EBA REPORT

COUNTERPARTY CREDIT RISK (INTERNAL MODEL METHOD AND CREDIT VALUATION ADJUSTMENT) BENCHMARKING EXERCISE

EBA EUROPEAN BANKING AUTHORITY

Contents

List of figures and tables

Abbreviations

A-CVA	Advanced Credit Valuation Adjustment
BCBS	Basel Committee on Banking Supervision
CCP	Central Counterparty
CCR	Counterparty Credit Risk
CRD	Capital Requirement Directive 2013/36/EU
CRR	Capital Requirement Regulation EU 575/2013
CSA	Collateral Swap Agreement
CVA	Credit Valuation Adjustment
CVA VaR	Credit Valuation Adjustment Value at Risk
CVaR	Credit Value at Risk
EAD	Exposure at Default
EE	Expected Exposure
EEPE	Effective Expected Positive Exposure
EPE	Expected Positive Exposure
EU	European Union
HPE(s)	Hypothetical Portfolio Exercise(s)
IMM	Internal Model Method
IMV	Initial Market Valuation
LGD	Loss Given Default
MKT	Market
MtF	Mark to Future
NCA	National Competent Authority
NS	Netting Set
OFR	Own Fund Requirements
OTC	Over the Counter
PFE	Positive Future Exposure
RWA(s)	Risk-weighted asset(s)
S-EEPE	Stressed Effective Expected Positive Exposure
(S-)VaR	(Stressed-) Value at Risk
SFT	Secured Financing Transactions
SIGTB	Basel Standard Implementation Trading Book Subgroup
TFSB	Task Force Supervisory Benchmarking

1. Executive summary

This report presents the results of the supervisory benchmarking study pursuant to Article 78 of CRD and the related draft technical standards on the internal approaches applied for Counterparty Credit Risk (CCR) and Credit Valuation Adjustment (CVA) risk. In particular it focuses on the Internal Model Methods (IMM, disciplined by Section 6 'Internal Model Method' of Part 3, Title II, Chapter 6 of the Regulation (EU) No 575/2013 (CRR)) and the Credit Valuation Adjustment (CVA, disciplined by Part 3, Title VI 'Own funds requirements for Credit Valuation Adjustment Risk' of the CRR) .

The analysis is based on the data coming from the hypothetical portfolio exercise 2014-15 on counterparty credit risk for a sample of nine EU banks that the EBA has conducted in strict cooperation and leveraging on the data collected at the global level by the Basel Committee on Banking Supervision (BCBS).

In the spirit of Article 78 of the CRD 2013/36/EU that mandates the EBA to develop regulatory and implementing technical standards to support the Competent Authorities' (CAs) assessment on internal approaches used for computing own funds requirements, the EBA has computed benchmarks on counterparty credit risk and provided detailed feedback and bank-specific reports to the Competent Authorities. These reports have allowed each Competent Authority to compare its own submission with the EU sample, detecting the most relevant deviations and anomalies. In particular the benchmarking tool enables Competent Authorities to compare the outcomes of institutions' internal models and to identify the non-risk-based variability across firms.

Although the size of the sample is relatively small and the data were submitted on a voluntary basis, the main findings of the report provide useful insight into EU IMM and CVA models, which can be summarised as follows. First, there is evidence of variability on initial market values (IMV) estimated by the IMMs across banks especially for equity and foreign exchange OTC derivatives. Second, for interest rate derivatives this variability is lower, probably due to more consistency in pricing models and simulation techniques than is the case for equity and FX OTC derivatives. Third, the variability is also observed when comparing risk and stress measures such as EEPE and S-EEPE[1].

Data available are not sufficient for calculating own funds requirements for counterparty credit risk (e.g. PDs and LGDs are not available). However, it was possible to compute the EAD. The results show wide dispersion across banks. Banks' EAD ranges from –30% to +60% with respect to the benchmark (i.e. the empirical mean for the sample). It is important to note that this result should be interpreted with caution since there is a relevant heterogeneity related to both the alpha factors (the multiplicative factor applied to EEPE to obtain the EAD) and extra 'trade-dependent add-ons' (extra charges that may be imposed by supervisors) that cannot be controlled when analysing estimates from the hypothetical portfolio.

[1] A formal definition of these metrics is provided in Annex 7.1.

It should also be emphasised that, as the quantitative analysis is based on hypothetical portfolios, this report can focus solely on 'potential' variations and not actual variations. The analysis shows variability in this hypothetical portfolio, but that cannot lead to the conclusion of possible real under- or overestimations for counterparty credit risk charge. In any case, it surely helps to elaborate possible supervisory activities for addressing uniformity and harmonization efforts, and to promote more in-depth future investigations on this matter.

When computing capital requirements for the A-CVA implied by the hypothetical portfolio, the analysis shows that banks' estimations[2] lie in a narrower range when the EE profile is fixed and in a wider interval when the EE is left free (i.e. coming from banks' IMM). This is a theoretical computation because, among other things, the non-financial counterparties are exempt under certain conditions.

Given the limited number of banks included in the exercise, the objective of the hypothetical portfolio exercise was not to draw a final judgement on the key drivers of variability and the calculation of the implied capital charges but to provide supervisors with insights into how to increase comparability and reduce the variability effects attributable to non-risk-driven behaviours across the banks.

In particular the report provides inputs for Competent Authorities on areas that may require their further investigations, such as accentuated IMV variability for foreign exchange and equity OTC derivatives. Supervisors may also pursue other possible routes for reducing variability such as monitoring prudent selection of stress periods, privileging the use of CDS spread name curves when liquid and tradable, and applying conservatism when allowing banks to model an own alpha factor.

Besides that, since the hypothetical portfolio is composed of a small number of positions, this naturally means that it indicates only the potential level of variability and not the actual level which would be associated with a real portfolio in common practice.

Last but not least, this report aims to provide a framework that could be considered useful for the purpose of upcoming benchmarking exercises under Article 78 of the CRD. Thus, the type of analysis conducted (i.e. the statistical tools chosen, the graphs and tables elaborated, the methodology defined, the feedback given, the discussions held, etc.) provides the right path for future investigations and activities on these issues.

[2] One bank is using a multiplying factor greater than 3 imposed by its Regulator.

2. Introduction

European legislators have acknowledged the need to ensure consistency on the calculation of risk-weighted assets for equivalent portfolios, and the revised Capital Requirements Regulation and Directive (CRR and CRD, respectively) now include a number of mandates for the EBA to deliver technical standards, guidelines and reports aimed at reducing uncertainty and differences in the calculation of capital requirements.

In this regard, Article 78 of the CRD requires the EBA to produce a benchmarking study on both credit and market risk to assist competent authorities in the assessment of internal models, highlighting potential divergences among banks or areas in which internal approaches might have the potential to underestimate an own fund requirement which is not attributable to differences in the underlying risk profiles. Competent Authorities shall share this evidence within colleges of supervisors as appropriate and take appropriate corrective actions to overcome these drawbacks when deemed necessary.

The EBA has devoted significant effort to the analysis of the consistency of outcomes in risk-weighted assets (RWAs) in order to understand the causes of possible inconsistencies and inform the regulatory repair process. The ongoing EBA work on benchmarking, supervisory consistency and transparency is fundamental to restore trust in internal models and the way banks calculate asset risks.

The use of internal models provides banks with the opportunity to model their risks according to their business models and the risks faced by the bank itself. The introduction of a benchmarking exercise, that has just been set by the EBA and will be performed from the last quarter of 2015, does not change this objective, but instead helps to identify the non-risk-based variability drivers observed across institutions.

In the past few years the regulatory framework for Market Risk and Counterparty Credit Risk has been strengthened and has become a core issue due to the financial crisis that became recrudescent with the Lehman default on 15 September 2008.

Following the crisis, the measurement of counterparty credit risk (CCR) was reinforced within the Basel III framework, in particular the computation of RWAs based on internal model approaches consisting of two components: the Internal Model Method (IMM), although already introduced under the Basel II framework, and the Credit Valuation Adjustment Value at Risk (CVA VaR).

The IMM enables to produce the exposure profiles which are fed into the calculations for credit risk capital requirements (both SA and A-IRB) and management, while the CVA VaR estimates the capital charge for fair value risk stemming from market changes in the creditworthiness of the relevant counterparties.

During 2014 and 2015 the Basel Committee for Banking Supervision has been assessing the variability for banks' internal models for counterparty credit risk (IMM) and credit valuation adjustment (CVA).

According to its mandate the EBA conducted a parallel exercise on IMM and CVA by using the data of EU banks participating in the Basel 2014/2015 exercises, received from EU National Competent Authorities (NCAs) through their Task Force Supervisory Benchmarking (TFSB) members.

During the first phase of the exercise the EBA has provided feedback through an 'ad hoc' report sent to National Competent Authorities (NCAs) to help them identify areas of material differences in the risk metrics calculations in each jurisdiction by analysing and comparing banks' data with EU benchmarks.

Furthermore, the EBA has combined qualitative and quantitative analysis in order to identify the main drivers of variability among banks in their RWA or OFR computation.

This report summarises the EBA 2014/2015 market risk benchmarking exercise on CCR and CVA. In section 3 the main features of the hypothetical portfolio exercise are described, providing details about the sample, portfolios and the preliminary outlier analysis. In section 4 an investigation about the main drivers of the IMM variability is provided, looking at the dispersion of banks' figures by netting set and trade, and, in section 5 an analysis focusing on CVA is provided. Finally, in the Annex further technical details of the regulatory framework for counterparty credit risk are provided.

3. Main features of the CCR and CVA HPEs

This exercise aims to assess the variability of IMM and CVA VaR models across participating banks. The analysis focuses on regulatory risk metrics such as the Effective Expected Positive Exposure (EEPE)[3] computed for a number of hypothetical trades and netting sets[4] (i.e. sets of trades with a single counterpart). The effect of common collateralisation practices is also assessed for some netting sets by considering different forms of margining.

The measurement of CCR-related RWA based on internal model approaches consists of two components: the IMM and the CVA. The IMM is used to produce exposure profiles to calculate counterparty credit risk requirements relating to default, while CVA VaR estimates the capital charge for fair value risk stemming from market changes in the creditworthiness of the counterparties.

For the sake of precision, RWAs in this matter are computed, on the one side, via EAD fed into the credit risk framework, and, on the other side, via the CVA charge, which is considered both a counterparty credit risk and a market risk charge.

An analysis of the potential variability of CCR-related RWA therefore requires an assessment of both IMM and CVA VaR models.

3.1 Overview of the CCR and CVA HPEs

The EBA 2014/2015 market risk benchmarking exercise on CCR and CVA variability is based on the data of nine EU banks[5].

IMM models have been assessed by measuring the variability across EU participating banks of the regulatory risk metrics (i.e. EEPE and stressed EEPE) computed for a number of trades and netting sets. The effect of common collateralisation practices has also been assessed for a subset of netting sets. For the purpose of this exercise only plain-vanilla derivative instruments (e.g. swaps, forwards, options) and simplified netting sets have been used. Similarly the analysis of the CVA capital charge has been kept relatively simple.

As explained in the next section, banks were asked to submit CVA data in two phases, first using ‘their own’ (‘free’) EE profile and then, in order to obtain comparable outcomes, using a ‘fixed’ one.

The data were computed according to the following reference dates:

[3] See Annex 7.1

[4] See Annex 7.3

[5] See Annex 7.2

- **Booking of hypothetical trades and calculation of initial market values** (IMV): Wednesday 1 October 2014, at 2 p.m. UTC

- **Reporting date** (for the computation of EEPE and CVA results): Friday 31 October 2014, at 2 p.m. UTC

In addition to the market values provided for each trade, banks submitted the value of each trade and netting set on the reporting date for the IMM analysis (EEPE and S-EEPE), and CVA VaR results for two netting sets (#15 and #24[6]) and for a limited number of real counterparties[7]. EE profiles for the two netting sets were also computed. Between January and February 2015 banks were asked to produce CVA risk measures according to a fixed EE-profile and to recalculate the results with a revised trade #10.

Furthermore, the EBA has also collected qualitative information through a questionnaire filled out by all participating banks. This qualitative information shows some features of actual firms' derivatives portfolios subject to CCR and was combined with HPE figures to provide a more comprehensive analysis.

3.2 Data submission and outlier analysis

As explained in the previous section the exercise has been articulated in two steps regarding the submission of the data. In step 1, the banks were asked to calculate CVA VaR using their own estimates of expected exposure (EE) profiles (i.e. 'free' EE profile). In step 2, the banks were asked to calculate the CVA VaR using a 'standard' or 'fixed' EE-profile. The fixed EE-profile is based on an average or median of the EE-profiles that banks submitted under step 1. Using the standard EE-profile would allow the isolation of the effect of differences in the CVA VaR modelling on the variability across banks (i.e. excluding variability due to differences in EE-profiles mainly).

The final data coming from step 2 for EU participating banks were collected by the EBA during the second half of February 2015.

After the data collection was completed, the EBA produced an 'ad hoc' tool for each NCA to compare its banks' results with EU benchmark results. The tool enables NCAs to get a clearer idea of their banks' positioning with respect to the entire EU sample.

EBA representatives also joined some of the on-site visits conducted in March 2015 to participating banks (specifically, one visit to a participating bank from the UK, one visit to a participating bank from Italy, and one visit to a participating bank from Germany at its London premises) to have a better understanding of the logics behind the approaches used by banks for their internal models relative to IMM and CVA.

[6] While initially results were requested for netting set #25, a resubmission was requested to produce results for netting set #24.

[7] See Annex 7.3

For the purpose of the exercise, potential outliers were removed from the panel data either when it was considered that banks did not implement properly the exercise following the feedback sent from SIGTB's data quality analysis team, or when trades or netting nets had IMV results that were deemed to be too far away from the median.

Finally, an outlier analysis has been carried out, as explained in the next paragraph.

3.2.1 Outliers[8] and main statistics[9]

As a preliminary step, an analysis of the Initial Market Valuation (IMV) data is performed to check for potential outliers. When an IMV outlier is detected, it is removed from the overall dataset together with the EEPE and S-EEPE values associated to that corresponding instrument or netting set.

The tables in Annex 7.4 show the outliers (in red) for both trades and instruments and the missing data (in white).

Outliers are defined as those values that are more than 2.33 times the standard deviations from the median. The choice of this range is supported by the classical Gaussian confidence theory. Once detected, those values have been filtered out from the dataset.

Looking at the tables reported in Annex 7.4, one bank did not provide results for any equity HPEs with forward contract because it does not have supervisory authorisation to model these types of derivatives. One bank has not provided results for two IR trades: trade #5 related to SONIA expressed in GBP, and trade #7 related to a 5-year term swaption expressed in USD. The red cells show outliers following the previously defined statistical criteria.

It can be seen that one bank in particular tends to provide more outliers than others in the sample; this is much more evident for the observations provided at netting-set level.

Also, the descriptive statistics from the EU sample are reported in Annex 7.5 to provide an understanding of the empirical distribution of the sample, by showing the quantiles at 25th, 50th (median) and 75th percentiles. This gives an idea about the hypothesised 'true value' (median) and the dispersion estimated by the interquartile range (IQR = 75th percentile – 25th percentile).

For CVA risk measures all data provided by EU participating banks have been considered. In Annex 7.5 the main statistics regarding both CVA VaR and CVA S-VaR data are reported. The statistics are shown for both free-EE profile (i.e. the EE profile is estimated by each participating bank with its own internal models and own assumptions) and fixed EE-profile data (i.e. the EE profile is the same for all participating banks as agreed within Basel SIGTB).

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8 See tables in Annex 7.4

9 See tables in Annexes 7.4 and 7.5

4. IMM variability analysis

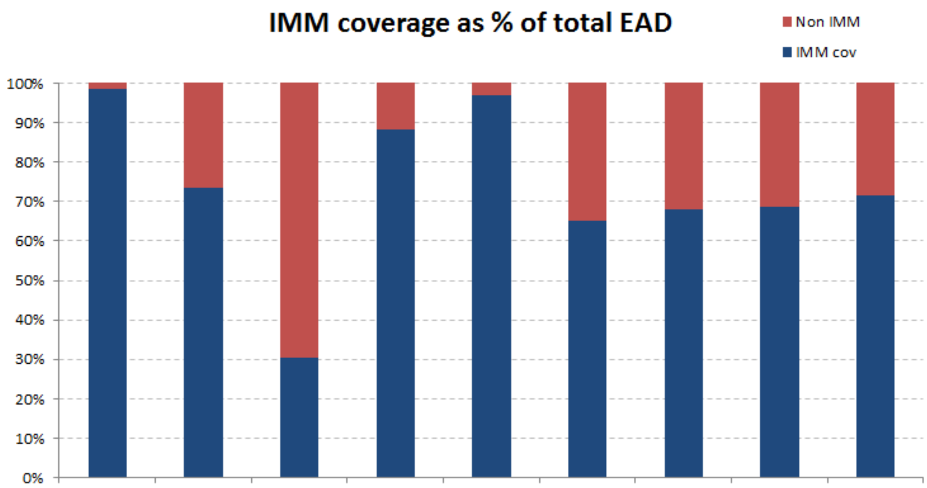
4.1 IMM qualitative information

Based on the information received from the qualitative questionnaire submitted by EU participating banks, the following main features of the EEPE models can be emphasised.

