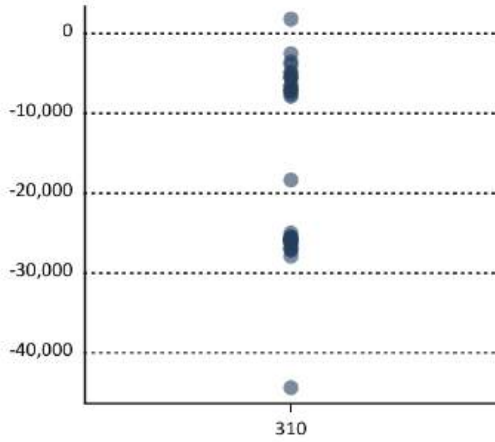
IMV(level) - instrument 308



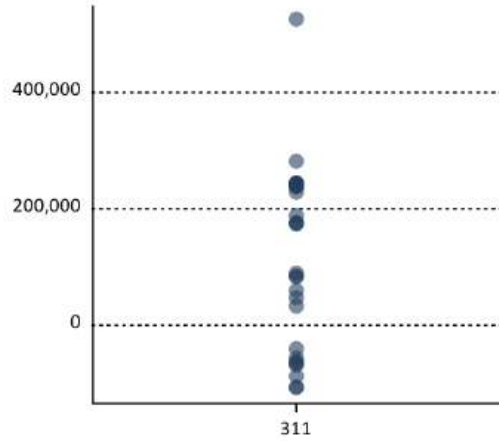
IMV(level) - instrument 309



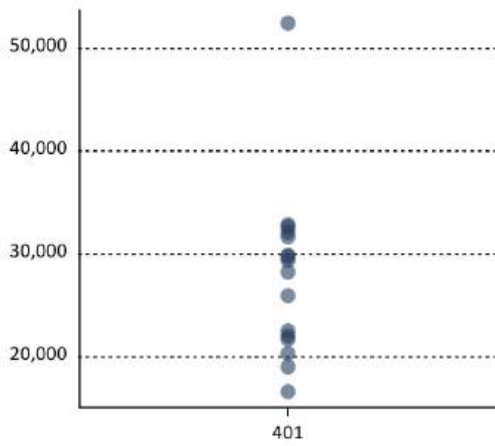
IMV(level) - instrument 310



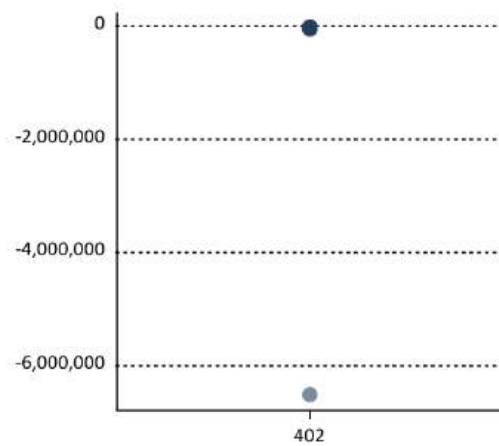
IMV(level) - instrument 311



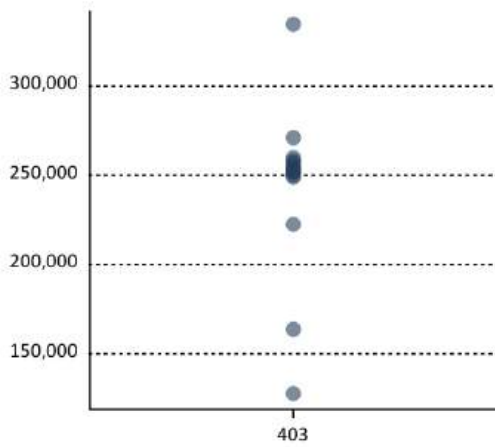
IMV(level) - instrument 401



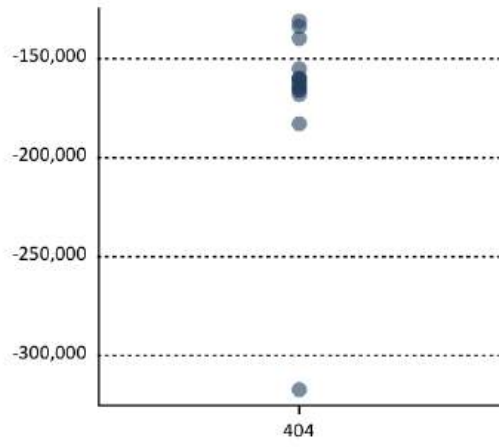
IMV(level) - instrument 402



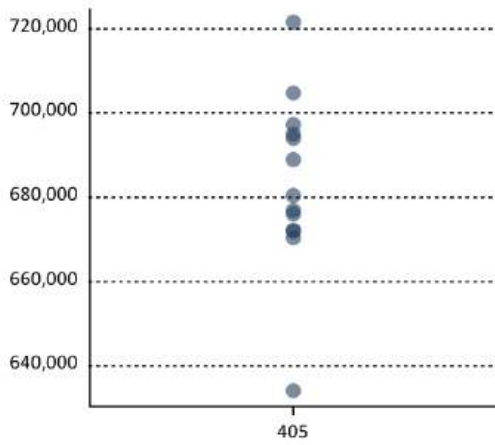
IMV(level) - instrument 403



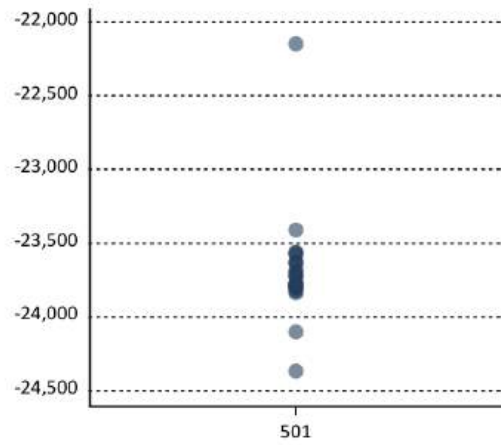
IMV(level) - instrument 404



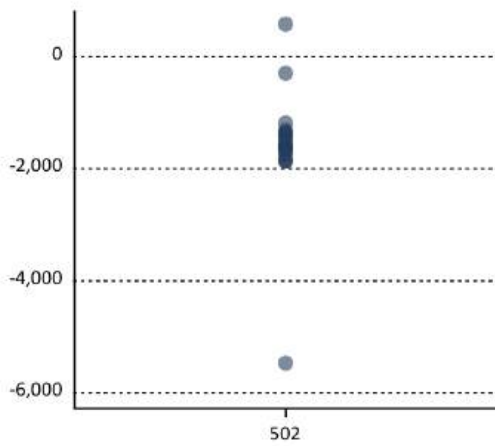
IMV(level) - instrument 405



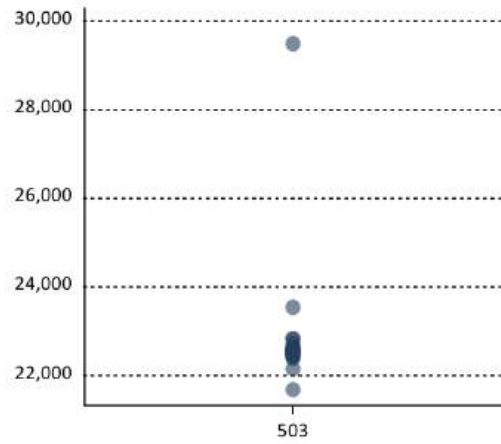
IMV(level) - instrument 501



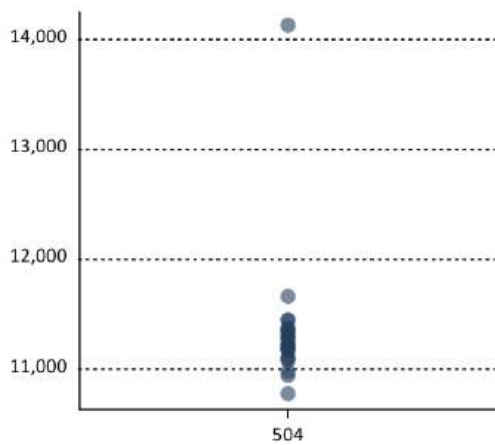
IMV(level) - instrument 502



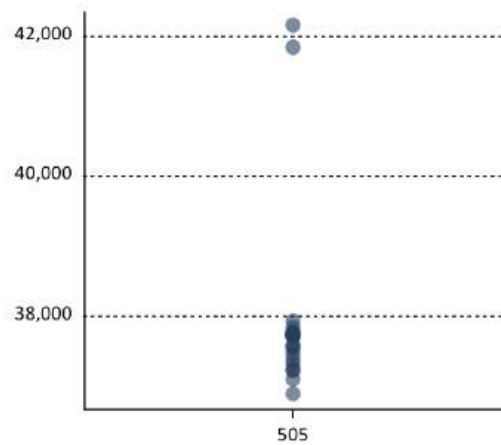
IMV(level) - instrument 503



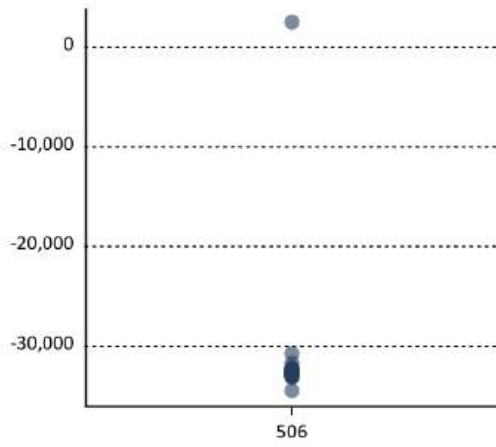
IMV(level) - instrument 504