4.1.1 IMM coverage

The IMM coverage can be expressed in terms of percentage of total EAD in order to get a first understanding of the importance, in terms of the extent of exposure, of the IMM for a bank's actual derivatives portfolio.

Figure 1: IMM coverage in percentage of EAD

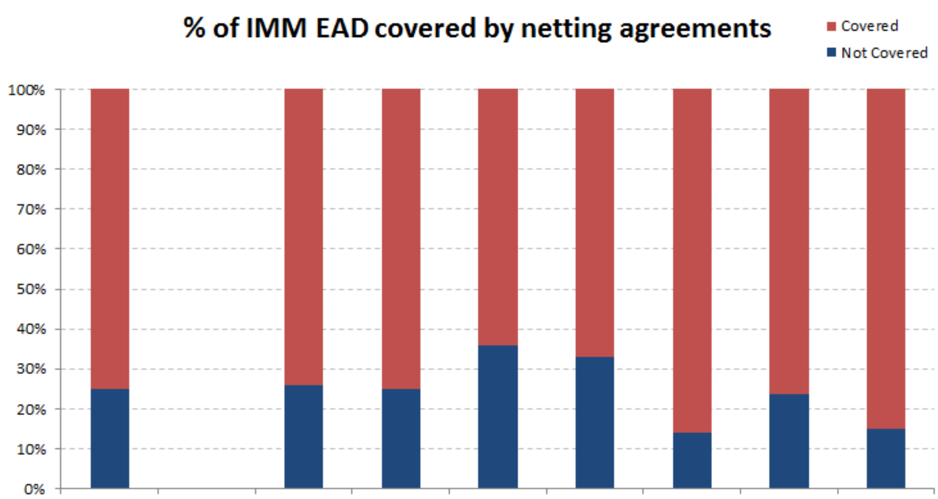


As can be seen, on average the IMM coverage is very significant for all the banks except for one, for which it is only 30%. For the remaining banks the IMM coverage ranges from 66% to over 95%. That means that *a relevant quote of EAD for banks' derivative portfolio is under the IMM approach*. This is an important point to keep in mind because it means that nearly all banks use their IMM for a large proportion of their derivatives portfolio. As the use test requirements of the CRR are quite extensive it can be presumed that the IMM is used not only for regulatory purposes but for managerial ones as well. Furthermore, let us assume an EAD for banks' derivative portfolios, calculated using an IMM approach, to be an appropriate reference point in the context of total CCR capital charge.

In order to understand the materiality as well, from the questionnaire, the breakout of CCR EAD in terms of IMM EAD vs. non-IMM EAD is as follows: IMM EAD goes, across banks, from a minimum of around EUR 22 billion to a maximum of over EUR 200 billion, with an average of around EUR 70 billion; the non-IMM EAD goes, across banks, from a minimum of around EUR 0.35 billion to a maximum of around EUR 74 billion, with an average of around EUR 30 billion.

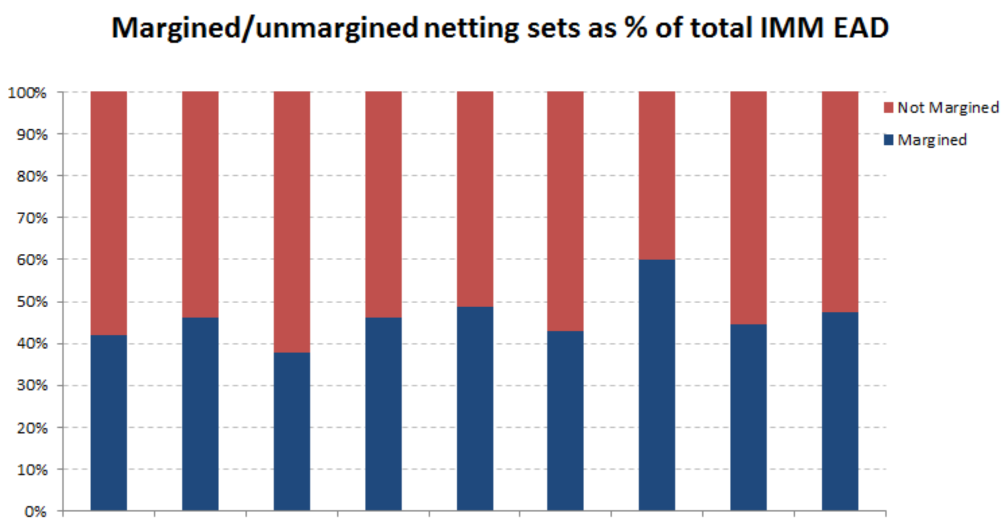
4.1.2 Netting and margining effects

Figure 2: Use of netting agreements in percentage of EAD



Apart from one bank that did not provide the information, it is possible to see that the percentage of IMM EAD covered by netting agreements is over 65%. Therefore, *the majority of IMM exposure is covered by netting agreements*.

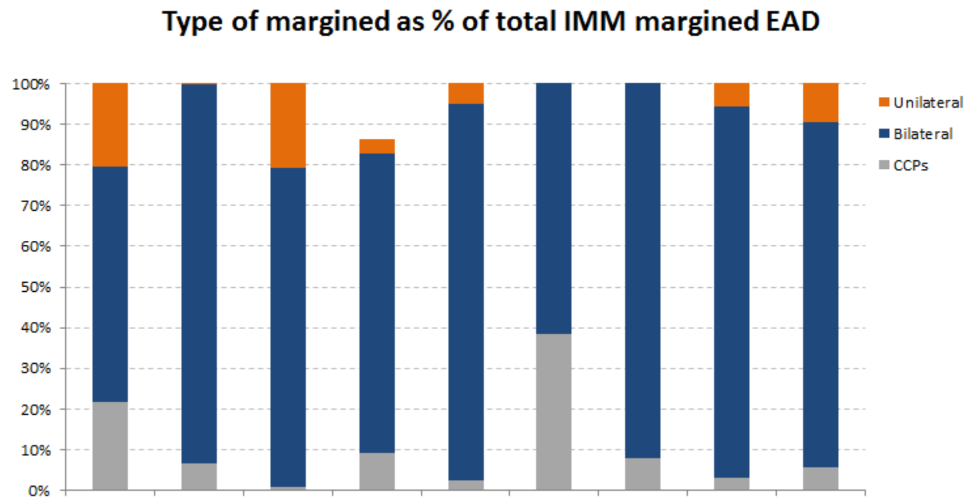
Figure 3: Margined vs. unmargined netting agreements used by European banks



For most banks the ratio of margined to unmargined netting sets is around 50%. This leads us to believe that in terms of trade count, the portion of margined netting sets is probably much higher since margined EAD is normally lower than unmargined EAD.

The most commonly used margin agreement is the bilateral one (Figure 4). The portion of CCP cleared agreements remains low. *There is evidence of a large homogeneity in the EU sample on this matter*.

Figure 4: Use of margining



4.2 IMM quantitative analysis

As a starting point for the quantitative analysis, the responses coming from the questionnaires were analysed in order to get a first impression of possible variation in the use of the IMM across participating banks. A summary of the most important information retrieved is given here:

- Five banks in the panel have the IMM approval for their entire counterparty credit risk exposure ('full adaption') and four banks have approval for only a part of their counterparty credit risk exposures ('partial use').
- The type of netting agreement most commonly used is ISDA 2002. The percentage of IMM EAD not covered by netting agreements equals, on average, 23.87% (five banks are over the mean; one bank did not answer). The range is the interval [14–32.90%].
- All banks use Monte-Carlo simulation approaches.
- Four banks use a total of 1 000 scenarios in their Monte-Carlo simulations. The other banks have a greater number of scenarios that range from 2 000 to 5 000. Only one bank uses a different number of scenarios depending on instruments/portfolios, up to 10 000. Intuitively, a larger number of scenarios can improve convergence of expected exposure measures since they are averaged over time and over many simulations. Due to a very

limited number of banks participating in this exercise, it is not possible to give robust statistical evidence for this expectation, although such an expectation seems reasonable.

- Banks calibrate the IMM using historical market data, market implied data and, also, a mixture of both depending on the risk factor. The calibration frequency for most banks is on a monthly or weekly basis. The stress calibration data are usually updated on a quarterly basis.

- Most banks in the EU sample assume correlations between risk factors within an asset class and across different asset classes.

- All banks model the margin mechanisms by using different assumptions to reflect how collateral is exchanged in the future, and when the counterparty may default.

- Additionally, banks provided their main risk factors and how they model the development of those risk factors in the IMM. The most relevant risk factors are modelled with stochastic processes with drift, especially for IR and FX.

Given the small sample of banks, a quantitative analysis is performed by using the ratio between each data point and the median computed across banks for each single netting set or trade as a metric. We opted for the median as the mean can be more adversely affected by the range of results when computed on small and highly volatile sample. It can be noted that in some cases, typically where the median is close to zero, it is better to compare absolute values to avoid artificially magnifying the level of dispersion.

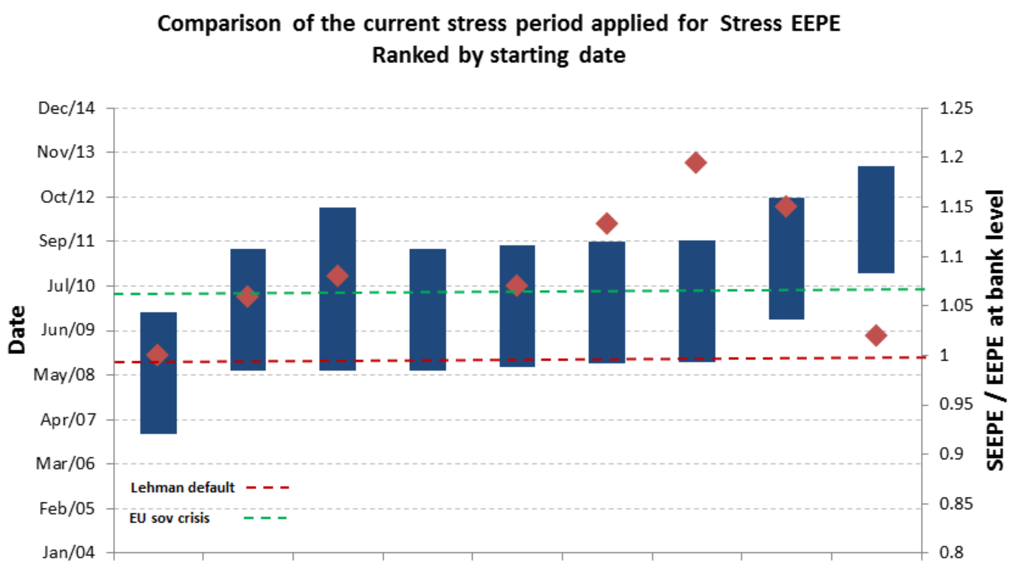
The tables in Annex 7.5 report the statistics for IMV, EEPE and S-EEPE.

The results show that for the EEPE measures, most banks are between 50% and 150% of the median. Dispersion is at a lower level for interest rate trades, while it is higher for foreign exchange trades and for equity trades. This evidence from comparing the results associated with each trade is reported in the figures below (see Figures 6 and 7). Additionally, by comparing Figure 6 with Figure 7 and Figure 8, it is possible to see that for many trades the range of dispersion tends to attenuate.

The corresponding market values (IMV) tend to show more dispersion, especially for some particular trades, which may be attributed to different simplifications in the IMM pricing functions used by participating banks; however, as can be seen, this characteristic tends to attenuate when risk measures like EEPE and S-EEPE are computed. Furthermore, IMV for the trades are shown in absolute values, too, in order to show that for some trades with results around 0 the induced dispersion is not as high as might be expected by looking at the relative values only.

For the purpose of computing EEPE using a stress calibration, banks must determine a three-year stress period that implies financial stress to the credit default spreads of a selection of representative counterparties. As shown in Figure 5, most EU banks have set this stress period around the financial crisis.

Figure 5: Comparison of the stress periods for IMM risk measures



The choice of the stressed calibration period seems to be a relevant factor for the corresponding stress measures. As can be seen, S-EEPE is more conservative (as a ratio of EEPE) when the stress period starts after mid-2008 *allowing to include both Lehman default and the EU sovereign crisis* (see Figure 5).

As can be seen from this graph, the ratio between S-EEPE and EEPE lies in the interval [1–1.20] with values close to each other. The largest difference, across banks, for this ratio is less than 20% in this sample. One bank did not provide this information.

4.2.1 IMM variability by trades

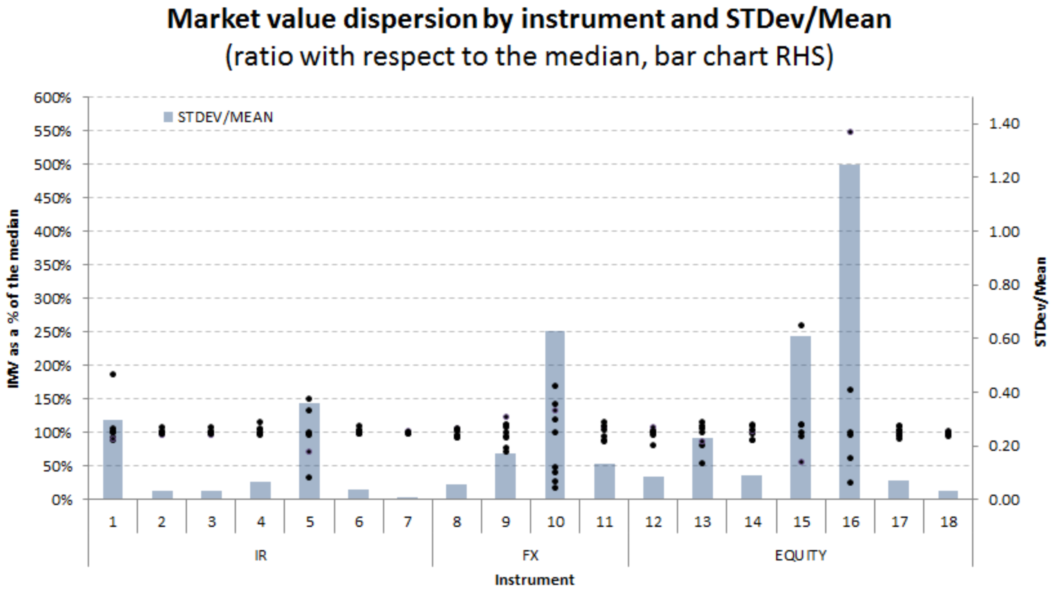
Banks' submissions were analysed and compared via a classical statistical dispersion analysis looking at the ratio between each data point by trade or netting set and the respective median across banks. We also chose for comparison purposes the variation coefficient[10] in order to get more insights into the magnitude of dispersion by trades and netting sets for all IMM risk measures.

The market value dispersion chart shows that *for a few trades the dispersion is quite high*. This is often the case when the median is very close to zero[11] and, therefore, the actual results are divided by a small number close to zero, which leads to a high ratio, compared with the absolute outputs. In order to overcome this drawback, IMVs were analysed in absolute terms too. For other trades market risk values are more aligned.

[10] The variation coefficient is the ratio between the standard deviation (STDev) and the mean. In the dispersion charts it is represented by the vertical bars.

[11] See also the main statistics tables in Annex 7.5

Figure 6: Comparison of trades' IMV for all asset classes in percentage of the median and by variation coefficient



Trade #10 (10-year cross currency swap) and trade #16 (1-year FTSE 100 index forward) show the highest variability, but it tends to diminish across the sample when the risk measures are computed. Trade #5 (2-year OIS swap on SONIA) is the most variable IR derivative trade in the portfolio.

Variability of the EEPE and stressed EEPE results

Looking at the EEPE and S-EEPE results (see Figures 7 and 8) the dispersion is lower than the one observed for IMVs. Additionally, the ratios between S-EEPE and EEPE are quite stable and greater than 1 for almost all the trades (see Figure 9).

For these risk measures, as was the case for IMV, trade #5 and trade #16 are the ones that show more dispersion across the banks.

Figure 7: Comparison of trades' EEPE for all asset classes in percentage of the median and by variation coefficient

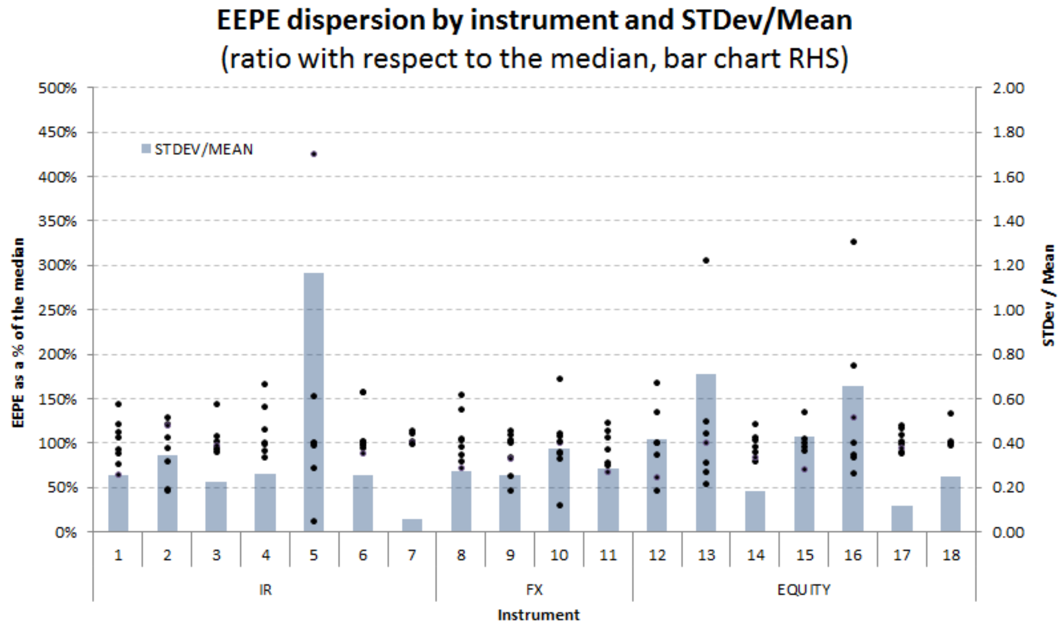
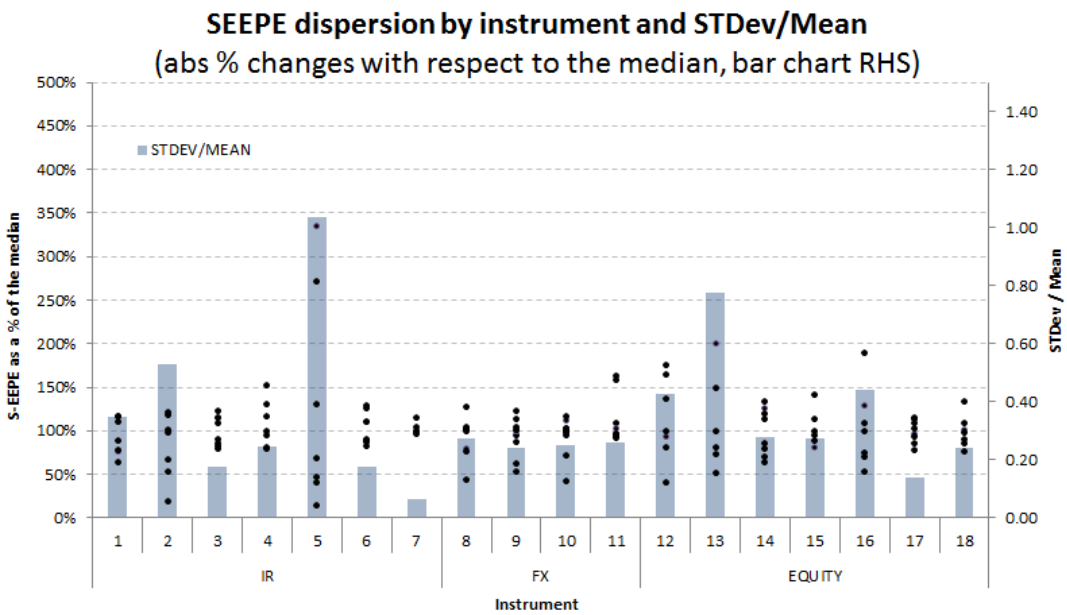


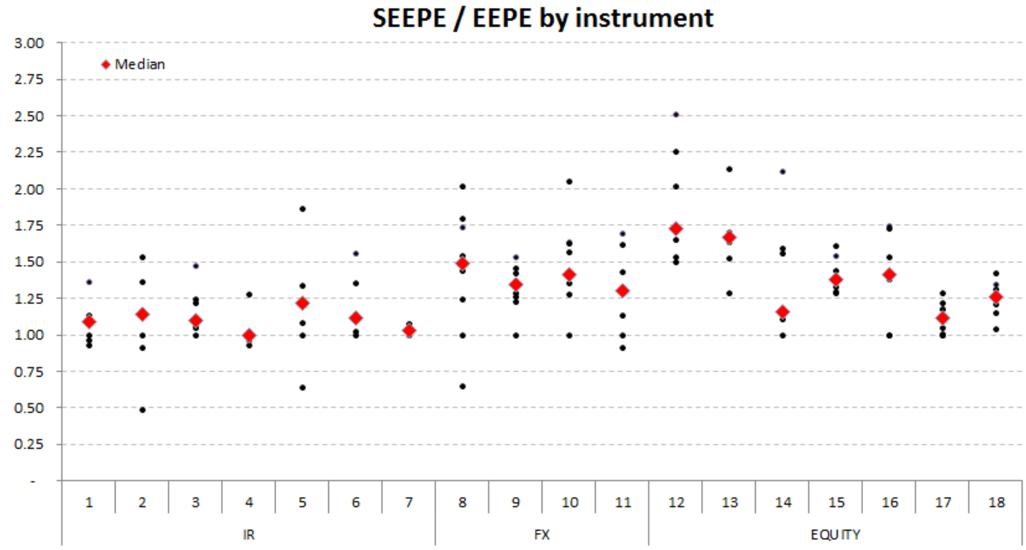
Figure 8: Comparison of trades' stressed EEPE for all asset classes in percentage of the median and by variation coefficient



We also include a chart about the behaviour of the ratio S-EEPE/EEPE in order to find out for which asset class this ratio is more conservative in the hypothetical portfolio exercise. On average, FX and equity tend to show a wider distance between these two exposure values, i.e. produce a higher ratio.

S-EEPE / EEPE ratios

Figure 9: Comparison of ratio S-EEPE over EEPE by instruments



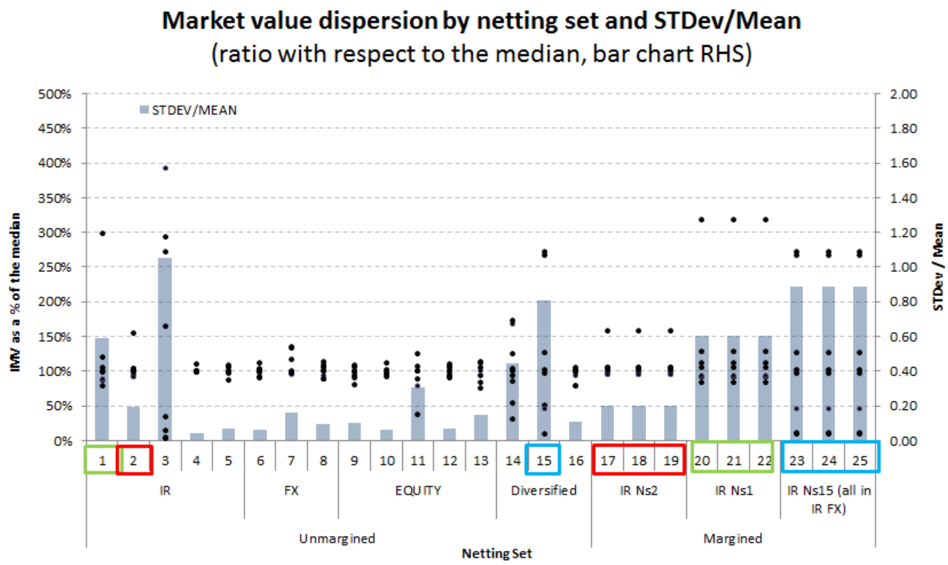
4.2.2 IMM variability by netting sets

Looking at Figure 10, regarding the dispersion by netting sets, the high dispersion of the NS #3 in relation to IMV results is attributable to the fact that it contains trade #5 that, as seen before, has a very low median. NS #15 also shows high dispersion as it includes the IR and FX trades, which are the ones showing the highest dispersion, as described in the paragraph above. NS #23, NS #24 and NS #25 also have high dispersion as they incorporate the dispersion effect of all trades across the asset classes (referring to IR and FX, included in those netting sets).

In relation to margined netting sets, the reader should refer to the different margining specification reported in Table 4 in the Annex. In summary, the unmargined netting set #2 is used for netting sets #17, #18 and #19 with different margining assumptions; the same happens for the unmargined netting set #1 that is used for margined netting sets #20, #21 and #22; and the same for the unmargined netting set #15 which is used for margined netting sets #23, #24 and #25.

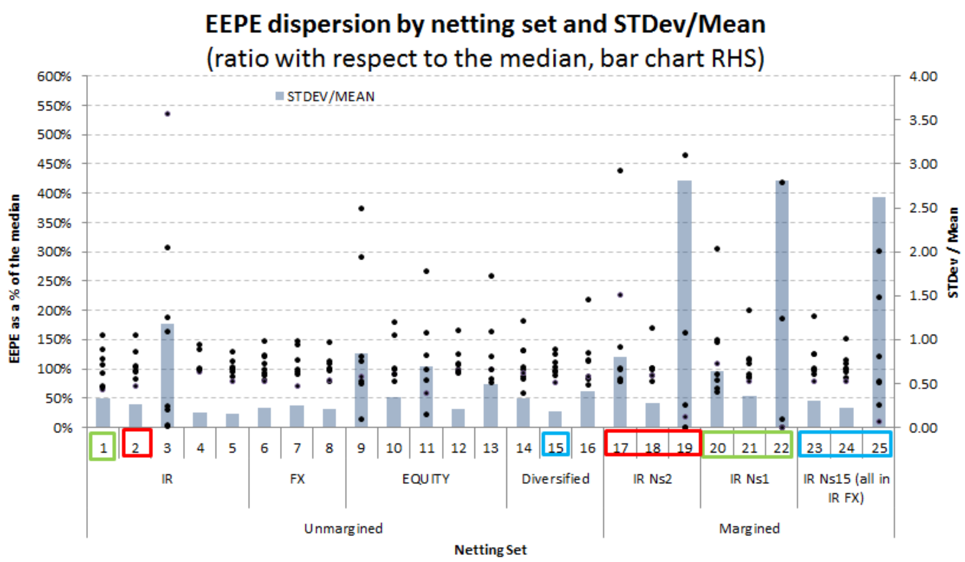
In the following charts these corresponding netting sets are highlighted in order to gain insight about the impact of different assumptions on margining.

Figure 10: Comparison of netting sets IMV for all asset classes in percentage of the median and by variation coefficient



As for dispersion findings, different hypotheses on margining do not affect the initial market valuation, as reasonably expected.

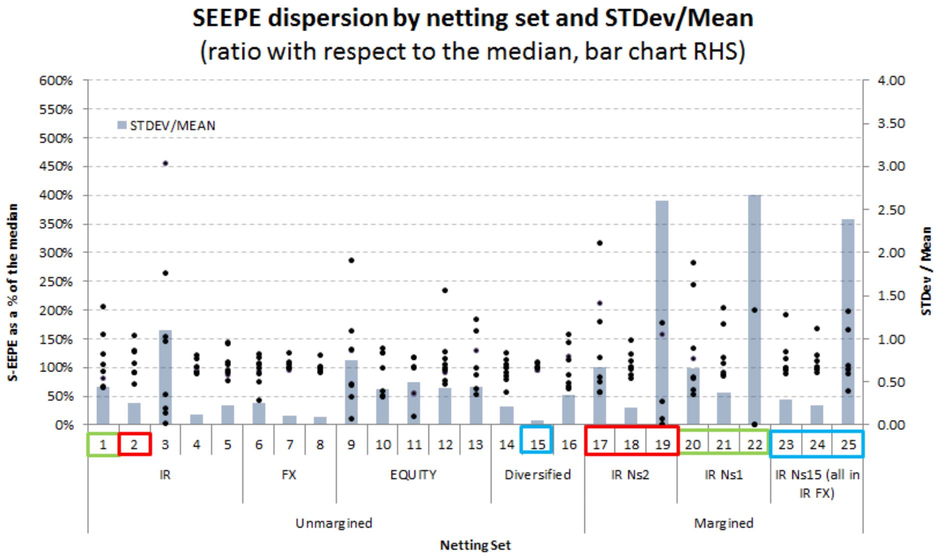
Figure 11: Comparison of netting sets' EEPE for all asset classes in percentage of the median and by variation coefficient



The margin feature seems to be relevant on risk measures when an independent amount is introduced on margining (#19, #22, #25). Indeed, when an independent amount is modelled, there is evidence of higher dispersion in terms of both EEPE and S-EEPE that is due mainly to high-level figures reported by one bank (see also Table 15 in the Annex).

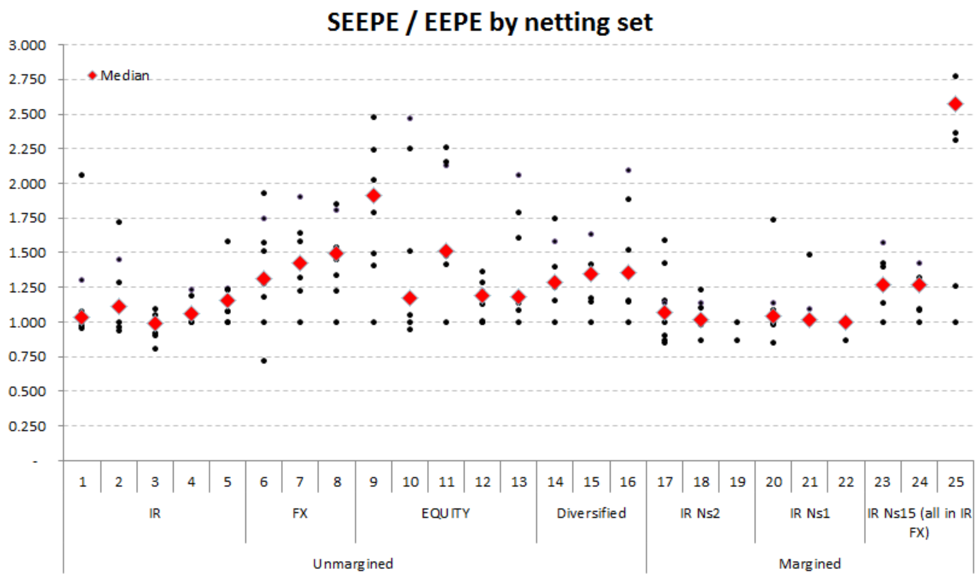
The same evidence applies also to S-EEPE as shown in the following chart.

Figure 12: Comparison of netting sets' S-EEPE for all asset classes in percentage of the median and by variation coefficient



Again, the pattern for the ratio S-EEPE/EEPE helps to detect the netting sets for which S-EEPE and EEPE values are distant to each other in terms of level, both for margined and unmargined netting sets. In any case, these results are affected by the previous evidence relative to the dispersion, and, obviously, results are affected by modelling assumptions as well. However, since for many HPE trades and netting sets this ratio is higher than the banks' real portfolio; it suggests that the HPE is not necessarily representative of banks' real derivative portfolio.

Figure 13: Comparison of ratio S-EEPE over EEPE by netting sets



Variability analysis of margined netting sets

The dispersion for (non-stressed) EEPE is slightly higher than for S-EEPE, although it reiterates the same magnitude. Looking at margined and unmargined netting sets, the introduction of the different margined agreements does not necessarily decrease the dispersion.

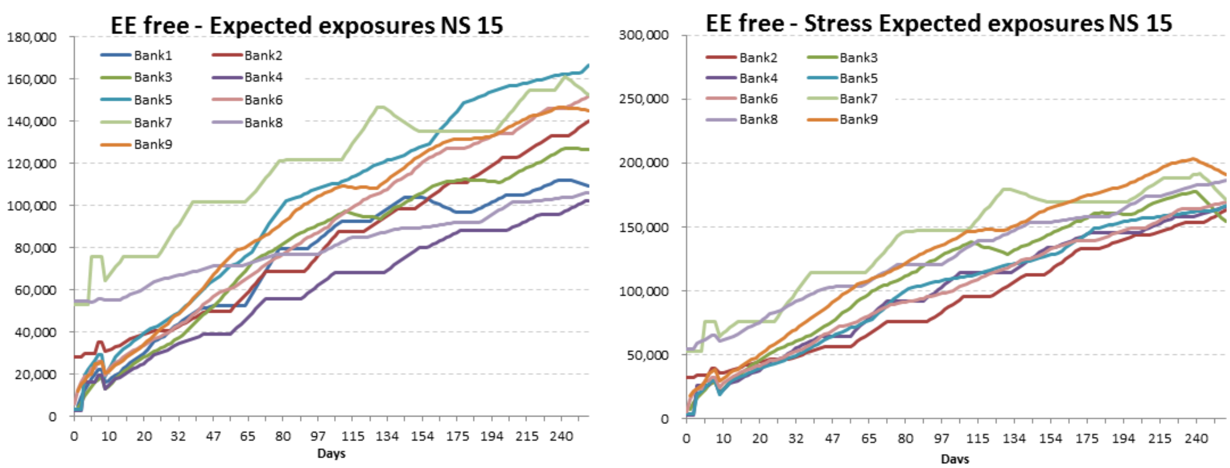
4.2.3 EE profiles

EE profile for netting set #15 (unmargined)

We report the estimated trajectory of EE and S-EE profile provided by participating banks, with their internal methods, for the all-in netting sets #15 and #24. A linear interpolation technique has been applied to EEs of banks that have used different time steps. One bank appears more volatile than the others, probably due to the usage of dynamic grid points for the computation of the EE profile. The EE profiles for the margined netting set #24 are more stable (with the exception of one bank), and lower than the unmargined ones due to the effect of collateralisation (i.e. credit mitigation effect of the CSA). In general EE and stressed EE profiles have the same pattern and are similar also in terms of levels.