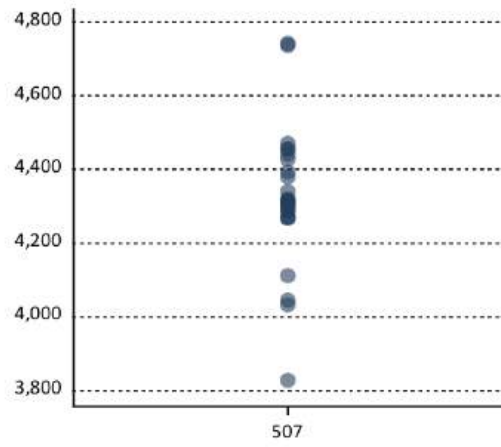
IMV(level) - instrument 505



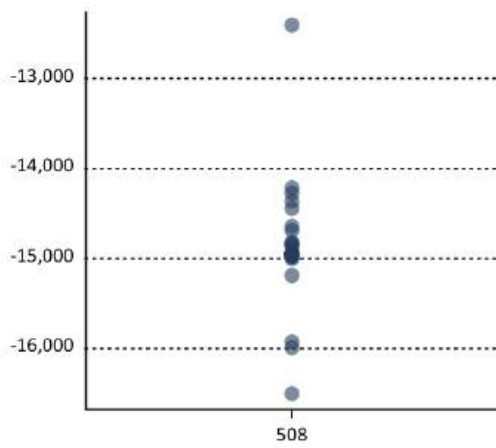
IMV(level) - instrument 506



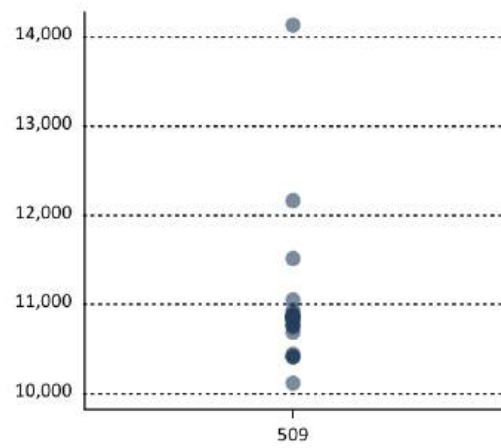
IMV(level) - instrument 507



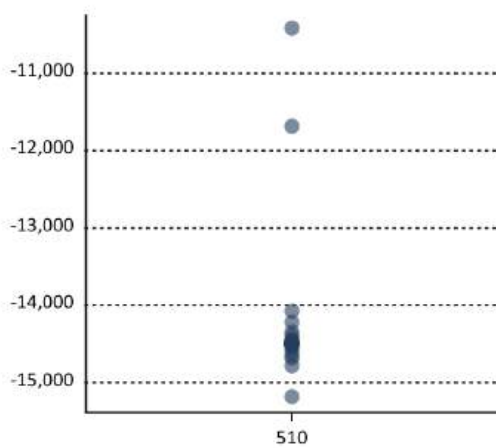
IMV(level) - instrument 508



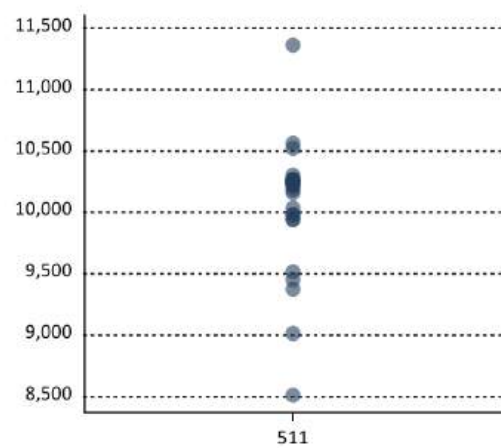
IMV(level) - instrument 509



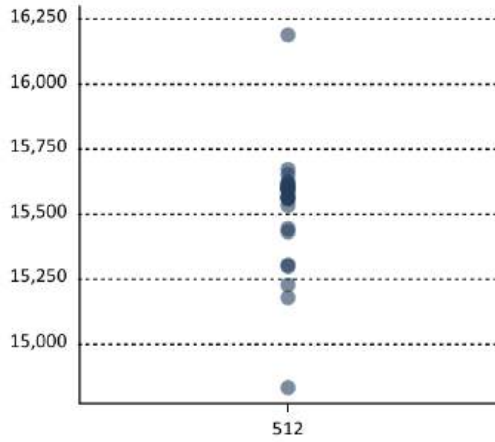
IMV(level) - instrument 510



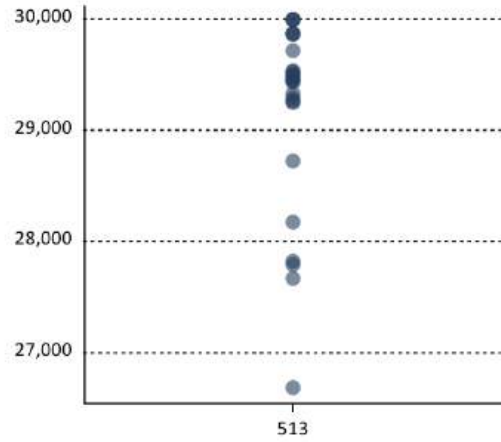
IMV(level) - instrument 511



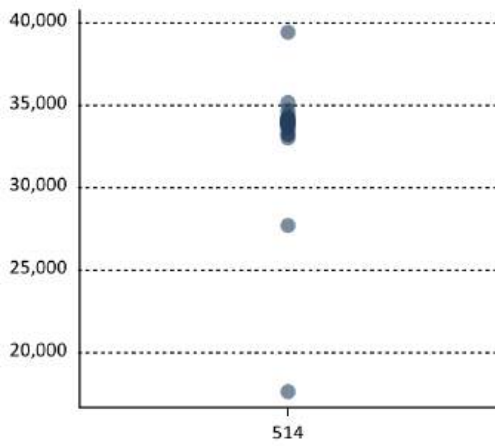
IMV(level) - instrument 512



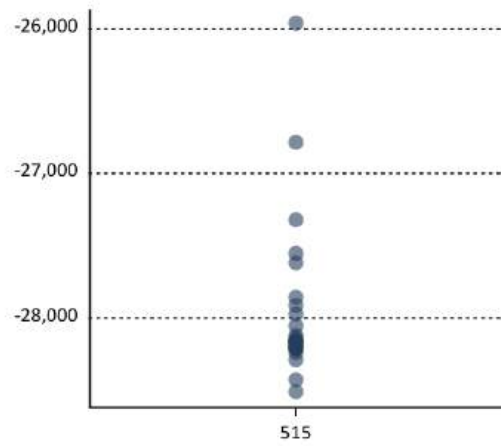
IMV(level) - instrument 513



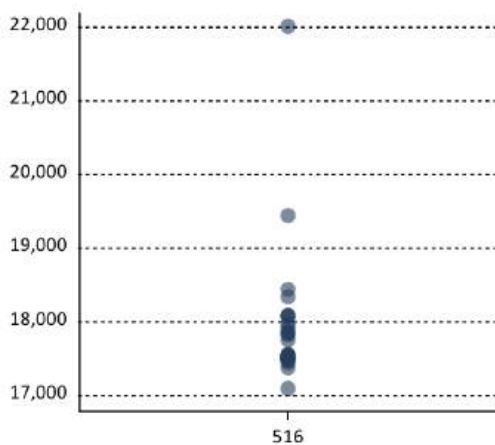
IMV(level) - instrument 514



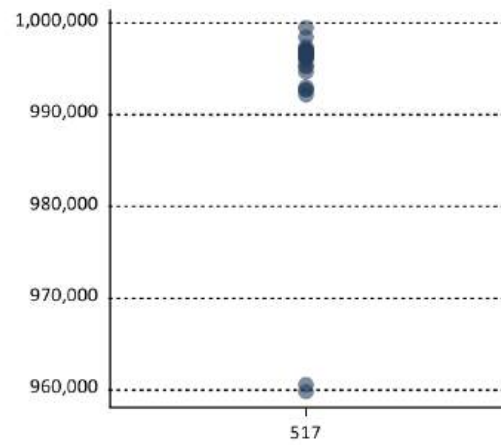
IMV(level) - instrument 515



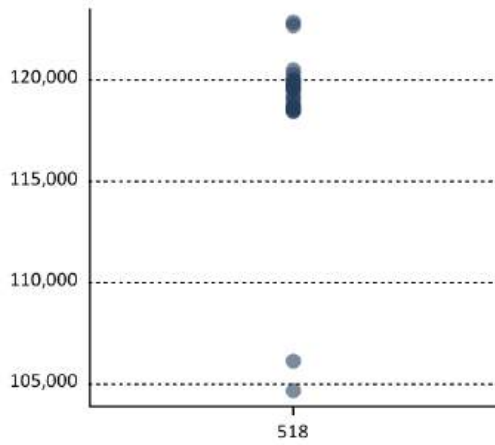
IMV(level) - instrument 516



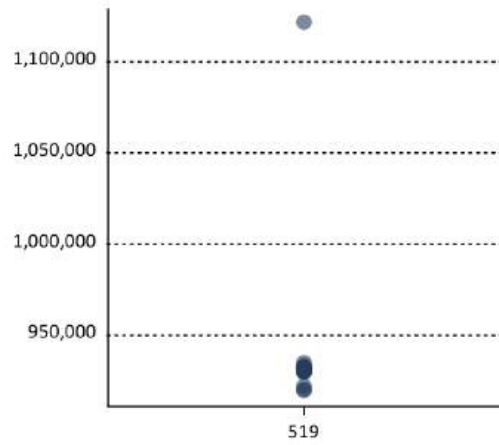
IMV(level) - instrument 517