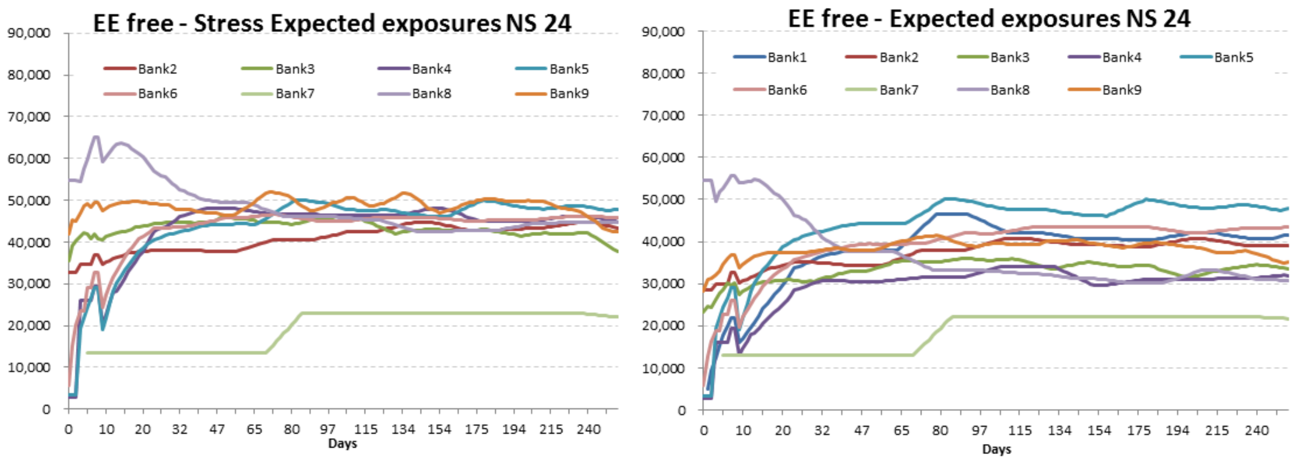
In this part the charts show the profile up to a horizon of 1 year ahead since this is what is used to estimate the EEPEs.

Figure 14: Comparison of EE profile and stressed EE profile up to 1 year for netting set #15



As expected, the addition of margining tends to produce smoother and lower levels as can be seen below.

Figure 15: Comparison of EE profile and stressed EE profile up to 1 year for netting set #24



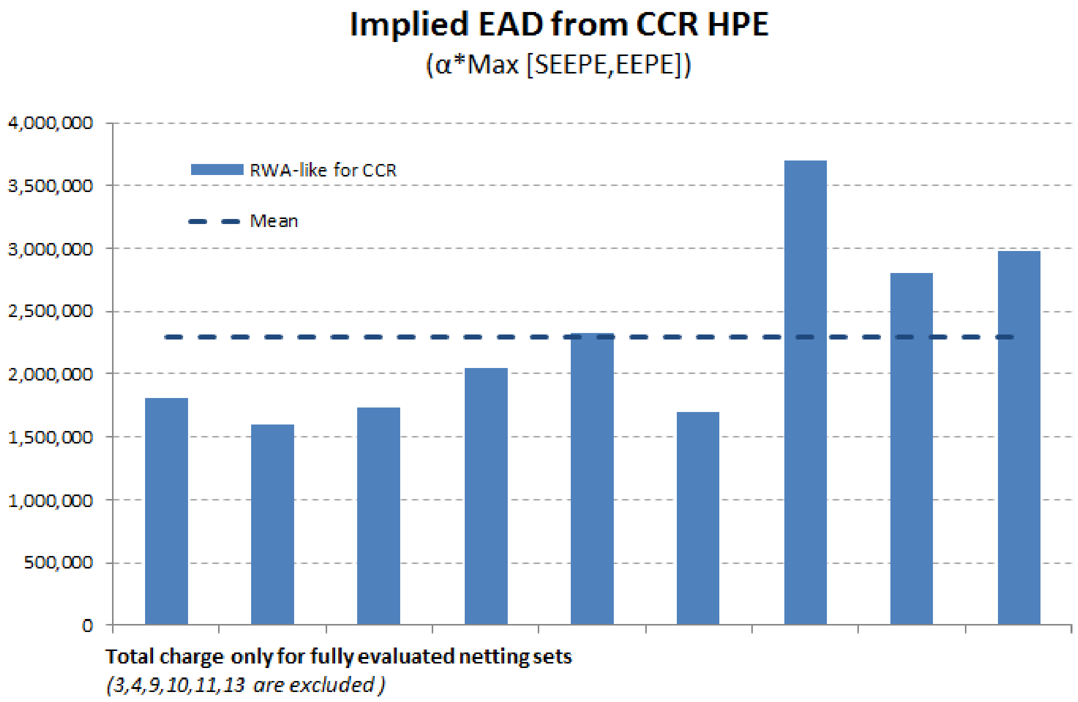
4.2.4 Implied EAD from HPE

In accordance with Part 3, Section 6, Title II, Chapter 6 of the CRR the own funds requirements for counterparty credit risk depend on the estimated IMM risk measures. These estimates are multiplied by a factor alpha, as described in the Annex, to produce the EAD that feeds, in practice, a bank's IRBA model to compute RWAs. In this analysis, key elements needed to estimate the implied RWAs, such as for instance, PD and LGD, are not available.

Since it is not possible to obtain OFRs, we compare implied EAD across banks coming from common netting sets in the hypothetical portfolios.

In this sample it is important to keep in mind that there is an important level of heterogeneity with respect to the alpha values or RWA add-ons. One bank is granted approval to estimate its own alpha floored at 1.2; two banks use a factor alpha greater than the standard value (1.4) as imposed by their regulator; two other banks use the standard value for alpha factor but they are charged with extra add-ons for certain derivative products calculated with the IMM. Only four banks out of nine are currently using the default value of 1.4 for alpha without any other extra add-ons or with no other adjustment. Furthermore it should be pointed out that the 'trade dependent' add-on charges cannot be taken into account when considering an HPE.

Figure 16: Implied EAD from CCR HPE



A *large variability* can be inferred from the chart since EAD moves from around –30% to +60% with respect to the sample mean. This is partly attributable to the different regulatory discretions for the alpha parameter across EU banks. The possibility exists for NCAs to increase alpha accounts for weaknesses of banks' IMM. This option is in line with the multiplicative factor for CVA, which will be discussed later, and is usually driven by the experiences in the market risk modelling area. These measures help to improve banks' internal models, and banks' processes, and enable them to become more risk sensitive and much more adequate. Particular attention must be paid to internal choices of alpha when its own estimate is lower than the standard number.

However, as previously said, since key elements are not available, the variability observed in this hypothetical calculation shall not lead to the conclusion that institutions, whose implied EAD is below the mean, are underestimating counterparty credit risk capital charge. However, this graph should help to elaborate targeted supervisory initiatives and promote more in-depth future investigations on this matter.

5. CVA variability analysis

5.1 CVA qualitative information

According to the qualitative questionnaires, seven banks out of nine have IMM positions that are not included in the Advanced-CVA (A-CVA). It mainly occurs for Securities Financing Transactions (SFTs). According to Article 382(2) of the CRR an institution shall include SFTs in the calculation of own funds requirements if the Competent Authority determines that the institution's CVA risk exposures arising from those transactions are material. However, five banks reported that they included in the A-CVA other non-IMM positions such equity swaps, dividend swaps, exotics and hybrid derivatives.

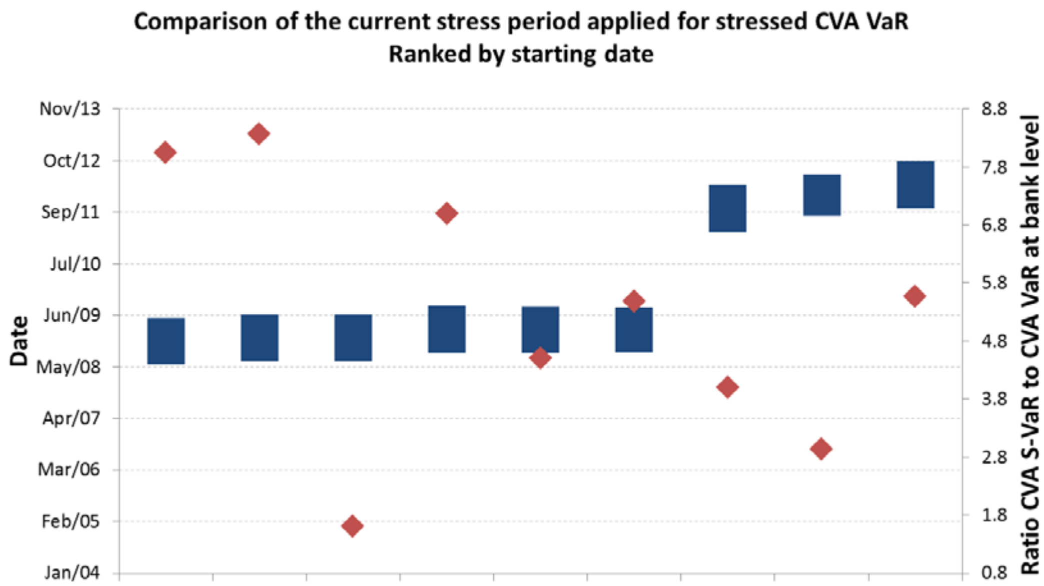
Other important points determined from the qualitative questionnaire are as follows:

- The percentage of counterparties having their own CDS listed (i.e. for which there is no need to use a proxy) is, on average, 17.83%, with a median equal to 12.50%. The maximum coverage reported by banks was 68%, while the minimum was 2%.
- The single name CDS curve used for the purpose of calculating CVA has on average 11 tenors (five banks out of nine, mode 11).
- Six banks retrieve market implied Loss given Default (LGD_{MKT}) from the data provider Markit. Remaining banks use a flat rate of 60%, or equivalently a recovery rate equal to 40%.
- Six banks reported using the same credit risk factors in A-CVA VaR as the ones used for market risk purposes for the same counterparties.
- The basis risk for illiquid counterparties modelled using a proxy credit spread is taken into account by six banks out of nine. For the remaining three banks, the specific risk VaR model may need improvements in order to include basis risk.
- The preferred choice for banks is to model the 1-day VaR (or S-VaR) and then to scale it by the 'square root of time' to derive the 10-day VaR (or S-VaR).
- Seven banks out of nine reported that they hedge the risks associated with accounting CVA.
- The majority of banks stated that they use a name-specific CDS curve for the listed counterparties in the HPE. For non-tradable names banks confirmed that they follow the EBA RTS in order to define corresponding proxy spreads.
- Regarding the stress period used for the CVA S-VaR, Figure 17 below shows that choosing a period that starts before 2010 results in a higher CVA S-VaR / CVA VaR ratio. Hence, the

use of a 2008-2009 stress period leads to more conservative CVA S-VaR results for the HPE portfolios.

- The average ratio between S-VaR and VaR is around 528%. Excluding the first observation (1.8), that shows a very low ratio compared to the stress period considered, this average rises to 574% (hence more than five times and close to six times). *This result is much greater than observed for IMM previously*.

Figure 17: Comparison of stress periods for CVA



- As for EEPE, the choice of the stressed calibration period seems to be a very relevant factor for the corresponding stressed CVA VaR measures.

- Finally, when a proxy is used instead of the specific CDS curve for the counterparty, CVA VaR shows more dispersion. This is due to the different ways that banks model proxy spreads. This point will be discussed in the following sections.

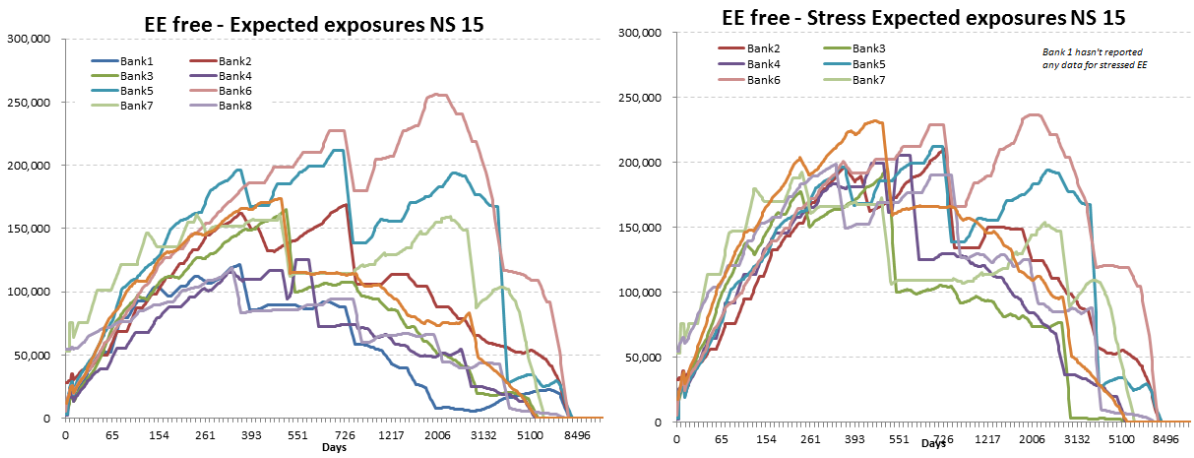
5.2 CVA HPE analysis

The CVA VaR amounts seem to be very sensitive to the EE (Expected Exposures) profile. To isolate the impact on CVA variability stemming from differences in EE-profiles across banks and CVA VaR modelling differences, participating banks were asked to run a second calculation using fixed EE-profiles. Therefore, results using both 'free' (i.e. internal own estimated) EE-profiles and 'fixed' (equal for all banks) EE-profiles are reported.

Here the trajectory estimated by banks from their own 'free' EE-profile until maturity that is relevant for CVA internal estimates is shown. In the previous analysis, referring to IMM, the same trajectories were shown but just up to 1 year, reflecting the different requirements for effective exposure calculations.

EE profile for netting set #15 (unmargined)

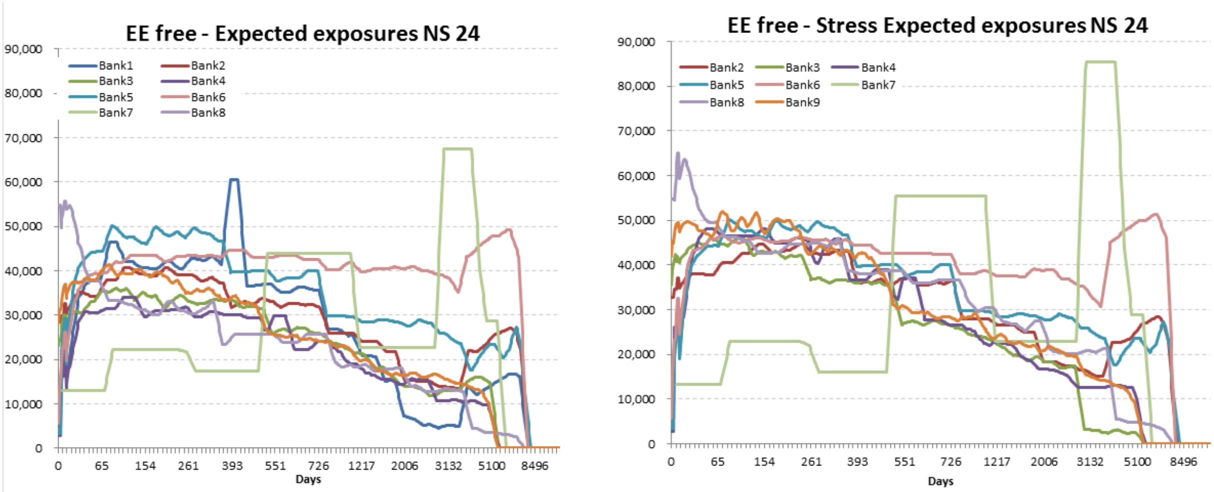
Figure 18: Comparison of EE-profile and stressed EE profile for netting set #15



EE profile for netting set #24 (margined)

As before, when margining is used, there is a smoother and lower pattern.

Figure 19: Comparison of EE profile and stressed EE profile for netting set #24



Now it is more visible that one bank, which is the only one using dynamic grid points, is more volatile than the others.

5.2.1 CVA VaR distance from the median: fixed vs free EE profile

In this section, the same dispersion analysis as the one previously conducted for IMM is applied to CVA VaR and CVA Stressed VaR. The CVA dispersion analysis shows that *after fixing the EE profile, the variability decreases across banks*. This means that exposure modelling is an important driver of variation.

When viewing the results, it is useful to refer to Table 5 in the Annex, in which the results per counterparties used for the CVA exercise are detailed.

In the HPE, there are five counterparties for which it is expected that a name-specific CDS curve would be used (1, 2, 3, 4, 6). This is important to note because not all participating banks used name-specific CDS curves for these counterparties but, for a variety of reasons, some of them used proxies.

Proxies are chosen taking into consideration the rating, industry and region of the counterparty. Institutions may use single name proxies, substituting the CDS spread of another individual name, which is often a parent company of the counterparty. This aspect naturally leads to more variability in the results.

Figure 20: CVA VaR dispersion by counterparties under fixed EE profile

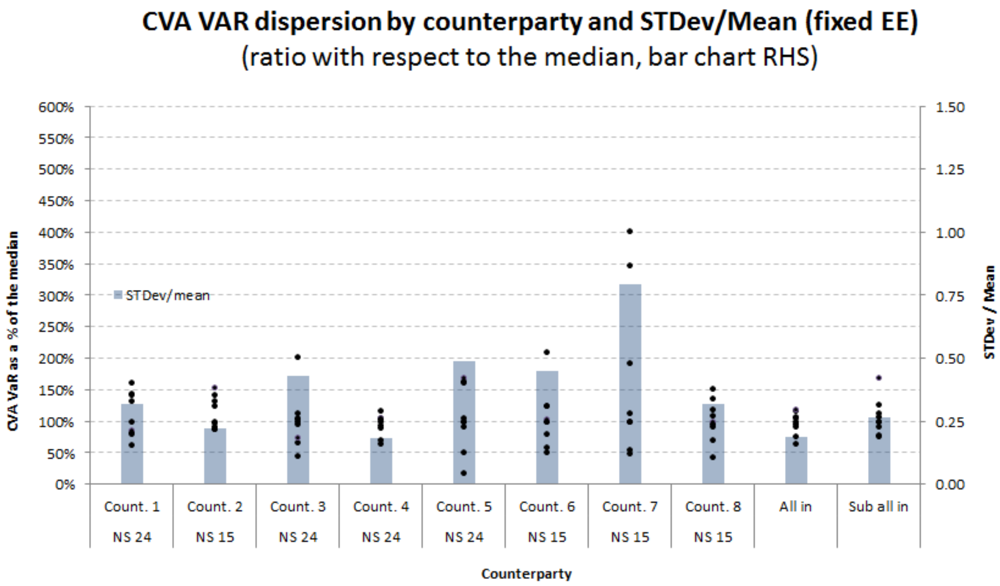
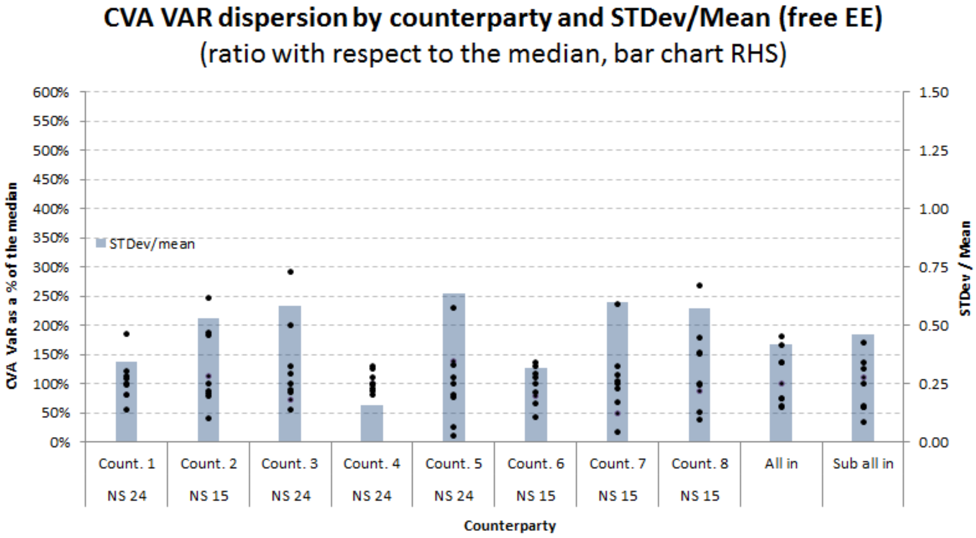


Figure 21: CVA VaR dispersion by counterparties under free EE profile



For the first four counterparties and counterparty 6, where name-specific CDS curves were assumed, there is evidence of more variability for the Industrial Bank of Korea (counterparty 3). As for counterparties 5, 7 and 8, where proxy spreads were assumed there is evidence of more variability for GROUPAMA (counterparty 5) and Dreyfus Commodities SA (counterparty 7). Furthermore, looking at the last two portfolios (All-in n. 9 and Sub-all-in n. 10 with expected liquid CDS curves) *the expected liquid CDS curves do not reduce variability because that is influenced by some banks in the sample that prefer to adopt proxies according to their own technical and/or judgemental analysis.*

Referring to the counterparties with assigned NS #15 (2, 6, 7, 8) and with assigned NS #24 (1, 3, 4, 5), both with EE-free and EE-fixed profile, the most volatile counterparty is counterparty 7 for the NS #15 group and counterparty 5 for the NS #24 group, respectively.

5.2.2 CVA Stress VaR distance from the median: fixed vs free EE profile

The same arguments apply to the CVA S-VaR analysis.

Figure 22: CVA Stressed VaR dispersion by counterparties under fixed EE profile

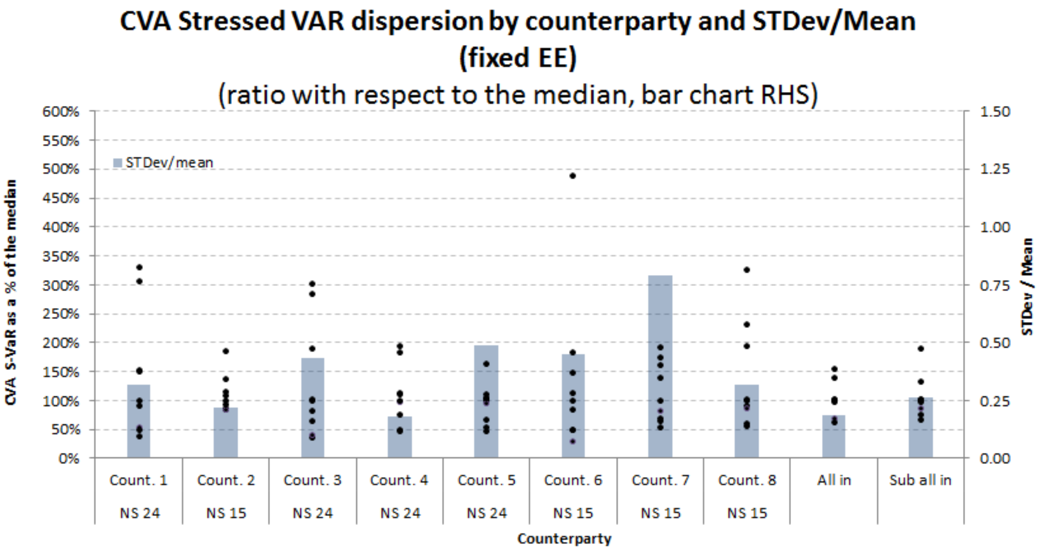
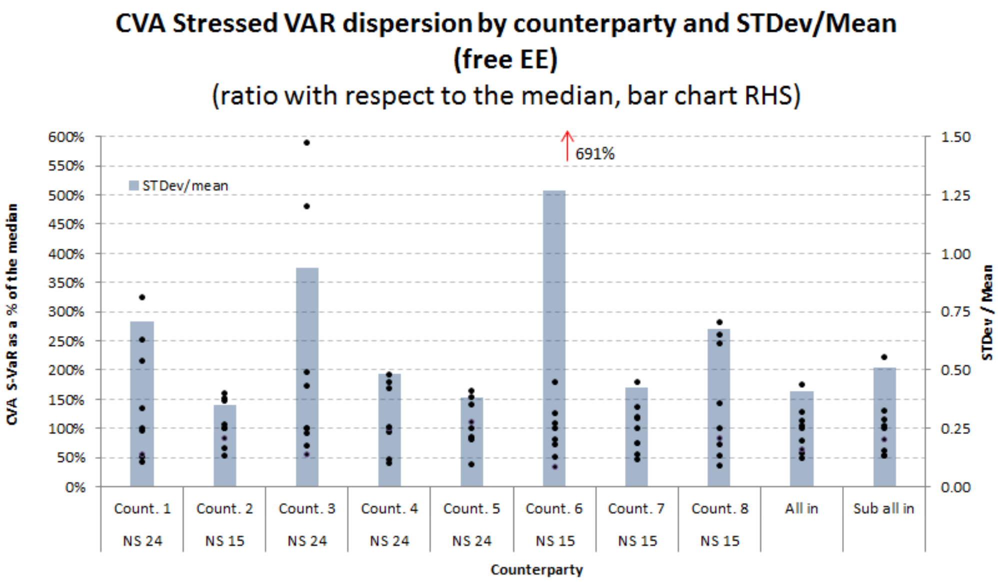


Figure 23: CVA Stressed VaR dispersion by counterparties under free EE profile



It is worth noting that CVA Stressed VaR shows more dispersion than CVA VaR, especially for certain counterparties. For instance, as can be seen in Figure 23, in the case of the free EE profile, counterparty 3 (i.e. the Industrial Bank of Korea) and counterparty 6 (i.e. General Electric Co.) show higher dispersion, presumably due to different modelling techniques across banks. The dispersion of results observed for counterparty 6 (General Electric Co.) is strongly affected by the results of one bank (Figure 23).

5.2.3 CVA Stress VaR over CVA VaR: fixed vs free EE profile

Here the CVA Stressed VaR / CVA VaR ratio is observed by counterparties and the estimated median from the EU sample is computed.

Figure 24: CVA VaR ratio by counterparties under fixed EE profile

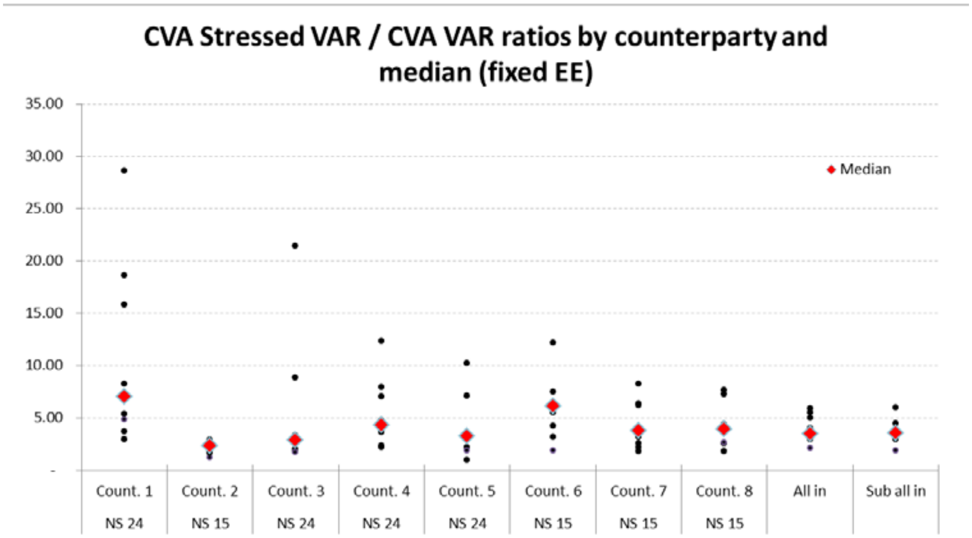
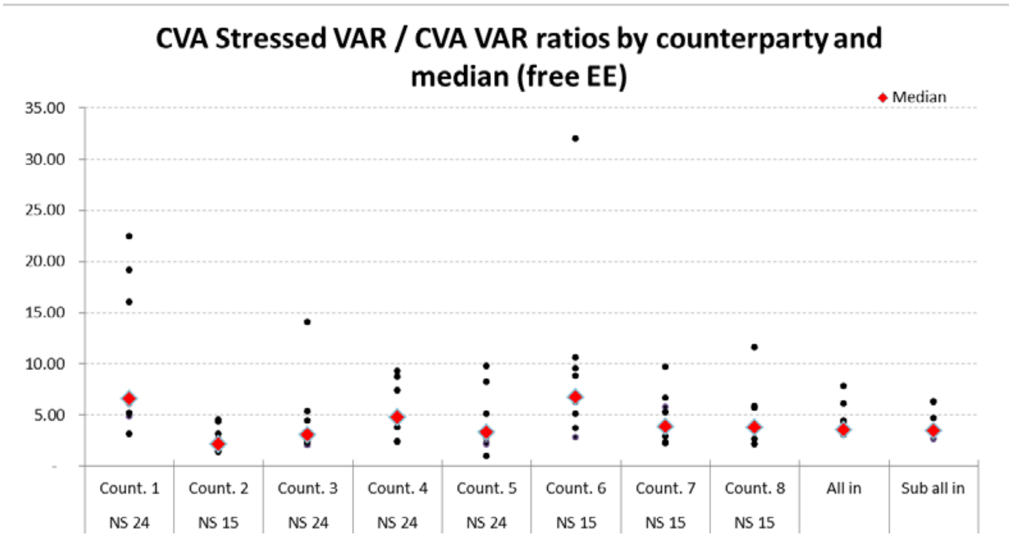


Figure 25: CVA VaR ratio by counterparties under free EE profile



As shown above, the median of the ratio seems to be stable across counterparties without changing too much when using free EE and fixed EE profile. Nevertheless *the dispersion by counterparties is significant for the majority of the counterparties*. Also for the hypothetical portfolio the average ratio CVA SVaR/CVA VaR is aligned with what was reported by banks in the questionnaires. Another source of variability is introduced by the fact that some banks shock spreads in absolute terms while others shock spreads in relative terms; additionally, it might be contingent to specific counterparties.

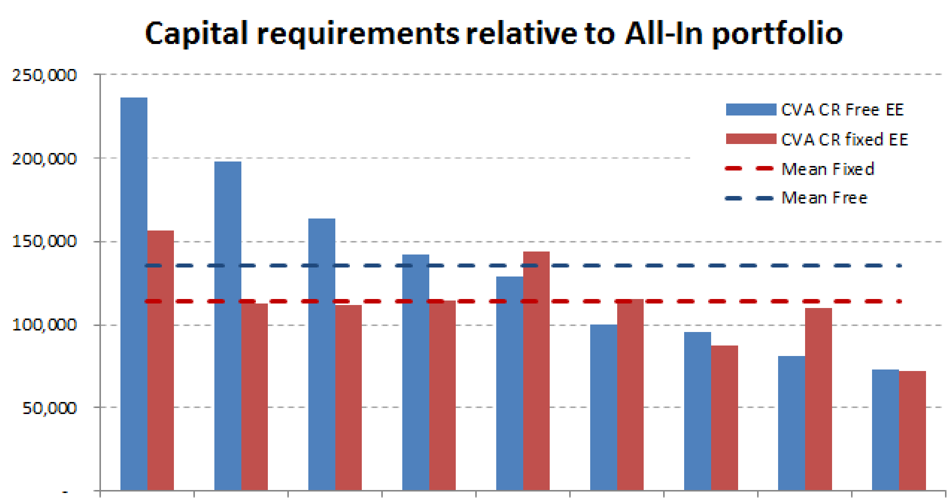
5.2.4 Potential capital requirements

Capital requirements for the A-CVA charge are computed as three times the sum of CVA VaR and CVA Stressed VaR. These charges are summed up to achieve the total capital charge attributable to the Credit Valuation Adjustment.

This analysis refers to the hypothetical portfolio 9 ('All-in') that includes all counterparties. Only one bank in the sample is required by its supervisor to apply a multiplier larger than 3.
Referring to the previous figures (Figures 20 and 21) that show variability for each counterparty under the fixed and free EE-profile, the choice of proxies inevitably affects the hypothetical own funds requirements. As a consequence the variability observed in this potential calculation shall not lead to the conclusion that institutions whose own funds requirements are below the mean are underestimating CVA risk, because these institutions might use more liquid CDS spread to assess the risk more adequately.