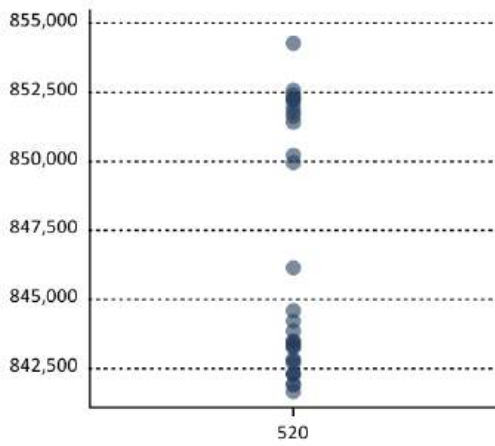
IMV(level) - instrument 518



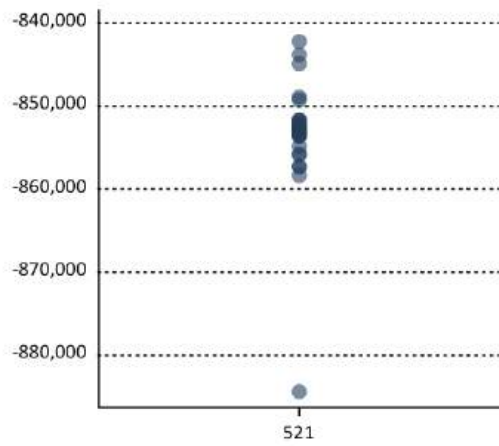
IMV(level) - instrument 519



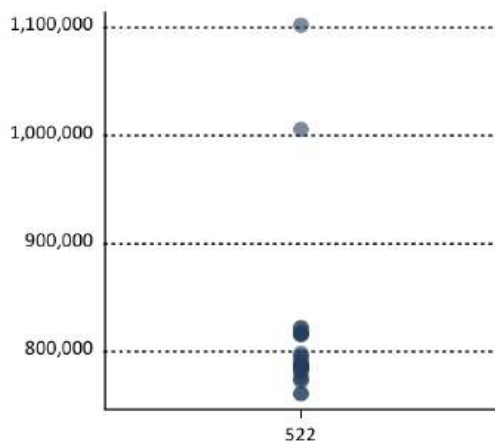
IMV(level) - instrument 520



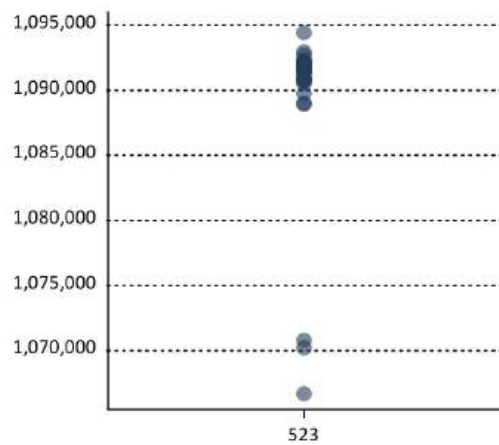
IMV(level) - instrument 521



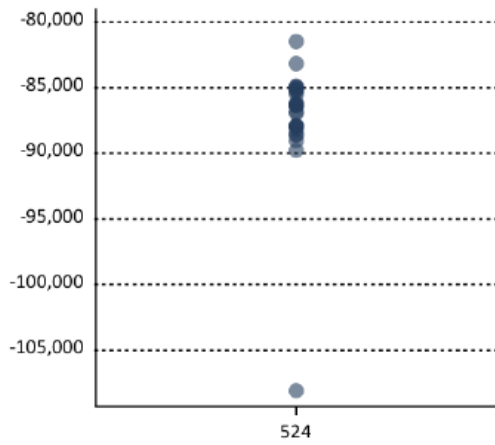
IMV(level) - instrument 522



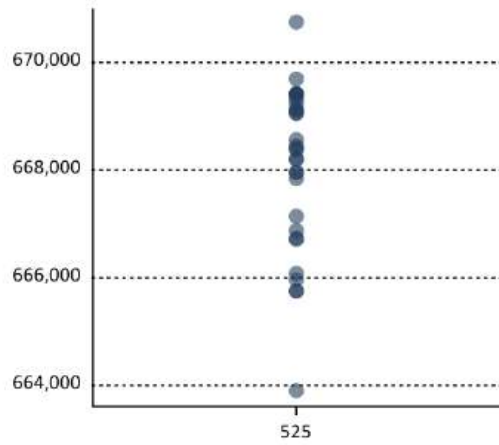
IMV(level) - instrument 523



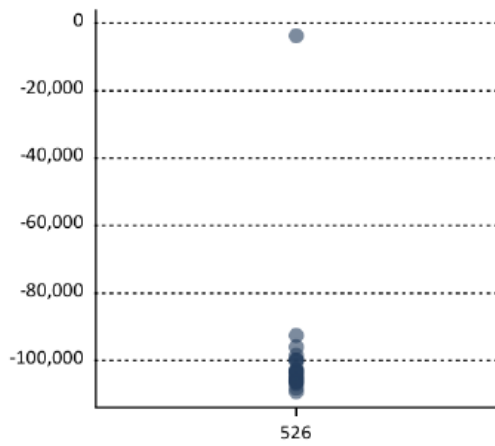
IMV(level) - instrument 524



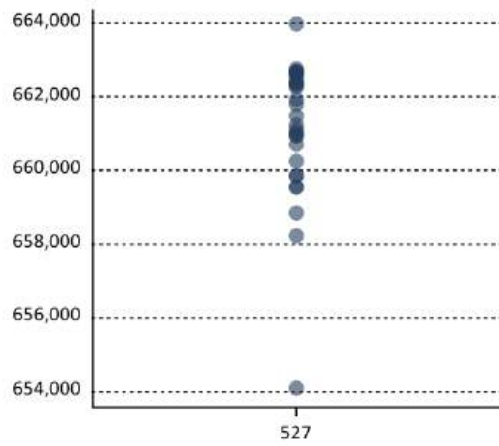
IMV(level) - instrument 525



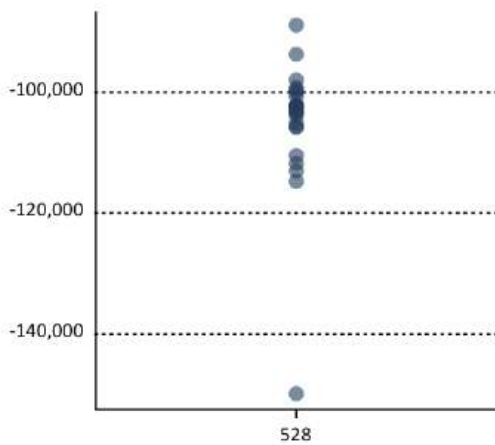
IMV(level) - instrument 526



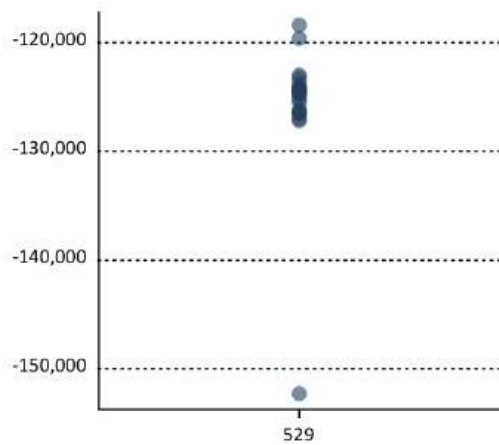
IMV(level) - instrument 527

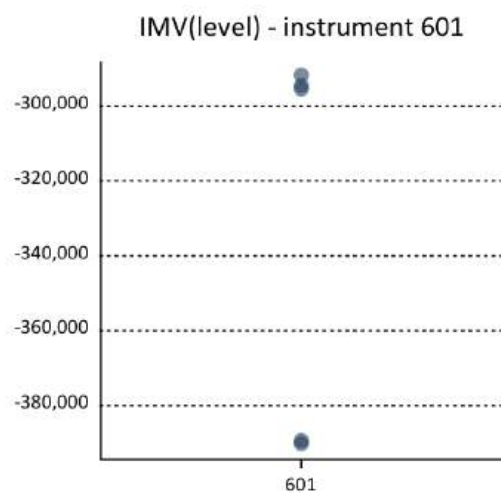
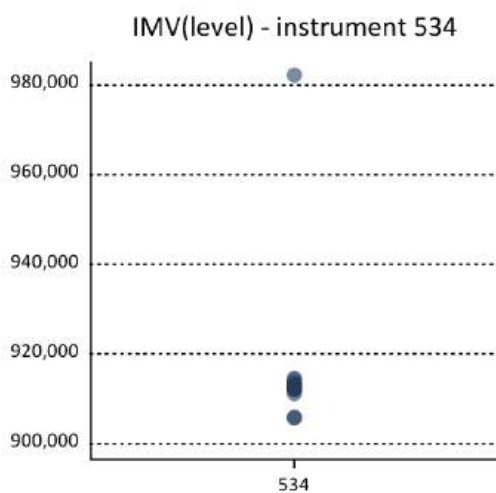
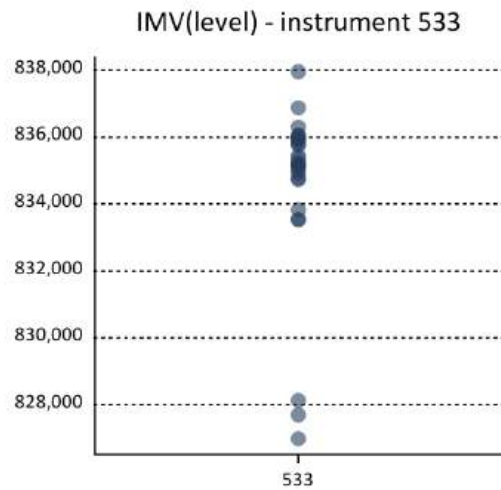
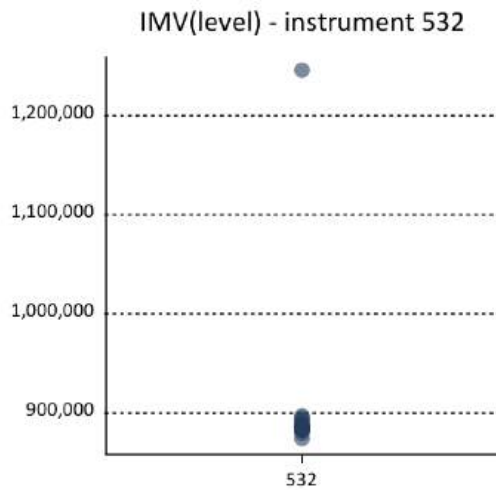
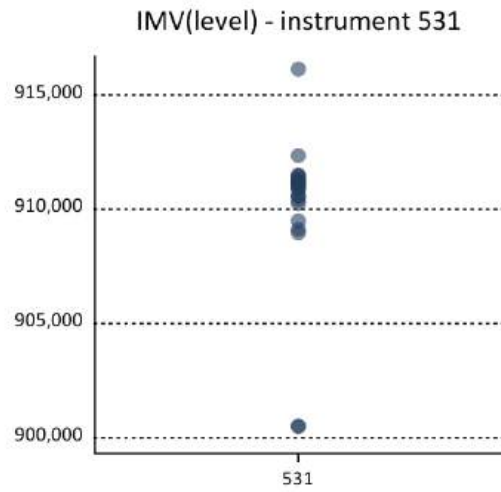
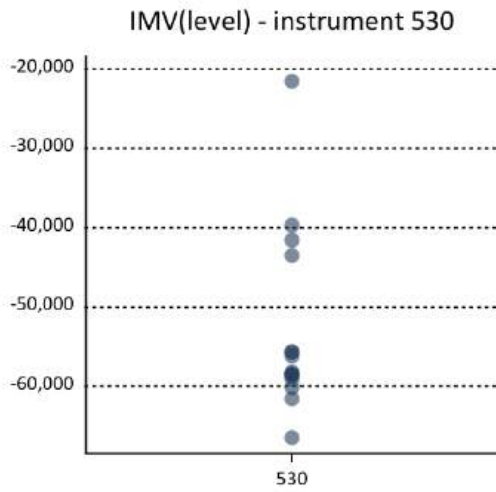