Globally, as can be seen in Figure 26, based on HPEs, *there is evidence of a large variability for the implied capital requirements* under both free and fixed EE profiles. The observed range for the implied capital charge is in the interval +/– 35% with respect to the sample mean in the fixed EE profile case, while it is much larger in the free EE profile case.

Figure 26: CVA risk charge by EE-profile



6. Summary of the relevant findings and limitations

This exercise exploits the framework (i.e. process, hypothetical portfolio settings, execution, etc.) agreed within the BCBS. The main challenge was to use the data collected by Basel SIGTB to achieve the very ambitious tasks set out in Article 78 of the CRD. The future exercises under Article 78 of the CRD should follow a similar approach but should be more targeted to the comparison of OFRs for institutions that are using a validated model for CCR and CVA capital charges. Besides that, an in-depth investigation about pricing models implemented by banks could be useful to explain better some variability observed in the provided market valuations. However, a baseline for elaborating policy options to deal with existing and reported issues in order to enhance harmonisation is provided. Also, the effort to promote further investigations is encouraged.

The most important findings concerning IMM are summarised as follows:

- Banks with large derivatives portfolios have very relevant IMM exposures.
- The majority of IMM exposure is covered by netting agreements, and there is a large homogeneity in the portion of margined over unmargined netting sets with respect to IMM EAD.
- The use of netting agreements and margining with bilateral contracts is largely widespread.
- There is an accentuated variability for FX and equity OTC derivatives with respect to IR OTC derivatives.
- The choice for a stress period is more prudent when it allows the inclusion of both the Lehman default and EU sovereign crisis.
- There is a large variability in the implied EAD from the HPE also attributable to different regulatory discretions. However, when the choice of a prudent alpha parameter accounts for model weaknesses, it should be particularly appreciated in the light of both more risk adequacy and harmonisation efforts.

The most important findings concerning CVA VaR are summarised as follows:

- The choice for a prudent stress period for achieving a higher ratio between S-VaR and VaR should be inside the financial crisis.
- Banks should privilege the use of CDS spread name curves when liquid and tradable. This enables greater accuracy and offers more harmonisation.
- The range of variability for capital charges implied by the HPE is quite relevant, especially under an internally estimated EE profile.

One of the main limitations of this exercise is represented by the limited number of participating banks, which implies a lack of robustness in a strictly statistical sense.

As the framework is based on hypothetical trades and netting sets, the analysis does not reflect the actual composition of each bank's derivative portfolio and, hence, any conclusion about under- or over-computation of capital charge levels cannot be drawn. Nevertheless this exercise helps supervisors to pursue many avenues for reducing variability and enhancing harmonisation in prudential practices regarding CCR in the EU banking sector.

7. Annex

7.1 Counterparty Credit Risk and the supervisory framework for Internal Models

Counterparty Credit Risk (CCR) refers to the risk that the counterparty to the transaction could default before the final settlement of the transaction's cash flows, as defined in Article 272(1) of the CRR.

In other words, the CCR is relevant when the bank has a potential profit and this profit is at risk if the counterparty defaults and cannot fully deliver on the derivative contract that it has traded with the bank. Derivatives fluctuate in value over time and, hence, the potential exposure of the bank on its counterpart can change considerably over the life of the derivative contract.

CCR exposure is measured at the level of the netting set following the rules reported by the CRR EU Regulation on Chapter 6 *et sequens*. Four methods can be used in order to compute CCR exposure; one of them is the IMM ('Internal Model Method') defined under Section 6 of Article 283–294 of Regulation (EU) No 575/2013 (CRR).

The IMM has to meet all of the requirements set forth in the CRR previously cited, and it has to be applied to all material exposures subject to a CCR-related capital charge, with the exception of long settlement transactions, which are treated separately, and with the exception of those exposure that are immaterial in size and risk.

As said before, the potential exposure of the bank on its counterpart can change over time during the life of the derivative contract; hence, an important objective is to examine the banks' modelling of the expected exposure profiles.

In order to fully understand an IMM approach, it is necessary to define and differentiate some exposure measures first.

1. **Current Exposure** means the larger of zero or the current market value of a transaction or portfolio of transactions within a netting set with a counterparty that would be lost upon the default of the counterparty assuming no recovery on the value of those transactions in bankruptcy.
2. **Expected Exposure** (EE) is defined as the average exposure on any particular future date t (before the longest maturity of all transactions in the netting set), where the average is taken across future values of relevant market risk factors, such as interest rates, foreign exchange rates, equity and commodity returns, etc. The model is supposed to estimate EE at a series of future dates (t_1, t_2, t_3, etc.), from the current date to maturity. The curve of EE in time, as the future date varies, provides the '***EE profile***'.
3. **Effective Expected Exposure** (Effective EE) at a specific date means the maximum expected exposure that occurs at that date or any prior date, i.e.

$$Effective\ EE_{t_k} = \max\{Effective\ EE_{t_{k-1}}, EE_{t_k}\},$$

where the current date is denoted as t_0 and $Effective\ EE_{t_0}$ equals current exposure.

4. **Expected Positive Exposure** (EPE) is the weighted average EE over time up to a future date (for example, for dates during a given year), where the weights are the proportion that an individual expected exposure represents of the entire time interval. When calculating minimum capital requirements, the averages is taken over the first year or, if all contracts within the netting set mature within less than one year, over the time period of the longest maturity contract in the netting set.
5. **Effective Expected Positive Exposure** (EEPE) is calculated as a weighted average of Effective EE during the first year of future exposure or, if all contracts within the netting set mature within less than one year, over the time period of the longest maturity contract in the netting set, i.e.

$$Effective\ EPE = \sum_{k=1}^{\min\{1\ year, maturity\}} Effective\ EE_{t_k} \cdot \Delta t_k$$

Where the weights $\Delta t_k = t_k - t_{k-1}$ allow for the case when future exposure is calculated at dates that are not equally spaced over time.

These concepts are related to **Exposure at Default** (EAD) since it is simply defined as the exposure valued at the (random future) default time of the counterparty.

In general, Expected Exposure measures should be calculated based on the distribution of exposures that accounts for the possible non-normality of the distribution of the exposures, including the existence of leptokurtosis ('fat tails'), where appropriate.

Such exposure models are also supposed to capture transaction-specific information in order to aggregate exposures at the level of the netting set and to take into account the *effects of margining* (i.e. the nature of margin agreements (unilateral or bilateral), the frequency of margin calls, the margin period of risk, the threshold of unmargined exposure, the minimum transfer amount, mark-to-market of the collateral posted, etc.).

When using the IMM, the exposure amount or exposure value is calculated as the product of a factor alpha times Effective Expected Positive Exposure (EEPE) as follows:

$$Exposure\ Value = \alpha * EEPE$$

where $\alpha = 1.4$, unless the competent authority requires a higher alpha or allows the institution to use its own estimate (in accordance with Paragraph 9 of Article 284).

Supervisors have the discretion to require a higher alpha. Factors that may require a higher alpha include high exposures to general wrong-way risk, particularly high correlation of market values across counterparties and other institution-specific characteristics of CCR exposures. More generally, alpha is set higher by supervisors when the model is deemed 'insufficiently conservative'.

Banks may seek approval from their supervisors to compute internal estimates of alpha subject to a floor of 1.2, where alpha equals the ratio of economic capital from a full simulation of counterparty exposure across counterparties (numerator) and economic capital based on EPE (denominator), assuming they meet certain operating requirements.

To measure counterparty credit risk internally, banks use mainly two measures: Positive Future Exposure (PFE), which is commonly used internally to monitor when the credit limits with the counterparts are breached, and EE, which is used, when combined with other quantities, for the calculation of EAD and the capital requirements due to counterparty credit risk. This last calculation may combine exposures with default probabilities and recovery estimates, and it also produces an approximation to Credit VaR (CVaR), typically over a one-year period ahead with a 99% confidence level.

Another important measure concerning counterparty credit risk is the **Credit Valuation Adjustment**, usually denoted by CVA.

CVA means the price of counterparty credit risk that firms are required to reflect in the price of their bilateral financial instruments, mainly derivatives. In theory, it should reflect today's best estimate (from a risk-neutral point of view) of the potential loss incurred on derivative transactions due to the default of the counterparty.

The estimate of the value of the derivatives portfolio in the future is called, as seen previously, an exposure profile. Each exposure profile starts from the current market data and will take into account, for each future date until maturity, several probabilistic scenarios for the evolution of the market factors. CVA is based on the positive exposure profiles, i.e. scenarios for which the derivatives portfolio has a positive market value.

Commonly firms use the Monte-Carlo simulation method to generate scenarios for the evolution of the risk factors in the future, and then combine these simulations with different types of pricing models to generate an estimate of the value of their derivative portfolio at each future date till maturity. This approach is called 'Mark-to-Future' (MtF).

CVA comprises two components: the credit risk component and the recovery risk component.

The credit risk component consists of the random variable 'time to default' for each derivative's counterparties.

The recovery risk component consists of the random variable 'recovery rate' upon default of the counterparties.

In the Basel II market risk framework, firms were required to hold capital against the volatility of their derivatives in the trading book. This was limited to the volatility of the default-free market value of derivatives, i.e. irrespective of the creditworthiness of the counterparty.

The fact that some large banks recognised significant CVA losses during the recent financial crisis led the Basel Committee to consider CVA risks as a potential source of financial instability against which capital should be held. Under Basel II the risk of counterparty default and credit migration were addressed but mark-to-market losses due to credit valuation adjustments (CVAs) were not. During the global financial crisis, however, roughly two thirds of losses attributed to a counterparty's credit risk were due to CVA losses and only one third were due to actual defaults.

Basel III introduced a capital charge against CVA risk in 2010 by issuing BCBS 'Basel III: A global regulatory framework for more resilient banks and banking systems'.

The Basel CVA risk charge allows two calculation methods: standardised and advanced. In the standardised approach the capital charge depends on a regulatory formula that approximates the dynamics of CVA risks in a simple manner.

This report focuses on only the advanced approach. The advanced method must be applied by banks with an approved IMM and an approved Specific Interest Risk Value at Risk (SIR VaR).

In the advanced approach the unilateral CVA is set with a single formula in order to measure CVA risks consistently across the banking sector, as reported by Article 383 of CRR No 575/2013:

$$CVA = LGD_{MKT} * \sum_{i=1}^{T} max\left\{0, exp\left(-\frac{s_{i-1} * t_{i-1}}{LGD_{MKT}}\right) - exp\left(-\frac{s_i * t_i}{LGD_{MKT}}\right)\right\} * \frac{EE_{i-1} * D_{i-1} + EE_i * D_i}{2}$$

where s indicates the counterparty's credit spread, EE indicates the counterparty's expected exposure, D indicates the common used risk-free discount factor, and, LGD is the counterparty's Loss Given Default estimated from its market liquid and tradable instruments.

Under the advanced approach, banks must simulate the credit spreads of all their counterparties over a 10-day horizon, calculate the resulting change of the regulatory CVA formula, reported above, for each counterparty and its eligible hedges, and compute the VaR and Stressed VaR (SVaR) at a 99% confidence level of the resulting distribution of CVA losses.

CVA VaR does not measure the default risk directly; it measures the risk of a mark-to-market loss due to either default or to adverse CVA change in value over time. This allows going further with Credit VaR that only measures the default risk.

The CVA risk charge is calculated as the sum of the VaR and SVaR multiplied by a coefficient of three, as follows:

$$A\_CVA\ Risk\ Charge = Max\ [CVA\_VaR_{t-1};\ kSTD * Average\ _{60-days}(CVA\_VaR_t)] + \cdots.$$

$$+ Max\ [CVA\_SVaR_{t-1};\ kSTD * Average\ _{60-days}(CVA\_SVaR_t)]$$

$$where\ kSTD = 3\ \text{(according to Article 383(5)(c)}$$

In this HPE the A-CVA risk charge may be inferred as follows:

$$A\_CVA\ Risk\ Charge = 3 * (CVA\ VaR + CVA\ SVaR)$$

The multiplicative factor three (3) may be increased by regulators based on their prudential supervisory tasks.

The advance unilateral CVA is defined by a single regulatory formula contained in Article 383 of the CRR (Regulation (EU) No 575/2013). This formula depends, net of all other variables, on the credit spread of the counterparty at each tenor, and on the EE to the counterparty at the same revaluation time (based on the IMM). These two variables are the two most important for the simulations to be performed to achieve the estimates for CVA VaR and CVA S-VaR.

According to CRR Article 383(1), when there is no CDS spread available for a counterparty, firms have to use a proxy spread that is appropriate having regard to the rating, industry and region of the counterparty. In practice the proxy spread methodology is applied to many counterparties subject to the advanced method, as can be seen from the EBA Report on CVA issued on February 2015.

Proxy spread methodology shows high diversity results between firms, as reported in the previously cited EBA report. On this theme, in 2013 the EBA has issued RTS regarding the determination of a proxy spread (EBA/RTS/2013/17).

Like market risk benchmarking, Counterparty Credit Risk (CCR) benchmarking is entirely based on hypothetical portfolios; hence, any relevant differences observed in RWAs should be attributable to modelling specificities. The variability analysis helps to distinguish changes on RWA attributable to spurious effects, for instance different modelling approaches to that which stems from an own risk profile.

7.2 Participating banks

The sample of our exercise is composed of a total of nine banks from five jurisdictions (DE, FR, IT, NL, UK) for both IMM and CVA hypothetical portfolio exercises.

Table 1: EU Participating banks

Member States	Number of participating banks	
	IMM	CVA
ITALY	2	2
UNITED KINGDOM	2	2
NETHERLANDS	1	1
GERMANY	2	2
FRANCE	2	2
TOTAL	9	9

All the above EU banks have participated on a voluntary basis.

7.3 Summary of trades, netting sets and counterparties

The hypothetical portfolio was defined with a total of 18 derivative trades summarised in Table 2 below: seven interest rate (IR) trades, four FX trades and seven equity trades.

Table 2: SIGTB HPE trades

Type	ID	Description	Base Currency
IR	1	20y IR swap receiver on 6M EURIBOR, Notional: 1 million	EUR
	2	5y IR swap payer on 3M USD LIBOR, Notional: USD(EUR 1 million*FX EUR/USD)	USD
	3	5Y IR swap receiver on 3M USD LIBOR, USD(EUR 1 million*FX EUR/USD)	USD
	4	2y IR swap receiver on 6M GBP LIBOR, Notional: 1 million	GBP
	5	2y OIS swap payer on SONIA, Notional: 1 million	GBP
	6	10y IR swap receiver on 3M USD LIBOR, Notional: 1 million	USD
	7	5y long swaption on 5y IR swap (3M USD LIBOR vs fixed), Notional: 1 million	USD
FX	8	1y FX forward, sell USD/Buy JPY, Notional: USD 1 million	USD
	9	2y FX forward, sell EUR/Buy USD, Notional: EUR(USD 1 million*FX EUR/USD)	EUR
	10	10y Cross-Currency Basis Swap, receive USD 3M LIBOR, Pay EUR 3M EURIBOR, Notionals: USD 1 million, EUR(USD 1 million*FX EUR/USD)	USD/EUR
	11	2y Cross-Currency Basis Swap, receive JPY 3M LIBOR, Pay USD 3M LIBOR, Notionals: USD 1 million, JPY(USD 1 million*FX JPY/USD)	USD/JPY
Equity	12	1y AXA forward, receive underlying, pay strike, Notional: 1 million (converted in units of shares)	EUR
	13	1y Metlife forward, pay underlying, receive strike, Notional: USD(EUR 1 million*FX EUR/USD) million (converted in units of shares)	USD
	14	6M Volkswagen AG forward contract, receive underlying, pay strike, Notional: 1 million (converted in units of shares)	EUR
	15	1Y DAX index forward, pay underlying, receive strike, Notional: 1 million (converted in units of shares)	EUR

	16	1Y FTSE 100 index forward, pay underlying, receive strike, Notional: GBP(USD 1 million*FX GBP/USD) million (converted in units of shares)	GBP
	17	1Y long call on Google OTM, Strike: 90%*stock price, Notional: 1 million (converted in units of shares)	USD
	18	1Y long put option S&P 500 Index, Strike: ATM, Notional: 1 million (converted in units of shares)	USD

Netting sets

A total of 25 netting sets (i.e. combinations of derivative trades with a single counterparty), both margined and unmargined, were specified for the purpose of the IMM and CVA HPE.

Table 3: Summary of the SIGTB HPE Netting Sets

Margined or Unmargined	Type of netting set	Netting set ID	Trades	Base currency
Un-margined	IR	1	1	USD
			2	
		2	1	USD
			3	
		3	4	GBP
			5	
		4	6	USD
			7	
		5	IR all-in (all 7 trades above)	EUR
	FX	6	8	EUR
			9	
		7	10	EUR
			11	
		8	FX all-in (4 trades: 8, 9, 10, 11)	USD
	Equity	9	12	EUR
			13	
		10	14	EUR
			15	
		11	12	GBP
			16	
		12	17	USD
			18	
		13	Equity all-in (7 trades: 12, 13, 14, 15, 16, 17, 18)	EUR
	Mixed asset classes	14	10	USD
			6	
		15	IR-FX all-in (11 trades)	USD
		16	IR-FX-Equity all-in (18 trades)	USD
Margined	IR	17	Same as netting set 2 (IR directional)	USD
		18	Same as netting set 2 (IR directional)	USD
		19	Same as netting set 2	USD

			(IR directional)	
		20	Same as netting set 1 (IR offsetting)	USD
		21	Same as netting set 1 (IR offsetting)	USD
		22	Same as netting set 1 (IR offsetting)	USD
	Mixed asset classes	23	Same as netting set 15 (IR-FX all-in)	USD
		24	Same as netting set 15 (IR-FX all-in)	USD
		25	Same as netting set 15 (IR-FX all-in)	USD

Table 4: Summary of the IMM margined netting sets

Summary of the IMM margined netting sets			
Type	ID	Description	Base CRCY
NS2 (IR)	17	Zero Initial Margin, Zero Independent Amount, Zero Minimum Transfer Amount, Zero Threshold Amount	USD
	18	Zero Initial Margin, Zero Independent Amount, USD 3K Minimum Transfer Amount, USD 30K Threshold Amount	USD
	19	Zero Initial Margin, USD 100K Independent Amount, USD 3K Minimum Transfer Amount, Zero Threshold Amount	USD
NS1 (IR)	20	Zero Initial Margin, Zero Independent Amount, Zero Minimum Transfer Amount, Zero Threshold Amount	USD
	21	Zero Initial Margin, Zero Independent Amount, USD 3K Minimum Transfer Amount, USD 30K Threshold Amount	USD
	22	Zero Initial Margin, USD 100K Independent Amount, USD 3K Minimum Transfer Amount, Zero Threshold Amount	USD
NS15 (All in IR FX)	23	Zero Initial Margin, Zero Independent Amount, Zero Minimum Transfer Amount, Zero Threshold Amount	USD
	24	Zero Initial Margin, Zero Independent Amount, USD 5K Minimum Transfer Amount, USD 50K Threshold Amount	USD
	25	Zero Initial Margin, USD 200K Independent Amount, USD 3K Minimum Transfer Amount, Zero Threshold Amount	USD

The different hypothesis on margining should help to understand how participating banks are modelling these parameters in their internal models, and, most of all, their impact on the provided results for this exercise.

Counterparties

For the purpose of the CVA analysis, banks were asked to provide the CVA VaR and stressed VaR for eight counterparties from different sectors, regions and ratings. Among the eight counterparties, five have liquid CDS and three do not, thus requiring the application of a proxy spread methodology.

Each counterpart was assigned to a specific netting set as follows:

- Netting set #15 (unmargined IR-FX all-in): for counterparties 4, 5, 7, 8.

- Netting set #24[12] (margined IR-FX all-in): for counterparties 1, 2, 3, 6.

Additionally, results were submitted for an all-in portfolio regrouping all counterparties and a sub-all-in portfolio regrouping counterparties which have a liquid CDS (1, 2, 3, 4 and 6)

Table 5: Summary of the HPE counterparties used for CVA

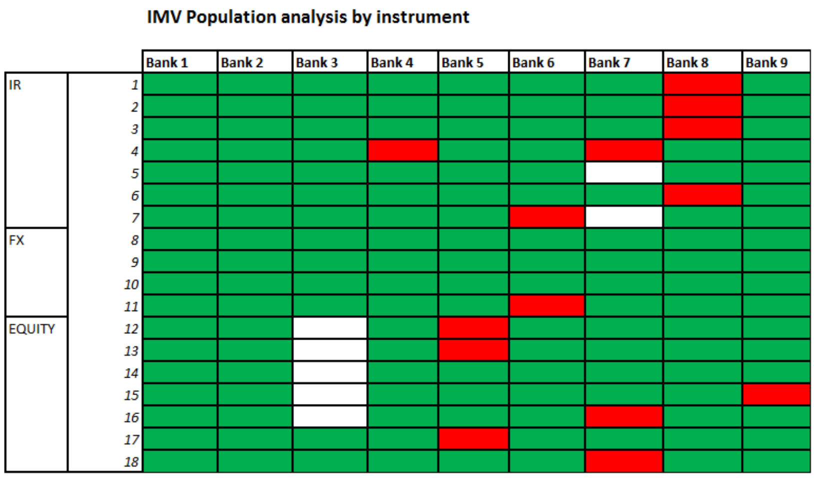
ID	Name	Description	Assigned netting set
1	PRUDENTIAL GLOBAL FUNDING LLC	US financial counterparty with a liquid CDS	24
2	BRITISH AIRWAYS PLC	EU NON-financial counterparty with a liquid CDS	15
3	INDUSTRIAL BANK OF KOREA	Asian financial counterparty with a liquid CDS	24
4	FIAT FINANCE NORTH AMERICA INC	North American financial counterparty without a liquid CDS but the European parent company has a liquid CDS	24
5	GROUPAMA GAN VIE	EU financial counterparty without a liquid CDS	24
6	GENERAL ELECTRIC COMPANY	US non-financial counterparty with a liquid CDS	15
7	LOUIS DREYFUS COMMODITIES SUISSE SA	European counterparty without a liquid CDS	15
8	ARCELORMITTAL BRASIL SA	South American counterparty without a liquid CDS	15
9	All-in portfolio	Includes all counterparties (1 to 8)	24 and 15
10	Sub all-in portfolio	Includes only counterparties with a liquid CDS (1, 2, 3, 4, 6)	24 and 15

[12] While these counterparties were initially assigned netting set #25, a resubmission was required by the SIGTB following the data quality analysis conducted in November 2014. Final submissions are thus based on netting set #24.

7.4 Outliers analysis

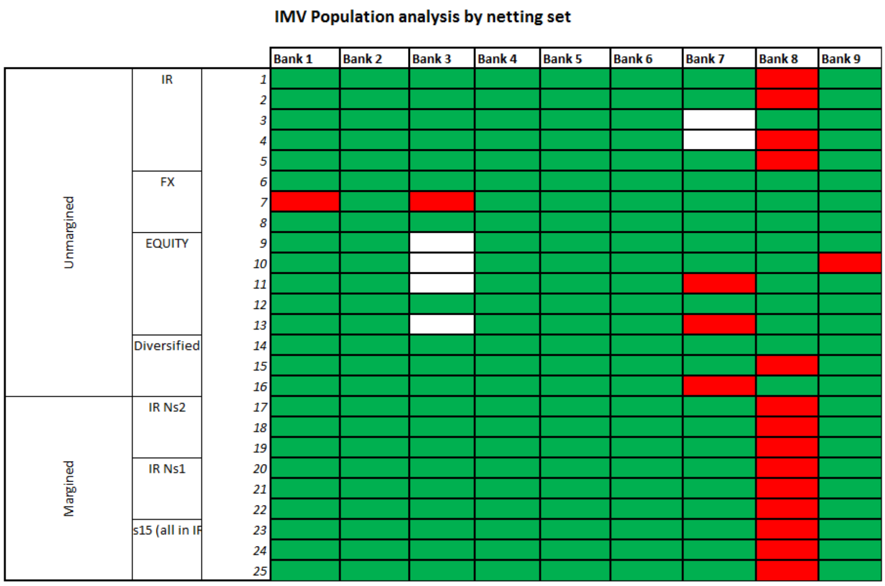
IMM instruments

Figure 27: IMV: Reported outliers (in red) and missing data (in white) for trade instruments and participating banks



IMM Netting sets

Figure 28: IMV: Reported outliers (in red) and missing data (in white) for netting sets and participating banks



7.5 Main stats

IMM instruments

Table 6: IMV: EU sample descriptive statistics for trade instruments

STATS
(Market Value - Trades)

	Min	*Max*	*Ave.*	*STD*	*STD/mean*	*25th perc*	*50th perc*	*75th perc*
TR 1	15,119	31,561	18,366	5,427	0.30	15,566	16,950	17,433
TR 2	-12,127	-10,969	-11,332	374	0.03	-11,397	-11,265	-11,075
TR 3	10,969	12,127	11,332	374	0.03	11,075	11,265	11,397
TR 4	3,347	4,045	3,569	238	0.07	3,424	3,464	3,640
TR 5	1,228	5,463	3,599	1,300	0.36	3,264	3,623	4,166
TR 6	13,721	15,364	14,215	555	0.04	13,829	14,049	14,369
TR 7	35,419	36,481	35,906	339	0.01	35,725	35,902	36,043
TR 8	-54,781	-47,297	-51,193	2,981	0.06	-53,547	-51,415	-48,871
TR 9	7,124	12,333	9,869	1,698	0.17	9,280	9,960	11,101
TR 10	1,120	10,151	5,305	3,346	0.63	2,427	5,951	7,942
TR 11	-31,547	-20,892	-26,927	3,663	0.14	-29,761	-27,355	-24,410
TR 12	-69,637	-52,408	-63,115	5,327	0.08	-65,249	-63,978	-62,640
TR 13	-42,679	-19,992	-34,726	7,906	0.23	-40,326	-37,102	-31,327
TR 14	56,681	71,446	63,644	5,726	0.09	58,926	63,578	67,775
TR 15	2,625	12,244	5,321	3,248	0.61	3,576	4,712	5,257
TR 16	627	24,092	6,989	8,726	1.25	1,965	2,497	8,890
TR 17	127,547	154,282	140,565	9,713	0.07	134,599	139,038	146,992
TR 18	52,093	56,863	54,597	1,723	0.03	53,126	55,305	55,651

Table 7: EEPE: EU sample descriptive statistics for trade instruments

STATS
(EEPE- Trades)

	Min	*Max*	*Ave.*	*STD*	*STD/mean*	*25th perc*	*50th perc*	*75th perc*
TR 1	24,798	55,005	38,581	9,758	0.25	32,690	38,259	43,849
TR 2	4,013	11,063	8,020	2,778	0.35	6,210	8,614	10,379
TR 3	16,320	28,296	20,070	4,527	0.23	17,179	18,100	21,244
TR 4	3,486	6,919	4,742	1,239	0.26	3,958	4,165	5,353
TR 5	39	2,483	709	827	1.17	304	332	733
TR 6	21,840	38,793	27,549	6,988	0.25	23,618	24,540	28,458
TR 7	35,949	41,540	37,791	2,252	0.06	36,458	36,482	38,825
TR 8	20,913	45,277	30,620	8,383	0.27	24,978	29,320	33,328
TR 9	14,712	36,245	28,454	7,206	0.25	26,087	31,746	33,048
TR 10	6,848	39,347	22,416	8,394	0.37	20,375	22,842	24,537
TR 11	11,747	26,868	17,718	5,079	0.29	13,432	17,511	20,383
TR 12	30,187	110,494	65,702	27,379	0.42	49,031	65,951	77,611
TR 13	35,798	200,677	78,849	56,053	0.71	47,875	65,519	77,101
TR 14	78,202	132,147	100,583	18,509	0.18	86,944	98,764	109,028
TR 15	40,515	127,486	67,073	28,778	0.43	53,576	57,201	68,578
TR 16	18,432	91,982	39,418	25,775	0.65	24,173	28,109	44,529
TR 17	128,074	172,899	148,162	17,121	0.12	135,084	144,662	160,542
TR 18	54,165	99,321	63,333	15,956	0.25	55,474	55,748	61,190

Table 8: Stressed EEPE: EU sample descriptive statistics for trade instruments

STATS
(Stress EEPE- Trades)

	Min	Max	Ave.	STD	STD/mean	25th perc	50th perc	75th perc
TR 1	27,911	78,078	45,477	15,880	0.35	33,859	43,768	51,313
TR 2	2,028	19,290	9,839	5,217	0.53	6,535	10,235	12,219
TR 3	17,891	27,777	22,559	3,924	0.17	19,149	22,499	25,989
TR 4	3,563	6,818	4,843	1,199	0.25	3,953	4,494	5,559
TR 5	73	2,848	941	975	1.04	233	515	1,479
TR 6	25,544	39,391	31,628	5,564	0.18	27,226	30,641	35,141
TR 7	36,982	44,533	39,212	2,600	0.07	37,657	38,557	39,550
TR 8	19,771	58,280	41,888	11,468	0.27	35,961	45,566	47,018
TR 9	21,440	48,667	37,143	8,907	0.24	34,856	39,846	41,641
TR 10	14,032	39,347	31,254	7,748	0.25	31,927	33,513	34,284
TR 11	17,613	31,406	22,021	5,668	0.26	18,444	19,320	23,515
TR 12	45,109	190,930	123,360	52,369	0.42	94,839	108,937	164,434
TR 13	54,376	395,913	153,830	118,976	0.77	79,574	103,953	181,708
TR 14	89,139	187,871	138,614	38,457	0.28	107,275	140,036	169,674
TR 15	62,543	127,486	87,040	23,725	0.27	71,310	77,822	99,406
TR 16	26,051	91,982	50,398	22,207	0.44	35,158	48,574	57,933
TR 17	128,065	190,884	164,700	22,713	0.14	151,022	165,773	183,495
TR 18	56,048	111,931	78,239	18,774	0.24	66,116	73,863	85,260

IMM Netting Sets

Table 9: IMV: EU sample descriptive statistics for netting sets

STATS
(Market Value - Netting sets)

	Min	Max	Ave.	STD	STD/mean	25th perc	50th perc	75th perc
NS 1	7,571	28,459	11,663	6,896	0.59	8,360	9,523	10,428
NS 2	30,250	50,524	34,327	6,694	0.19	30,707	32,638	33,697
NS 3	20	2,912	1,093	1,153	1.06	87	741	2,057
NS 4	49,658	55,781	50,962	2,157	0.04	49,986	50,231	50,545
NS 5	40,951	51,663	47,453	3,390	0.07	46,269	47,150	50,110
NS 6	-33,819	-27,445	-30,360	1,917	0.06	-31,157	-30,384	-30,011
NS 7	-30,553	-21,664	-24,985	4,001	0.16	-28,214	-22,483	-21,882
NS 8	-73,398	-56,869	-64,232	5,989	0.09	-68,577	-64,199	-59,588
NS 9	-98,049	-72,367	-88,513	8,812	0.10	-95,670	-90,264	-83,409
NS 10	62,212	75,161	67,101	4,192	0.06	64,549	67,038	68,098
NS 11	-65,193	-19,511	-47,107	14,370	0.31	-53,470	-51,709	-43,199
NS 12	178,616	216,287	196,454	13,354	0.07	186,699	197,076	209,528
NS 13	107,751	161,688	139,415	20,361	0.15	126,839	142,218	155,284
NS 14	4,080	22,311	13,430	6,009	0.45	10,985	12,938	16,113
NS 15	575	16,106	7,193	5,826	0.81	2,932	5,902	9,595
NS 16	152,242	202,896	182,567	19,541	0.11	173,851	191,494	194,081
NS 17	30,250	50,524	34,144	6,763	0.20	30,707	31,909	33,697
NS 18	30,250	50,524	34,144	6,763	0.20	30,707	31,909	33,697
NS 19	30,250	50,524	34,144	6,763	0.20	30,707	31,909	33,697
NS 20	7,571	28,459	11,501	6,966	0.61	8,291	8,922	10,428
NS 21	7,571	28,459	11,501	6,966	0.61	8,291	8,922	10,428
NS 22	7,571	28,459	11,501	6,966	0.61	8,291	8,922	10,428
NS 23	575	16,106	6,899	6,120	0.89	2,232	5,902	9,595
NS 24	575	16,106	6,899	6,120	0.89	2,232	5,902	9,595
NS 25	575	16,106	6,899	6,120	0.89	2,232	5,902	9,595

Table 10: EEPE: EU sample descriptive statistics for netting sets

STATS
(EEPE - Netting sets)