IMV(level) - instrument 528

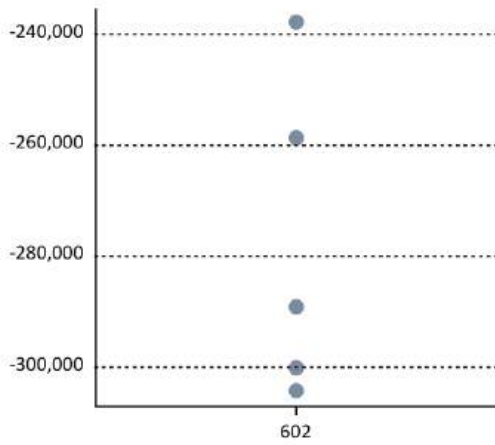


IMV(level) - instrument 529

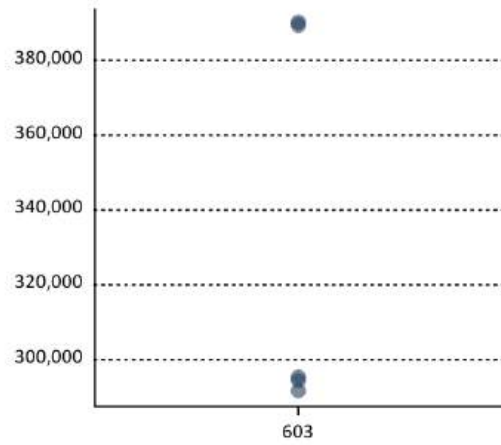




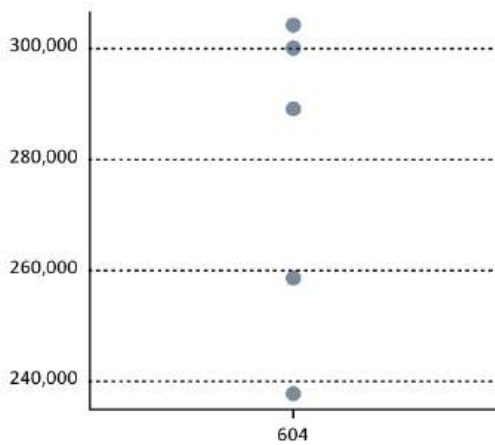
IMV(level) - instrument 602



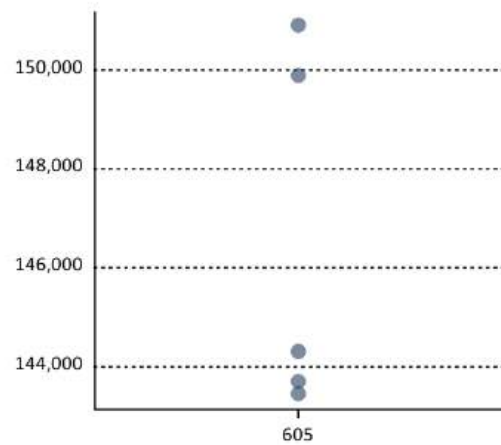
IMV(level) - instrument 603



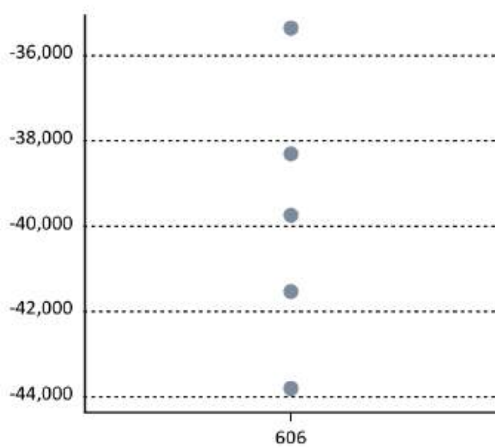
IMV(level) - instrument 604



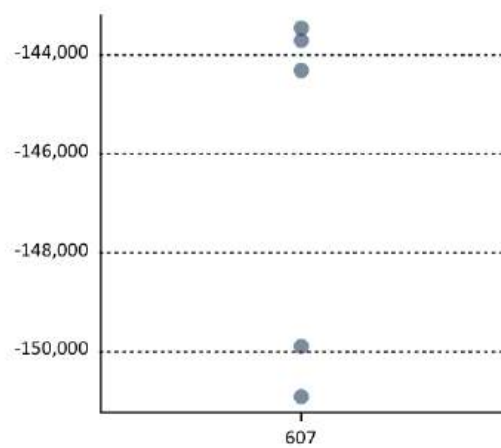
IMV(level) - instrument 605



IMV(level) - instrument 606



IMV(level) - instrument 607



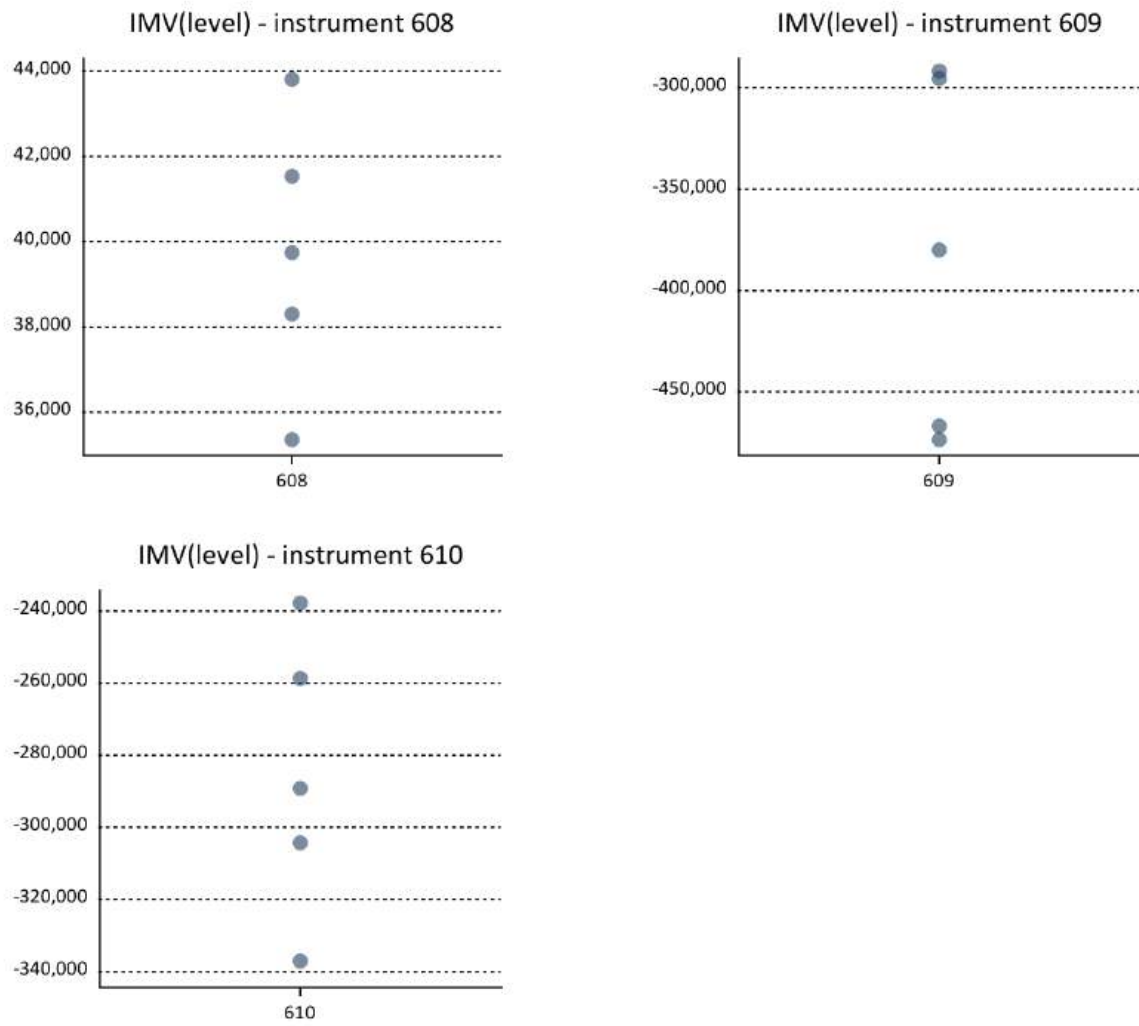


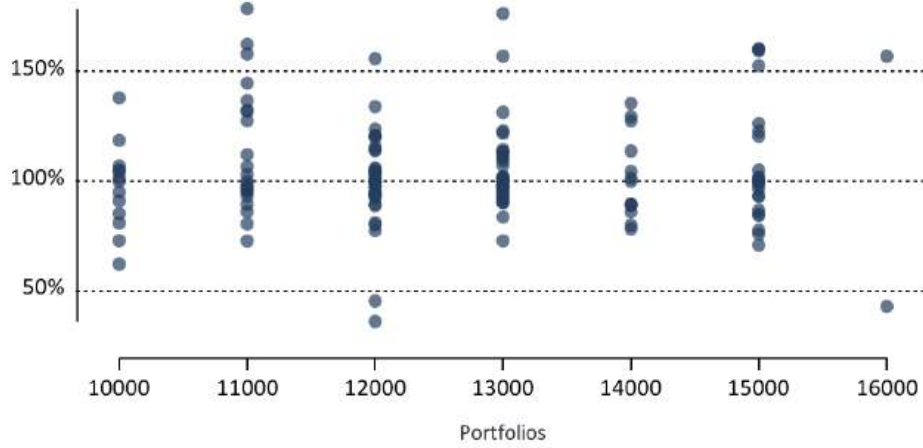
Figure 19: VaR submissions normalised by the median of each portfolio (by asset class)

VaR: All portfolios *(ratio with the median)*



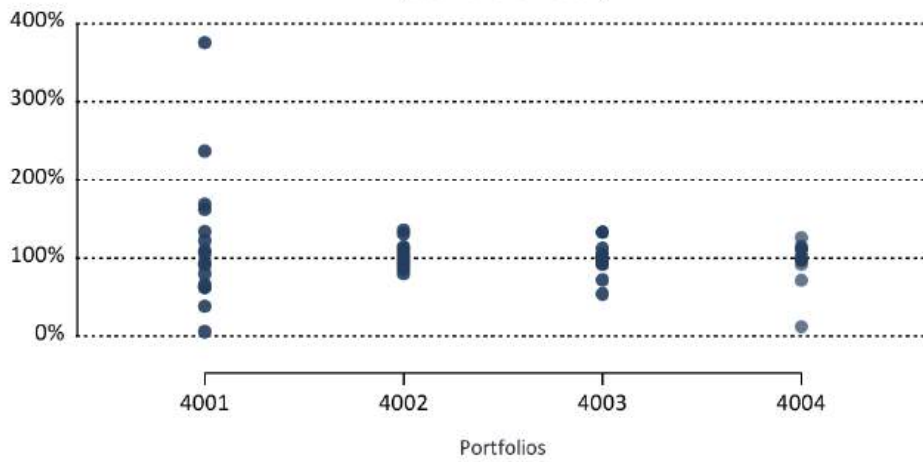
VaR: Aggregated portfolios

(ratio with the median)



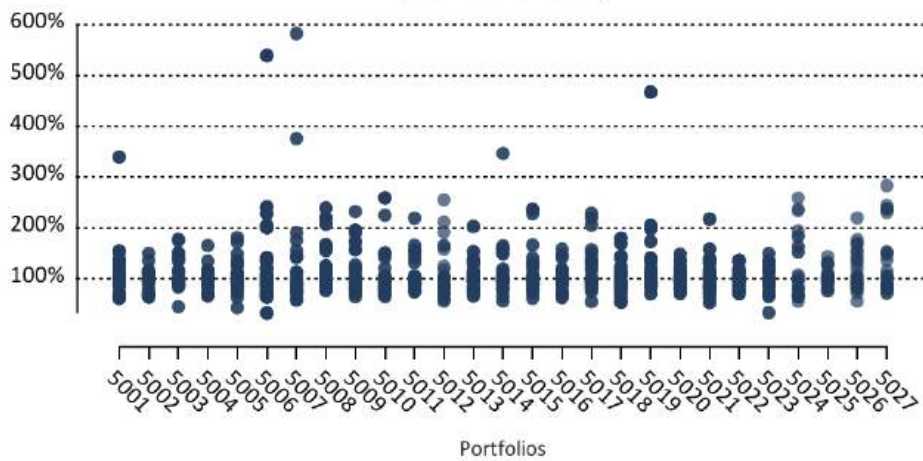
VaR: Commodities portfolios

(ratio with the median)



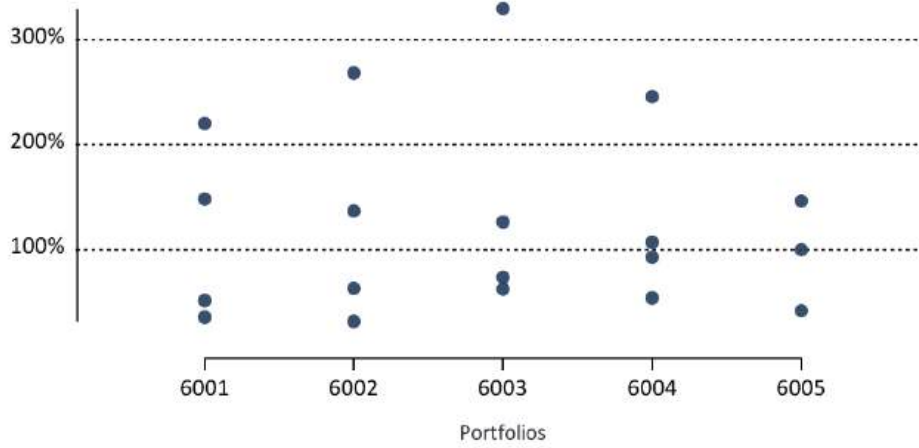
VaR: Credit Spread portfolios

(ratio with the median)



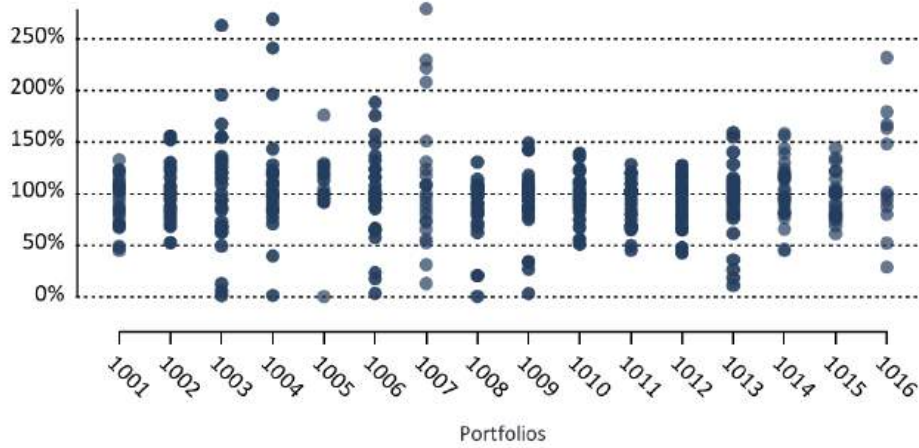
VaR: CTP portfolios

(ratio with the median)



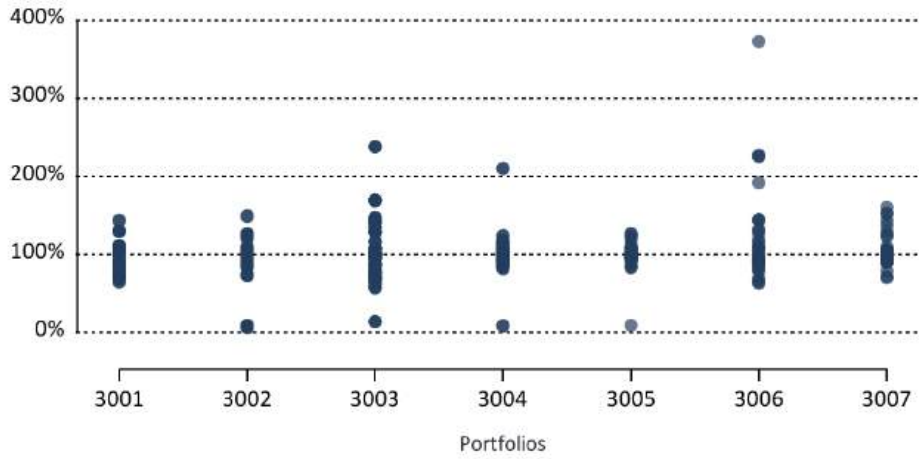
VaR: Equity portfolios

(ratio with the median)



VaR: FX portfolios

(ratio with the median)



VaR: Interest Rate portfolios

(ratio with the median)

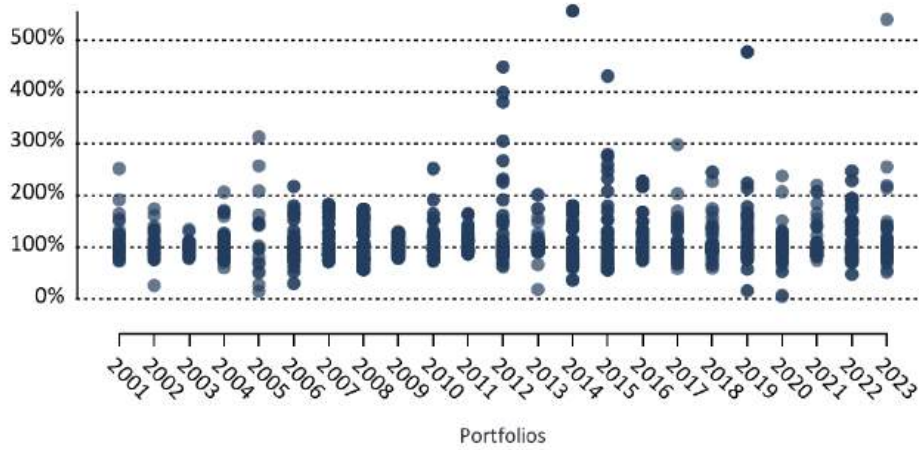
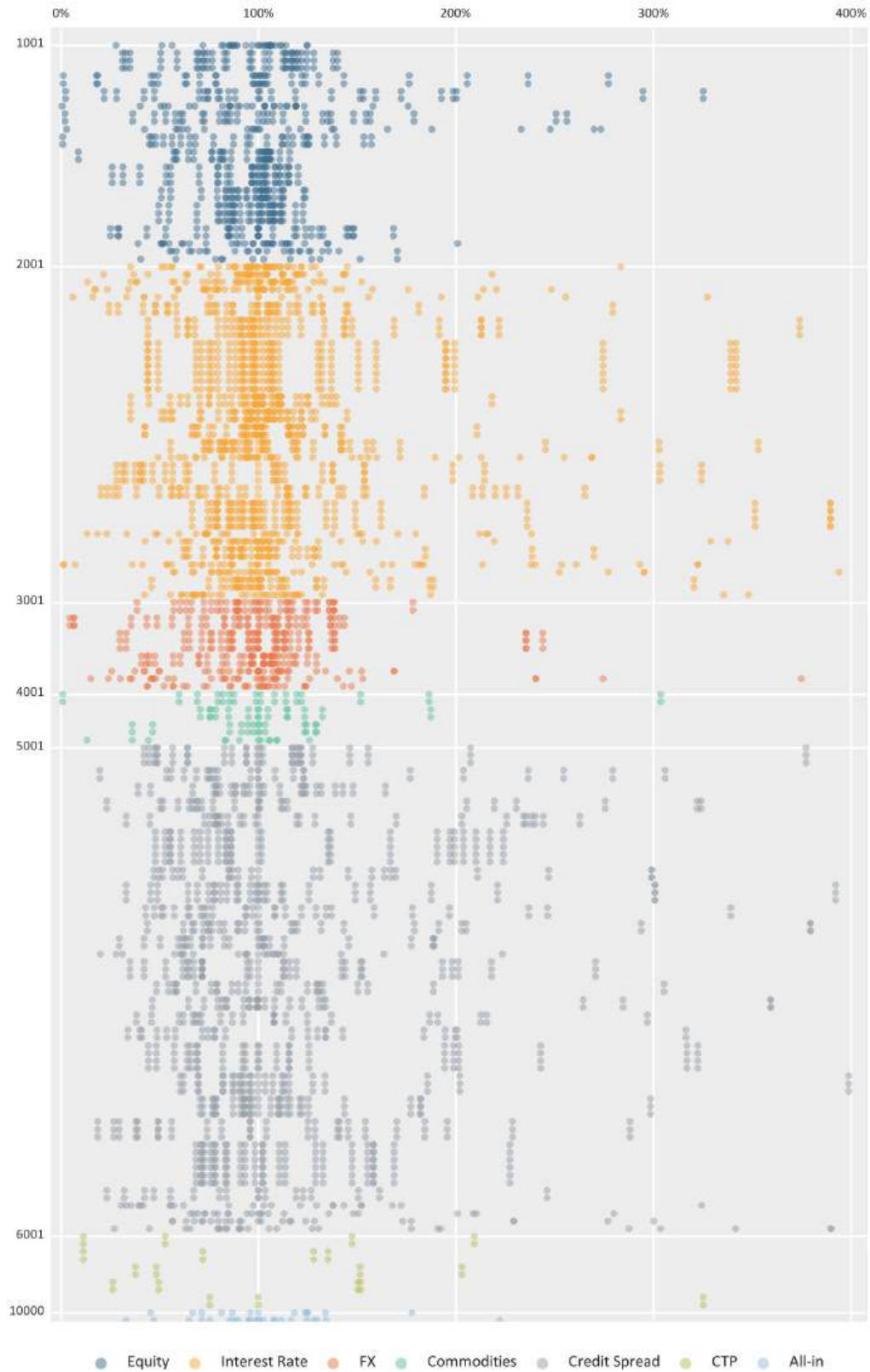


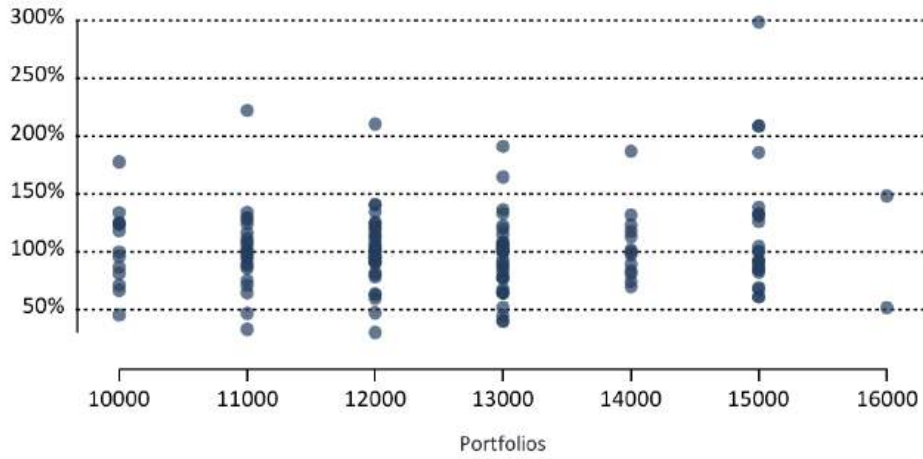
Figure 20: sVaR submissions normalised by the median of each portfolio (by asset class)

SVaR: All portfolios *(ratio with the median)*



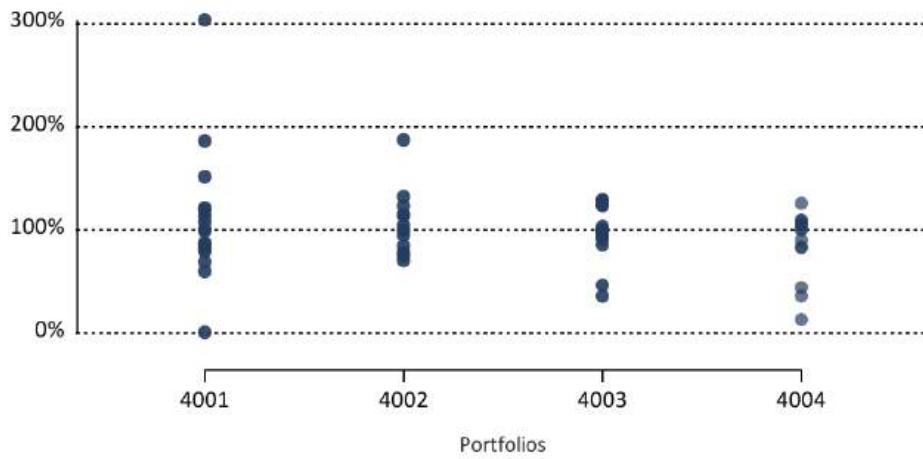
SVaR: Aggregated portfolios

(ratio with the median)



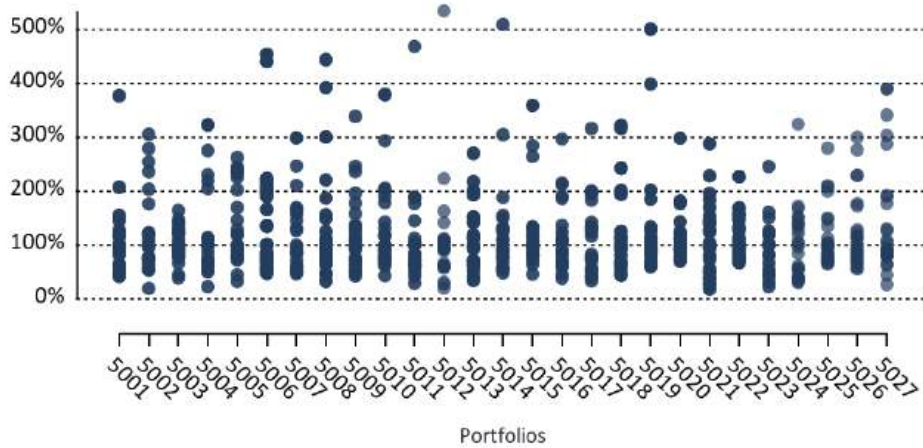
SVaR: Commodities portfolios

(ratio with the median)



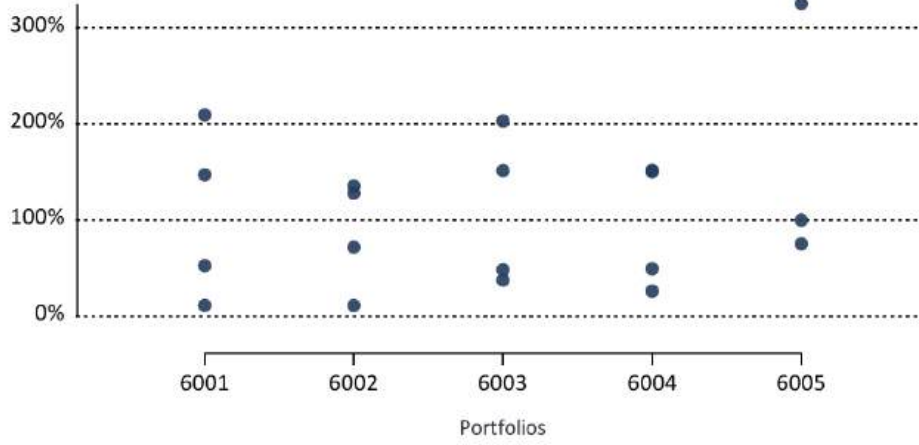
SVaR: Credit Spread portfolios

(ratio with the median)



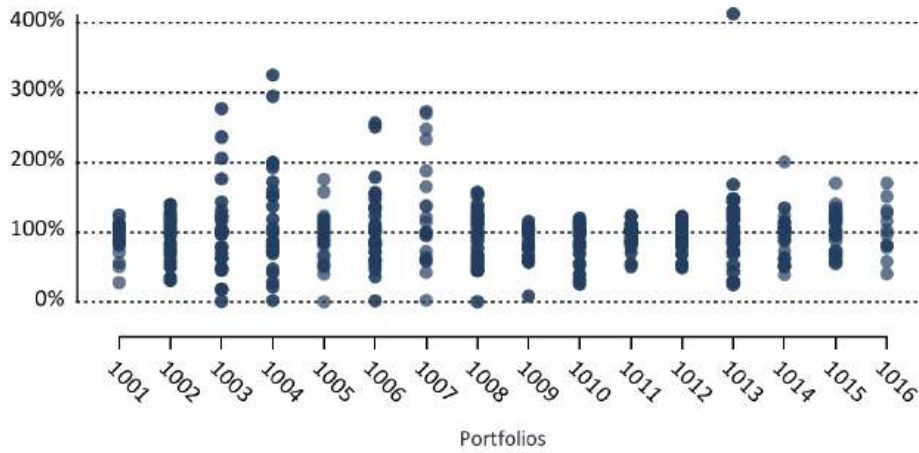
SVaR: CTP portfolios

(ratio with the median)



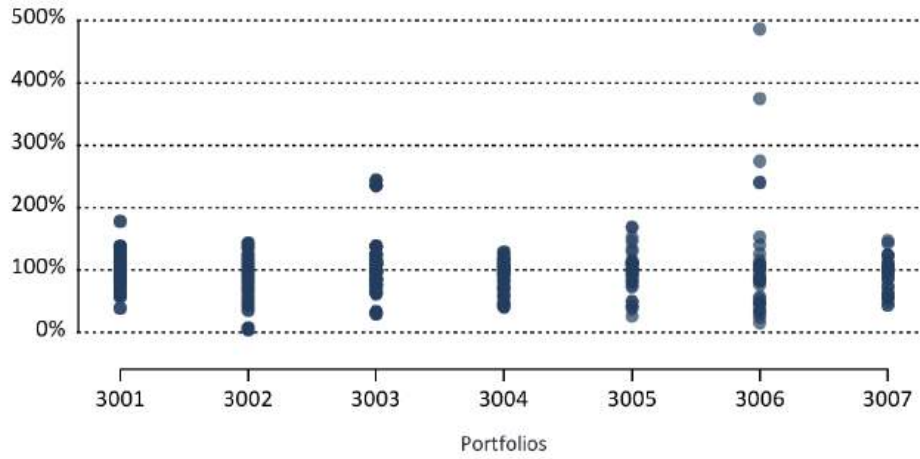
SVaR: Equity portfolios

(ratio with the median)



SVaR: FX portfolios

(ratio with the median)



SVaR: Interest Rate portfolios

(ratio with the median)

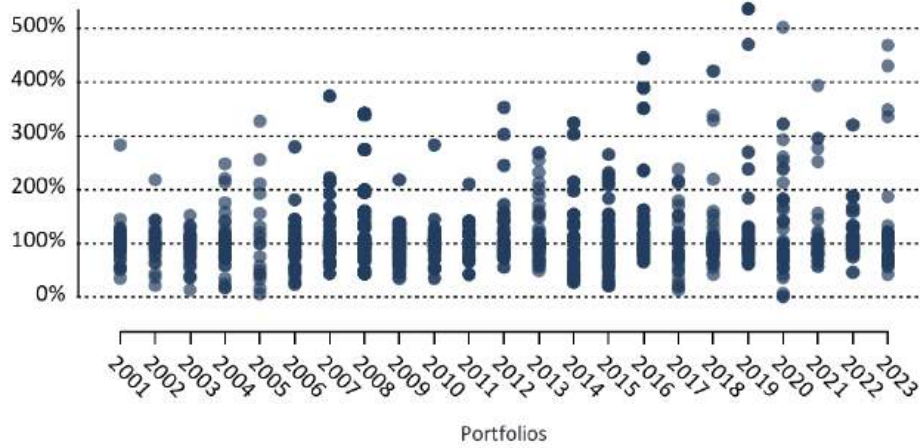


Figure 21: sVaR submissions normalised by the median of each portfolio (by methodological approach)

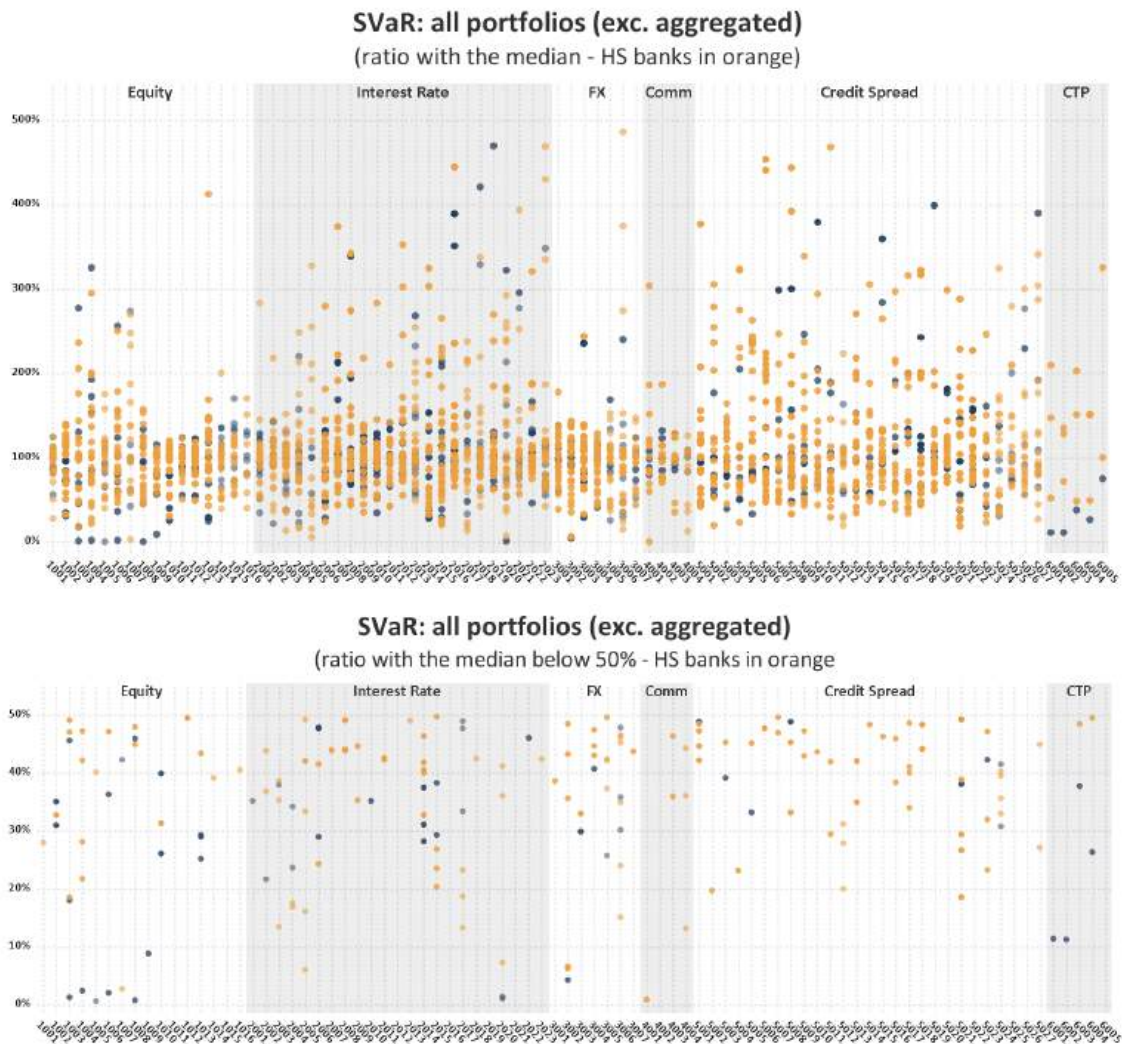


Figure 22: VaR ratio with median (focus on small banks)

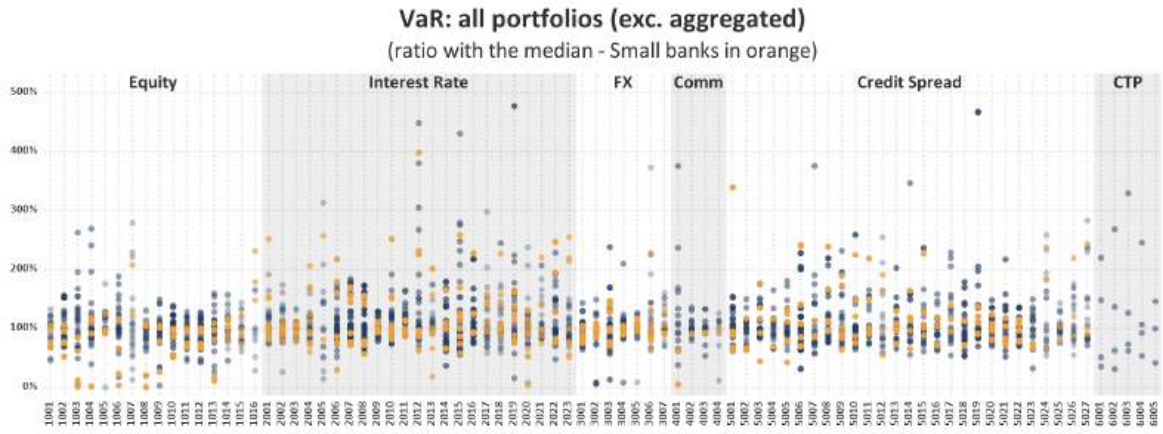


Figure 23: VaR ratio with median (focus on medium-sized banks)

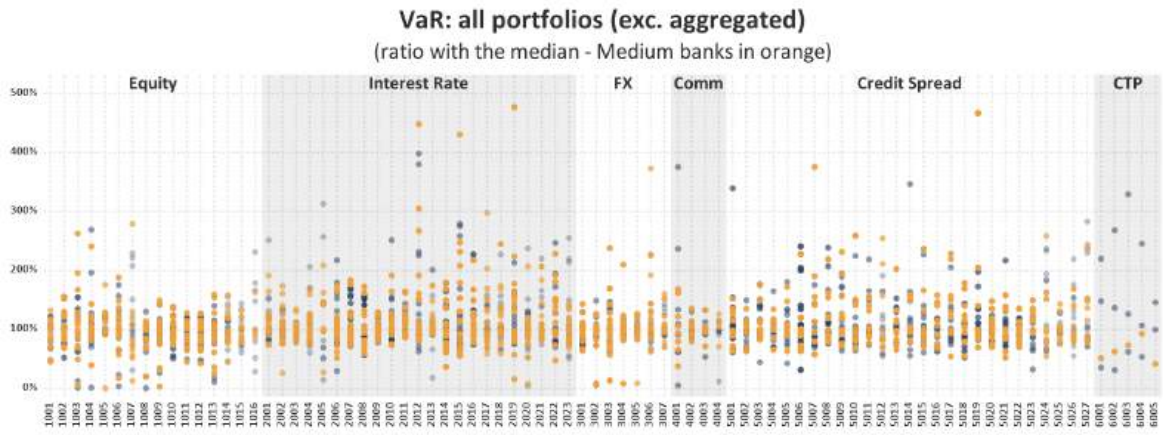


Figure 24: VaR ratio with median (focus on large banks)

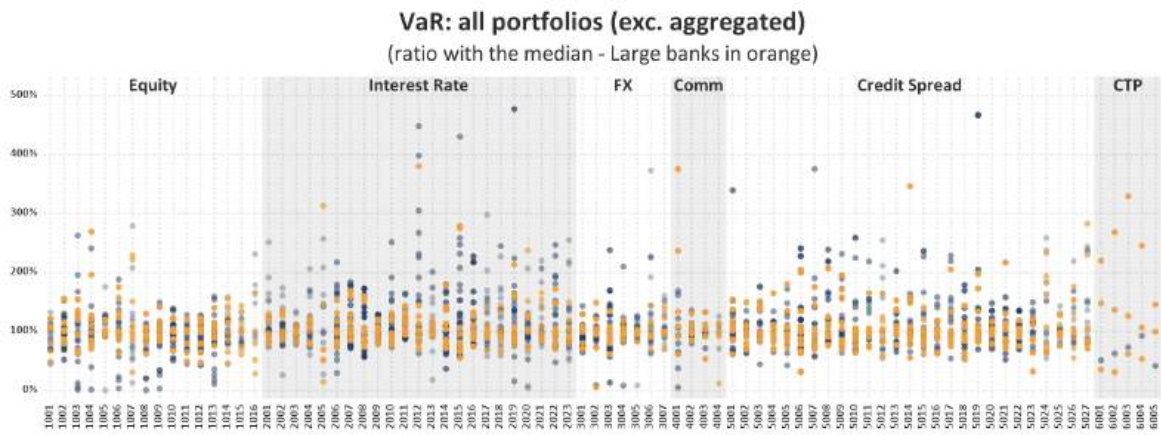


Table 37: VaR statistics (IR and CS asset classes – only banks with general and specific IR risk approval)

EU Statistics for VaR

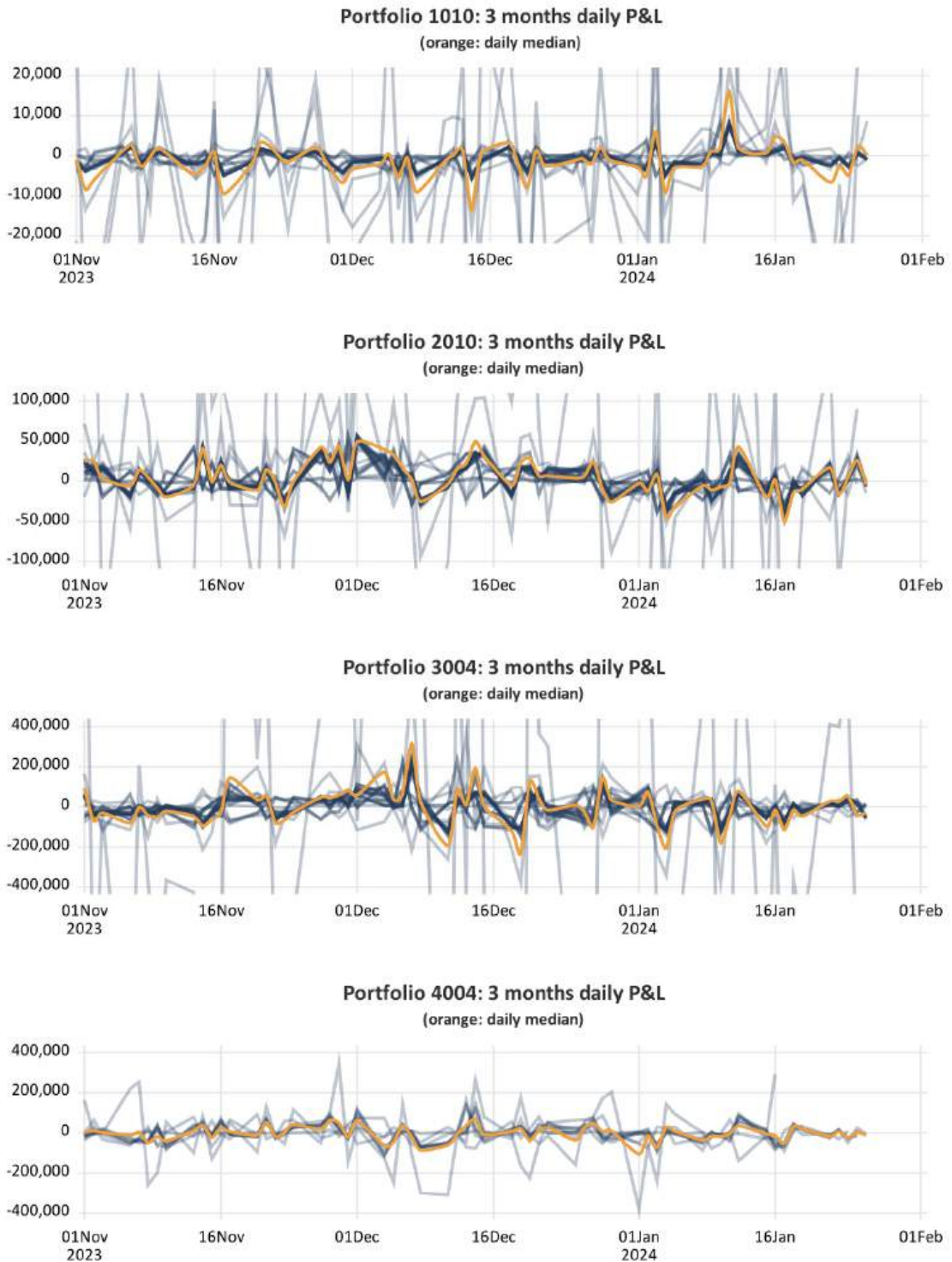
Port. ID	Other stats					Num. obs.	Percentiles							Interquartile range	
	Min	Max	Ave.	STDev	Coefficient of variation (STDev/Mean)		5th	10th	25th	50th (Median)	75th	90th	95th		
2002	144,168	258,202	194,763	33,254	17%	20	147,783	159,450	166,478	191,286	211,238	241,008	247,441	12%	
2003	148,754	239,967	184,268	26,382	15%	18	154,273	155,251	161,054	178,763	202,673	228,167	236,971	11%	
2004	23,181	31,062	27,840	2,055	7%	16	24,670	25,574	26,749	28,190	29,074	30,213	31,031	4%	
2004	67,975	138,801	112,522	23,598	19%	20	84,510	85,552	91,374	114,596	132,161	135,771	138,416	18%	
2005	4,620	64,885	30,903	20,903	68%	9	6,230	7,811	16,483	21,810	45,314	53,385	59,135	47%	
2006	18,671	45,678	28,846	6,930	24%	16	21,364	22,474	24,337	27,694	31,738	37,195	40,854	13%	
2007	61,099	116,190	81,589	18,855	23%	16	61,629	64,956	68,482	75,464	87,390	108,633	117,804	12%	
2008	58,948	131,950	89,011	28,491	32%	19	60,321	60,527	63,419	81,003	124,352	130,124	131,950	32%	
2009	171,470	240,874	204,149	18,773	9%	18	172,883	182,523	192,951	203,678	213,402	226,008	238,686	5%	
2010	129,752	232,375	175,521	30,199	17%	20	133,005	143,985	149,830	172,280	190,972	217,823	222,697	12%	
2012	352,795	508,469	422,712	50,974	12%	18	365,911	370,602	389,549	397,511	465,724	487,202	506,400	10%	
2012	55,388	150,338	82,330	23,296	28%	19	62,109	63,898	68,400	75,067	85,081	114,514	122,051	11%	
2013	28,039	53,227	42,375	5,500	13%	17	36,453	38,987	40,135	41,822	44,608	48,459	50,572	5%	
2014	25,727	39,339	43,665	9,852	23%	14	30,667	33,443	37,192	42,831	47,264	57,610	58,775	12%	
2015	6,534	39,941	11,900	4,337	36%	14	7,092	7,448	8,627	11,251	13,903	18,386	19,211	23%	
2016	94,258	179,909	123,812	24,567	20%	17	95,116	101,669	108,710	112,891	132,839	158,322	163,861	10%	
2017	19,701	45,864	30,379	7,857	26%	20	19,795	22,490	25,518	28,802	33,623	43,823	44,898	14%	
2018	15,905	35,185	23,988	4,867	20%	18	17,530	18,818	21,807	23,053	25,404	31,228	32,594	8%	
2019	8,190	18,782	12,255	3,694	30%	19	8,425	8,463	9,233	10,555	16,119	16,944	17,400	27%	
2020	30,832	56,841	43,553	8,060	19%	19	31,755	32,051	39,015	42,929	50,606	54,442	55,531	12%	
2022	31,387	63,040	40,136	9,624	24%	17	31,905	32,168	33,274	37,156	41,477	55,294	59,692	11%	
2022	152,112	353,823	228,061	67,465	30%	16	158,075	161,164	167,213	201,372	304,120	308,745	322,865	29%	
2023	19,646	57,227	38,609	10,436	27%	21	21,541	28,515	32,192	37,490	44,785	54,535	54,535	16%	
5004	4,259	9,491	7,049	1,539	22%	16	4,273	5,085	6,071	7,101	8,032	9,053	9,351	14%	
5002	15,771	22,093	22,212	3,828	17%	15	15,962	16,354	19,804	23,123	25,623	25,986	26,451	13%	
5003	3,387	5,976	4,315	969	22%	19	3,404	3,412	3,489	3,943	5,390	5,673	5,915	21%	
5004	7,157	12,278	9,958	1,834	18%	15	7,230	7,267	8,835	9,895	11,578	12,139	12,184	13%	
5005	3,321	6,121	4,478	650	15%	17	3,506	3,729	4,000	4,368	4,848	4,998	5,258	8%	
5006	2,322	14,499	7,050	2,549	36%	19	4,419	4,805	5,410	6,768	8,265	8,943	10,228	21%	
5007	21,691	71,614	42,213	15,879	38%	14	24,701	26,708	29,505	37,443	54,071	63,820	68,027	29%	
5008	54,021	114,856	75,262	19,381	26%	18	56,215	57,615	63,537	67,785	79,076	110,805	114,856	13%	
5009	5,414	33,360	8,633	2,526	29%	18	6,018	6,205	6,779	7,720	9,676	12,467	13,218	18%	
5010	33,737	30,295	20,290	5,094	25%	19	33,988	34,920	36,890	40,105	40,996	28,705	30,295	12%	
5011	26,110	49,744	35,858	6,676	19%	18	26,916	29,744	32,132	35,087	36,456	47,669	49,744	8%	
5012	1,554	5,763	2,986	1,170	38%	18	1,736	1,863	2,171	2,586	3,462	4,812	5,085	23%	
5013	30,066	21,007	15,299	3,219	21%	19	30,066	11,100	13,527	15,232	16,906	19,976	20,707	11%	
5014	2,231	8,357	4,219	1,343	32%	15	2,527	2,818	3,363	3,882	5,251	6,224	6,256	21%	
5015	14,571	39,179	23,634	6,143	26%	16	16,332	17,592	20,515	23,785	24,907	30,886	34,817	10%	
5016	27,466	59,819	40,886	8,941	22%	14	28,344	29,258	37,182	40,014	44,780	50,271	53,743	9%	
5017	12,754	36,677	23,858	6,874	29%	22	13,386	17,085	20,004	22,191	28,143	32,481	34,449	17%	
5018	34,311	89,229	58,119	15,192	26%	13	37,397	40,466	49,071	55,905	70,345	71,337	78,635	18%	
5019	7,123	20,848	11,711	4,207	36%	16	8,082	8,558	9,007	9,962	12,640	18,835	20,205	16%	
5020	138,540	200,472	163,664	23,963	13%	17	125,644	131,981	159,405	162,146	170,950	193,241	197,609	3%	
5022	14,740	32,470	23,736	4,799	20%	14	17,254	18,907	20,349	23,915	26,340	29,771	31,293	13%	
5022	134,514	192,805	156,288	21,607	14%	15	121,143	125,291	149,879	157,437	188,023	180,394	186,523	6%	
5023	40,813	94,343	67,167	17,653	26%	9	43,489	46,164	53,884	70,121	76,638	87,424	90,883	17%	
5024	19,679	69,802	38,155	17,067	40%	13	21,822	23,320	24,082	28,793	54,013	64,201	67,314	39%	
5023	39,882	66,740	51,422	6,647	13%	14	41,136	43,676	48,620	50,878	53,897	57,742	61,420	5%	
5026	20,340	43,473	31,458	7,022	25%	16	21,783	22,587	24,954	28,986	39,105	41,691	43,307	22%	
5027	14,486	30,822	21,976	6,121	28%	15	15,754	16,376	17,035	20,098	28,587	30,664	30,822	25%	
IR Cumulative	12000	280,584	447,514	171,430	47,869	13%	16	311,633	323,311	337,010	367,140	434,067	435,162	430,724	10%
CS Cumulative	10000	157,424	318,003	122,442	44,917	20%	15	167,925	178,241	197,663	220,411	225,486	274,570	297,216	7%

Table 40: VaR statistics (EQ asset class – only banks with general EQ risk approval)

EU Statistics for VaR

Port. ID	Other stats					Num obs.	Percentiles							Interquartile range	
	Min	Max	Ave.	STDev	Coefficient of variation (STDev/Mean)		5th	10th	25th	50th (Median)	75th	90th	95th		
Equity	.001	287,013	430,904	349,307	54,074	15%	5	292,976	298,598	316,828	353,223	358,509	401,972	416,443	6%
	.002						4								
	.003						2								
	.004						2								
	.005	51,728,788	70,540,542	57,284,091	8,009,150	14%	6	51,739,378	51,749,968	51,965,728	52,458,801	61,251,884	67,243,505	68,892,023	8%
	.006						1								
	.007						1								
	.008						1								
	.009						1								
	.010						2								
	.011						3								
	.012						3								
	.013						1								
	.014						3								
	.015						3								
	.016						3								
	Equity Cumulative	11000						1							

Figure 25: Additional P&L charts with examples of low IQD



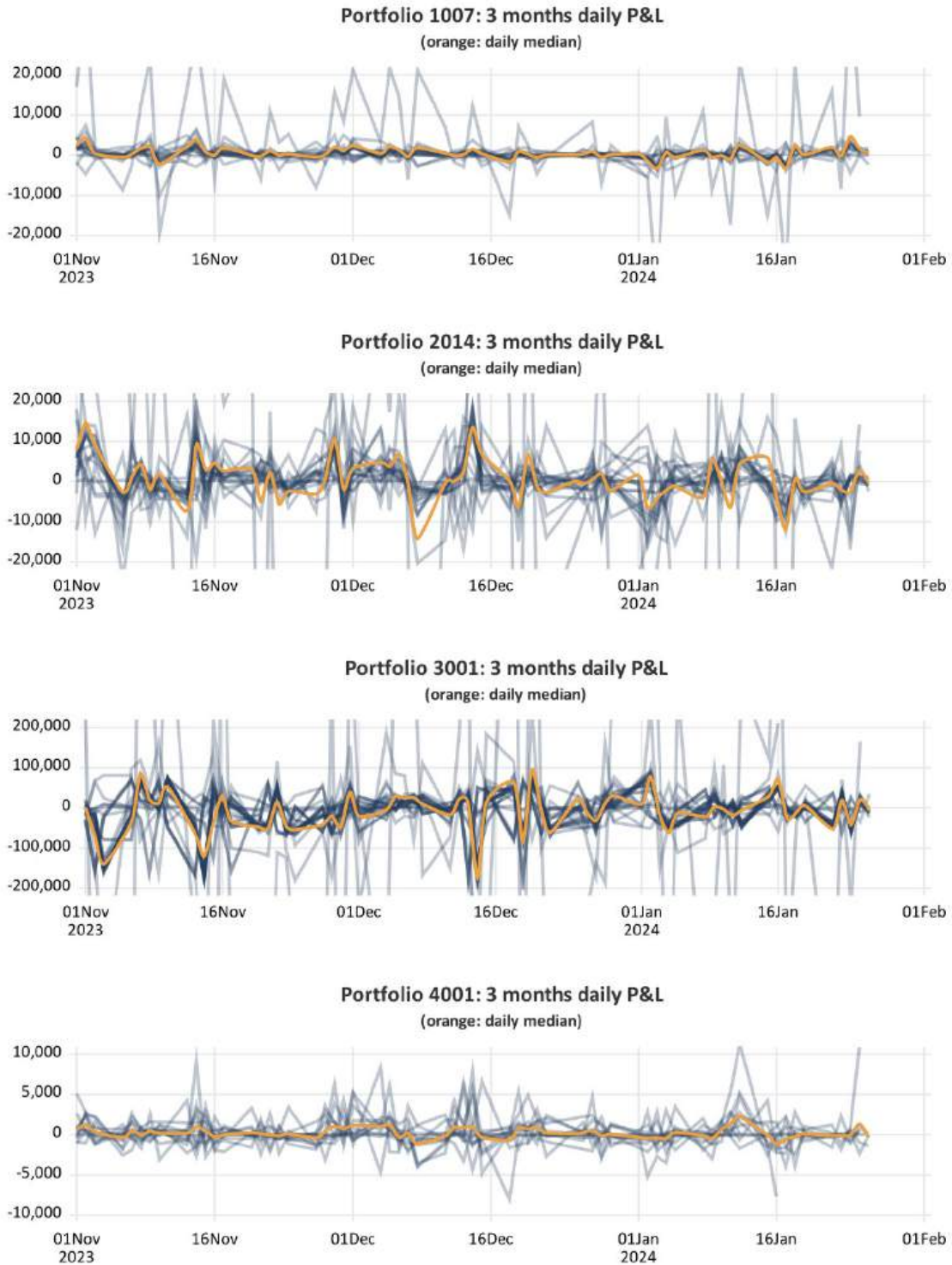
Portfolio 5022: 3 months daily P&L
(orange: daily median)



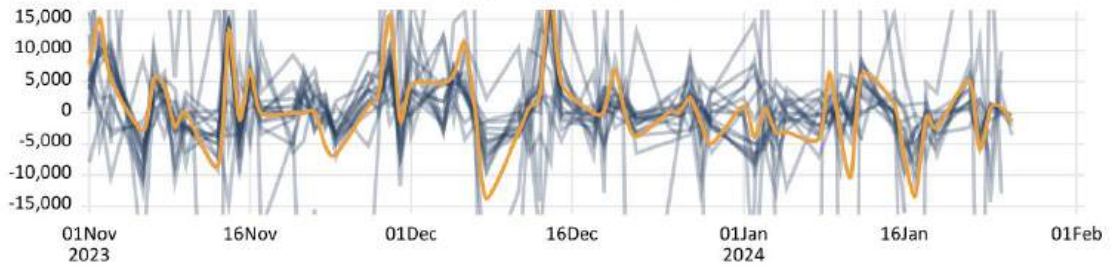
Portfolio 14000: 3 months daily P&L
(orange: daily median)



Figure 26: Additional P&L charts with examples of high IQD



Portfolio 5016: 3 months daily P&L
(orange: daily median)



Portfolio 11000: 3 months daily P&L
(orange: daily median)

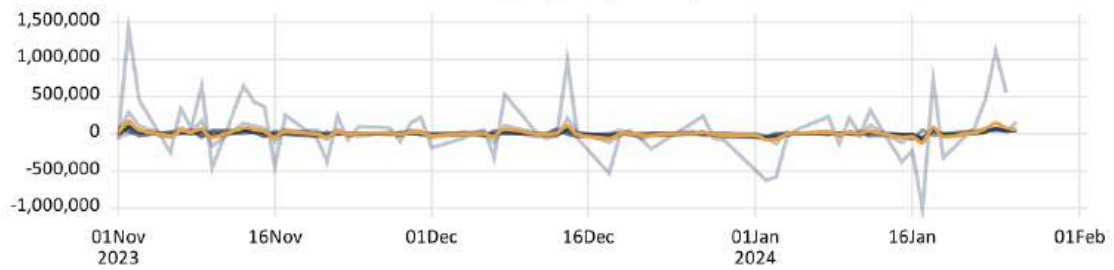


Figure 27: Comparison between IMV and truncated STD deviation method to select outliers for risk measures

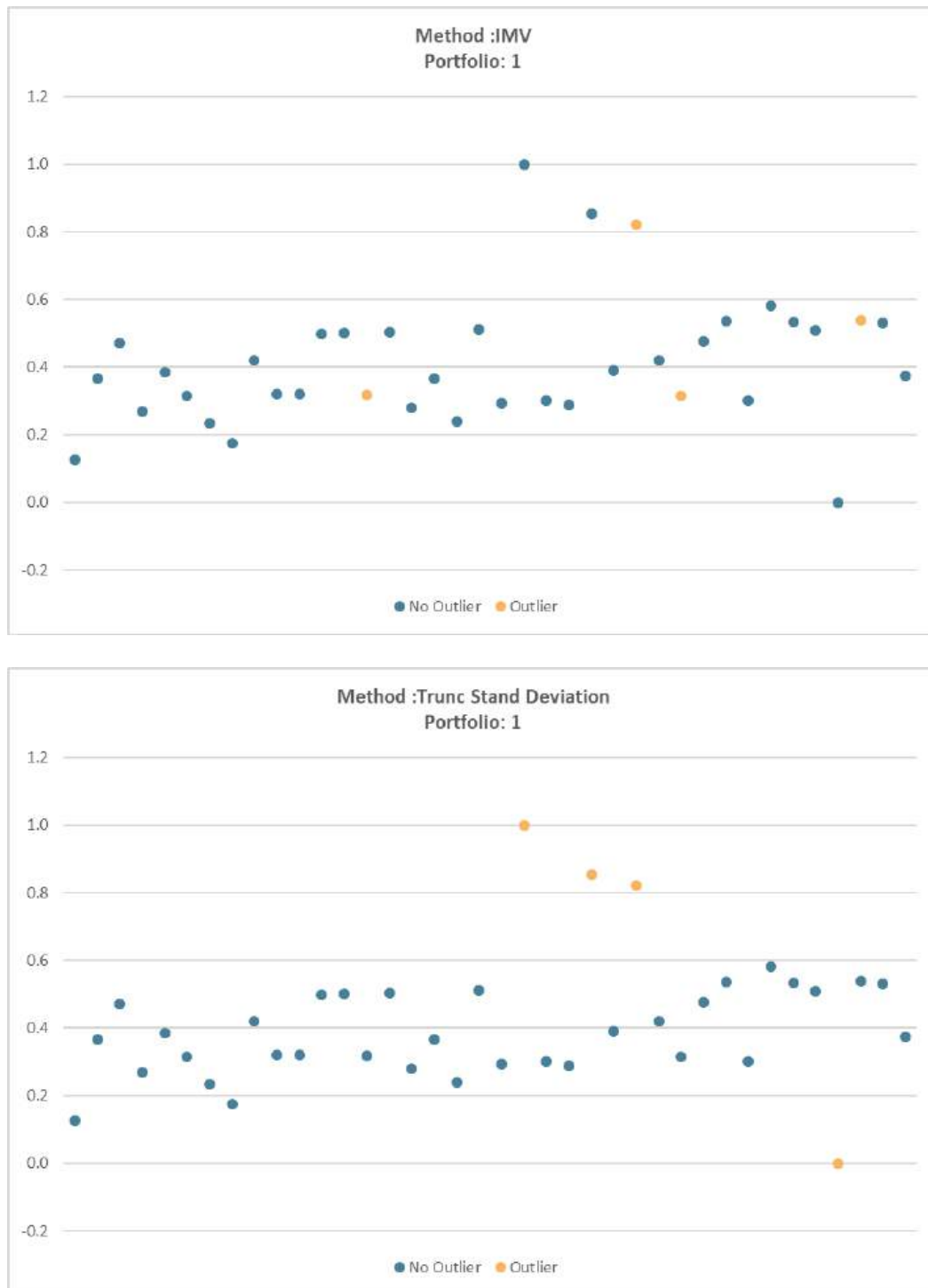


Figure 26. Example of dispersion in VaR submission for portfolio 1. Above the chart, marked in yellow: the portfolios which would have been excluded based on the IMV methodology outlier, which was used in 2019 (and before) to detect outliers among risk measures. Below the chart: the same submission, but marked in yellow, indicating the submissions that have been excluded in VaR and benchmarking statistics in the 2020 exercise (and onward) based on the +/- two times truncated standard deviation of the sample.

8. Annex 2 – Legal background

226. European legislators have acknowledged the need to ensure consistency in the calculation of RWA for equivalent portfolios, and the CRR and CRD include several mandates for the EBA to deliver technical standards, guidelines and reports with the aim of reducing uncertainty and differences in the calculation of capital requirements.
227. In this regard, Article 78 of the CRD requires the EBA to produce a benchmarking study on both credit and market risk to assist CAs in the assessment of internal models. The study should highlight potential divergences among banks or areas in which internal approaches might have the potential to underestimate their own funds requirements that are not attributable to differences in the underlying risk profiles. CAs are required to share this evidence within colleges of supervisors as appropriate and take appropriate corrective actions to overcome these drawbacks when deemed necessary. Directive (EU) 2019/878²⁰ of the European Parliament and of the Council of 20 May 2019 amending Capital Requirements Directive IV (CRD V) has not changed this mandate.
228. The EBA has devoted significant effort to the analysis of the consistency of outcomes in RWA, to understand the causes of possible inconsistencies and to inform the regulatory repair process. The EBA's ongoing work on benchmarking, supervisory consistency and transparency is fundamental to restoring trust in internal models and the ways in which banks calculate asset risks.
229. The use of internal models gives banks 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.
230. This MR benchmarking exercise is an MRWA variability assessment performed over a large sample of banks (43 banks at the highest level of consolidation across 13 jurisdictions within the EU). The banks participating in this exercise are those that have been granted permission to calculate their own funds requirements using internal models for one or more of the following risk categories:
- a) general risk of equity instruments;
 - b) specific risk of equity instruments;

²⁰ <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32019L0878&from=EN>

- c) general risk of debt instruments;
- d) specific risk of debt instruments;
- e) foreign exchange risk;
- f) commodities risk; and
- g) correlation trading.

231. Pursuant to Article 362 of the CRR, the general risk of debt instruments should refer to interest rate risk. Similarly, the general risk of equity instruments refers to the change in the value of indices.

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

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

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

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

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

Regulation (EU) 2019/876²¹ of the European Parliament and of the Council of 20 May 2019 amending the Capital Requirements Regulation as regards the leverage ratio, the net stable funding ratio, requirements for own funds and eligible liabilities, counterparty credit risk, market risk, exposures to central counterparties, exposures to collective investment undertakings, large exposures, reporting and disclosure requirements (CRR II) will have a significant impact on the market risk benchmarking exercise once it is fully implemented. However, for the time being the CRR framework will be applied for the purpose of the benchmark exercise in accordance with Article 78 of the CRD.

²¹ <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32019R0876&from=EN>



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