	Min	Max	Ave.	STD	STD/mean	25th perc	50th perc	75th perc
NS 1	26,012	62,621	40,448	13,358	0.33	27,801	39,744	48,432
NS 2	42,566	93,440	62,606	16,118	0.26	54,465	59,646	66,006
NS 3	10	3,814	1,126	1,332	1.18	167	711	1,550
NS 4	52,272	78,365	60,998	10,609	0.17	55,131	55,493	65,297
NS 5	52,742	86,159	67,343	10,277	0.15	62,116	66,738	70,719
NS 6	25,400	47,387	33,765	7,309	0.22	28,621	32,262	38,890
NS 7	17,435	36,024	26,602	6,759	0.25	22,760	24,464	31,385
NS 8	47,525	87,511	62,039	12,641	0.20	55,778	60,210	66,230
NS 9	6,953	172,965	66,854	56,591	0.85	35,946	46,315	75,988
NS 10	71,609	164,983	104,901	35,327	0.34	84,076	91,955	118,805
NS 11	9,651	111,771	48,674	33,490	0.69	29,139	41,877	59,570
NS 12	182,239	325,108	216,005	45,668	0.21	186,831	197,076	216,321
NS 13	134,137	450,171	224,306	111,377	0.50	158,188	173,686	247,888
NS 14	20,153	62,401	36,925	12,381	0.34	29,679	34,281	45,097
NS 15	82,225	143,061	111,361	20,300	0.18	99,501	107,357	123,766
NS 16	207,703	630,119	325,723	134,316	0.41	248,582	289,136	340,695
NS 17	10,784	60,823	21,490	17,311	0.81	11,244	13,842	22,051
NS 18	28,290	60,823	36,998	10,037	0.27	31,841	35,659	36,062
NS 19	0	60,823	7,661	21,481	2.80	3	25	160
NS 20	6,168	31,497	13,001	8,245	0.63	7,938	10,300	15,191
NS 21	15,225	38,199	21,146	7,433	0.35	16,550	19,138	22,114
NS 22	0	31,497	3,953	11,130	2.82	0	9	47
NS 23	27,277	65,686	39,124	12,089	0.31	32,717	34,541	43,179
NS 24	33,023	63,535	43,892	9,442	0.22	38,835	42,066	46,824
NS 25	58	65,673	8,767	22,999	2.62	355	525	1,271

Table 11: Stressed EEPE: EU sample descriptive statistics for netting sets

STATS
(Stress EEPE - Netting sets)

	Min	Max	Ave.	STD	STD/mean	25th perc	50th perc	75th perc
NS 1	27,397	87,500	47,538	20,715	0.44	32,588	42,271	55,617
NS 2	48,074	106,289	73,547	19,018	0.26	61,597	67,898	87,445
NS 3	31	3,769	1,166	1,280	1.10	222	827	1,503
NS 4	58,169	78,601	65,755	7,883	0.12	59,601	64,425	69,944
NS 5	58,132	107,004	79,664	18,159	0.23	68,260	74,769	87,599
NS 6	20,646	58,892	45,120	11,572	0.26	42,414	47,387	51,048
NS 7	33,231	44,256	36,834	3,708	0.10	34,790	35,026	37,871
NS 8	80,066	105,823	88,370	7,772	0.09	84,829	87,641	88,604
NS 9	12,457	302,112	120,594	90,276	0.75	68,179	105,747	148,205
NS 10	79,856	219,168	151,577	63,045	0.42	90,428	164,983	208,090
NS 11	14,285	111,771	75,864	37,122	0.49	51,562	94,749	103,561
NS 12	182,906	596,973	289,146	123,486	0.43	235,209	255,329	293,293
NS 13	146,160	508,888	307,339	137,428	0.45	206,527	275,223	404,025
NS 14	28,198	62,401	47,425	10,054	0.21	42,834	49,761	52,028
NS 15	134,130	154,405	141,860	7,113	0.05	137,202	140,288	144,773
NS 16	279,764	690,273	452,816	156,539	0.35	317,701	438,748	552,158
NS 17	9,614	53,111	23,059	15,459	0.67	11,951	16,774	31,506
NS 18	29,025	53,111	38,032	7,650	0.20	34,104	35,882	40,881
NS 19	0	53,111	7,140	18,601	2.61	22	276	1,104
NS 20	5,841	31,265	14,598	9,503	0.65	8,444	11,080	17,859
NS 21	16,239	38,886	22,838	8,662	0.38	16,673	19,127	25,230
NS 22	0	31,265	4,114	10,985	2.67	0	1	440
NS 23	38,548	82,913	49,700	14,434	0.29	42,471	43,244	51,404
NS 24	43,616	80,444	53,234	11,964	0.22	47,024	47,969	54,753
NS 25	961	82,893	12,011	28,650	2.39	1,528	1,635	2,847

CVA

Table 12: CVA VaR and CVA Stressed VaR: EU sample descriptive statistics for counterparties under EE fixed profile

STATS

CVA VAR (Fixed EE)

	Min	*Max*	*Ave.*	*STD*	*STD/mean*	*25th perc*	*50th perc*	*75th perc*
Count. 1	179	464	316	101	0.32	238	288	410
Count. 2	3,272	5,688	4,199	926	0.22	3,421	3,727	4,891
Count. 3	224	987	494	213	0.43	368	491	512
Count. 4	500	911	733	134	0.18	700	778	817
Count. 5	80	785	496	242	0.49	429	467	753
Count. 6	494	2,054	1,029	460	0.45	772	977	1,215
Count. 7	451	3,744	1,510	1,194	0.79	924	933	1,792
Count. 8	1,227	4,269	2,867	919	0.32	2,592	2,812	3,333
All in	5,109	9,538	7,770	1,441	0.19	7,273	7,999	8,607
Sub all in	3,752	8,261	5,233	1,380	0.26	4,490	4,903	5,547

STATS

Stress CVA VAR (Fixed EE)

	Min	*Max*	*Ave.*	*STD*	*STD/mean*	*25th perc*	*50th perc*	*75th perc*
Count. 1	847	7,320	3,136	2,405	0.77	1,195	2,214	3,374
Count. 2	6,953	15,133	9,059	2,687	0.30	7,014	8,179	9,431
Count. 3	582	4,805	2,126	1,611	0.76	1,023	1,595	3,028
Count. 4	1,633	6,746	3,759	1,810	0.48	2,618	3,485	3,969
Count. 5	722	2,457	1,419	525	0.37	1,020	1,512	1,579
Count. 6	1,839	30,150	8,522	8,661	1.02	3,077	6,170	9,084
Count. 7	2,319	8,215	4,910	2,224	0.45	2,905	4,264	6,840
Count. 8	4,798	27,846	11,820	7,862	0.67	7,321	8,525	16,611
All in	18,040	44,597	29,678	8,412	0.28	28,112	28,893	29,685
Sub all in	11,658	33,120	18,459	6,382	0.35	15,194	17,385	17,912

Table 13: CVA VaR and CVA Stressed VaR: EU sample descriptive statistics for counterparties under EE free profiles

STATS

CVA VAR (Free EE)

	Min	*Max*	*Ave.*	*STD*	*STD/mean*	*25th perc*	*50th perc*	*75th perc*
Count. 1	216	713	404	139	0.34	313	383	433
Count. 2	1,572	9,615	4,858	2,589	0.53	3,281	3,886	7,171
Count. 3	311	1,613	705	412	0.58	478	553	720
Count. 4	673	1,063	846	134	0.16	754	819	917
Count. 5	73	1,365	602	384	0.64	461	595	794
Count. 6	468	1,478	1,047	332	0.32	862	1,086	1,266
Count. 7	281	3,629	1,566	941	0.60	1,051	1,540	1,778
Count. 8	975	6,858	3,194	1,823	0.57	2,234	2,552	3,930
All in	4,722	14,465	8,771	3,677	0.42	6,002	7,940	10,926
Sub all in	2,181	10,619	5,950	2,748	0.46	3,764	6,202	7,825

STATS

Stress CVA VAR (Free EE)

	Min	*Max*	*Ave.*	*STD*	*STD/mean*	*25th perc*	*50th perc*	*75th perc*
Count. 1	1,196	9,002	3,917	2,783	0.71	1,517	2,763	5,995
Count. 2	5,529	16,142	10,896	3,815	0.35	8,355	10,126	14,941
Count. 3	816	8,578	3,002	2,820	0.94	1,323	1,454	2,868
Count. 4	1,598	7,686	4,536	2,199	0.48	3,766	3,972	6,725
Count. 5	594	2,614	1,690	645	0.38	1,333	1,580	2,223
Count. 6	2,407	47,282	10,986	13,922	1.27	4,954	6,839	8,573
Count. 7	2,729	10,520	5,875	2,488	0.42	4,359	5,838	6,981
Count. 8	3,776	28,836	14,473	9,752	0.67	7,393	10,183	25,014
All in	18,258	64,214	35,484	14,531	0.41	23,870	36,622	41,308
Sub all in	11,801	49,494	22,883	11,739	0.51	13,782	22,358	25,663

7.6 Variability analysis tables

IMM instruments

For IMV EEPE and S-EEPE possible outliers (values > 150% w.r.t the median) and less precautionary values (<50% w.r.t. the median) are highlighted. These tables report the applied analysis to filtered data as defined before.

Table 14: Deviation from the median for trades/instruments (IMV, EEPE, S-EEPE)

Deviation from the Median: *Market values - instruments*

IR	*1*	92.0%	99.7%	89.2%	91.2%	106.6%	100.3%	186.2%		101.6%
	2	100.2%	102.7%	100.7%	97.4%	98.4%	99.8%	97.9%		107.7%
	3	100.2%	102.7%	100.7%	97.4%	98.4%		97.9%		107.7%
	4	96.6%	105.7%	100.0%		98.2%	99.4%		116.8%	104.4%
	5	99.5%	100.5%	96.5%	71.0%	33.9%	150.8%			133.7%
	6	101.3%	103.9%	98.7%	97.7%	98.5%	101.7%	98.2%		109.4%
	7	100.5%	99.2%	100.0%	101.6%	99.8%			100.3%	98.7%
FX	*8*	95.7%		103.1%	105.6%	106.5%	93.1%	103.7%	92.0%	96.9%
	9	93.2%	71.5%	112.5%	123.8%	100.0%	107.8%	111.5%	77.0%	94.4%
	10	170.6%	18.8%	48.4%	133.4%	142.4%	120.5%	27.4%	100.0%	40.8%
	11	95.7%		115.3%	108.2%	110.5%		104.3%	89.9%	87.1%
EQUITY	*12*	102.1%	100.0%		108.8%		101.8%	99.7%	81.9%	96.1%
	13	81.3%	115.0%		87.5%		53.9%	110.1%	107.2%	100.0%
	14	98.4%	110.8%		101.6%	105.2%	89.2%	89.6%		112.4%
	15	95.2%	100.0%		56.6%		259.8%	111.6%	111.6%	
	16	25.1%	61.6%		547.3%	95.8%	164.8%		964.9%	100.0%
	17	102.2%	91.7%	109.8%	97.7%		111.0%	97.8%	104.4%	94.3%
	18	99.5%	96.4%	102.8%	100.8%		100.5%		95.0%	100.6%

Deviation from the Median: *EEPE - instruments*

IR	*1*	106.5%	93.5%	75.8%	64.8%	88.7%	143.8%	121.3%		112.4%
	2	105.7%	121.2%	128.4%	120.2%	80.0%	46.6%	48.3%		94.3%
	3	95.6%	90.2%	102.6%	97.4%	143.5%		108.6%		92.8%
	4	91.4%	100.0%	83.7%		140.9%	166.1%		116.1%	98.6%
	5	100.2%	152.5%	98.1%	425.9%	72.2%	11.8%			99.8%
	6	94.4%	98.3%	102.0%	89.0%	158.1%	157.7%	96.9%		101.7%
	7	99.9%	100.0%	101.8%	100.0%	111.0%			113.9%	98.5%
FX	*8*	103.5%		79.0%	71.3%	154.4%	87.3%	105.6%	137.9%	96.5%
	9	46.3%	63.7%	83.9%	82.2%	109.8%	104.1%	114.2%	100.0%	102.4%
	10	30.0%	81.9%	89.2%	100.0%	172.3%	90.3%	101.5%	107.4%	110.7%
	11	114.3%		74.6%	67.1%	106.8%		77.4%	122.6%	93.2%
EQUITY	*12*	45.8%	86.9%		61.8%		100.0%	134.8%	167.5%	100.6%
	13	54.6%	123.7%		100.0%		78.2%	68.0%	306.3%	111.6%
	14	79.2%	96.2%		84.1%	121.7%	89.3%	106.6%		103.8%
	15	105.0%	100.0%		70.8%		91.3%	96.0%	134.7%	
	16	87.3%	65.6%		128.9%	327.2%	187.9%		100.0%	84.7%
	17	98.2%	88.5%	108.8%	94.3%		117.6%	101.8%	119.5%	90.6%
	18	98.7%	97.2%	102.0%	100.0%		100.0%		133.0%	99.8%

Deviation from the Median: *SEEPE - instruments*

IR	*1*		89.0%	63.8%	76.9%	77.5%	117.2%	117.5%		111.0%
	2	101.2%	118.7%	98.8%		67.4%	53.4%	19.8%		121.4%
	3	81.9%	79.5%	86.2%	115.6%	115.5%	123.5%	108.9%		91.1%
	4	81.7%	94.3%	79.3%		130.6%	151.7%		100.0%	116.8%
	5	41.3%	131.4%	68.6%	335.4%	46.6%	14.2%			271.3%
	6	83.4%	90.0%	89.4%	110.7%	126.6%	128.6%	87.1%		110.0%
	7	95.9%	97.4%	97.9%	100.1%	105.0%			115.5%	100.0%
FX	*8*	43.4%		102.6%	79.5%	99.4%	100.6%	104.8%	127.9%	77.2%
	9	53.8%	62.4%	94.8%	100.0%	87.5%	113.1%	122.1%	100.7%	104.5%
	10	41.9%	71.0%	95.3%	111.3%	117.4%	100.0%	98.0%	102.1%	102.3%
	11	94.2%	162.6%	109.4%	103.2%	96.8%		91.2%	158.6%	95.9%
EQUITY	*12*	41.4%	80.4%		93.7%		100.0%	164.7%	175.3%	137.2%
	13	52.3%	100.0%		199.7%		80.3%	72.8%		149.9%
	14	63.7%	78.8%		125.6%	85.8%	69.9%	119.7%	134.2%	114.2%
	15	100.0%	94.3%		80.4%		89.0%	113.5%	142.0%	
	16	69.8%	53.6%		129.8%	189.4%	108.7%		100.0%	75.0%
	17	85.7%	77.3%	115.1%	96.9%		103.1%	114.4%	109.5%	92.9%
	18	85.6%	75.9%	109.1%	101.2%	134.5%	98.8%			90.8%

IMM Netting sets

Table 15: Deviation from the median for Netting Sets (IMV, EEPE, S-EEPE)

Deviation from the Median: *Market values - netting sets*

Unmargined	IR	1	86.6%	100.8%	79.5%	88.2%	120.9%	105.7%	298.9%		99.2%
		2	94.5%	100.3%	92.7%	92.9%	103.2%	99.7%	154.8%		103.3%
		3	34.6%	2.7%	4.1%	392.8%	293.4%	272.2%		14.2%	165.4%
		4	100.2%	100.0%	99.1%	99.9%	98.9%	111.0%			101.1%
		5	98.5%	101.4%	97.1%	107.1%	109.6%	106.0%	86.9%		98.6%
	FX	6	98.8%	91.6%	102.5%	102.0%	111.3%	90.3%	103.7%	99.0%	100.0%
		7		97.9%		96.4%	96.8%	100.0%	134.2%	135.9%	116.8%
		8		88.6%	114.3%	94.2%	99.8%	88.6%	108.4%	106.3%	100.2%
	EQUITY	9	99.1%	108.6%		105.7%	80.2%	89.9%	106.9%	93.3%	100.9%
		10	100.0%	112.1%		100.3%	95.9%	102.8%	92.8%	96.7%	
		11	100.2%	100.0%		78.8%	37.7%	106.6%		126.1%	88.3%
		12	100.0%	91.8%	106.3%	97.2%	109.7%	106.5%	90.6%	100.3%	94.7%
		13	94.3%	84.1%		100.0%	113.7%	105.5%		75.8%	112.9%
	Diversified	14	31.5%	104.2%	84.9%	167.4%	172.5%	55.0%	94.1%	124.5%	100.0%
		15	267.1%	50.6%	272.9%	46.8%	9.7%	97.4%	127.7%		102.6%
		16	79.5%	79.8%	101.0%	94.5%	106.0%	101.2%		99.0%	101.8%
Margined	IR Ns2	17	96.6%	98.0%	94.8%	95.1%	105.6%	102.0%	158.3%		105.6%
		18	96.6%	98.0%	94.8%	95.1%	105.6%	102.0%	158.3%		105.6%
		19	96.6%	98.0%	94.8%	95.1%	105.6%	102.0%	158.3%		105.6%
	IR Ns1	20	92.5%	93.1%	84.8%	94.1%	129.1%	112.8%	319.0%		105.9%
		21	92.5%	93.1%	84.8%	94.1%	129.1%	112.8%	319.0%		105.9%
		22	92.5%	93.1%	84.9%	94.1%	129.1%	112.8%	319.0%		105.9%
		23	267.1%	10.8%	272.9%	46.8%	9.7%	97.4%	127.7%		102.6%
		24	267.1%	10.8%	272.9%	46.8%	9.7%	97.4%	127.7%		102.6%
	Ns15 (all in IR F	25	267.1%	10.8%	272.9%	46.8%	9.7%	97.4%	127.7%		102.6%

Deviation from the Median: EEPE - *netting sets*

Unmargined	IR	1	106.9%	93.1%	70.3%	65.4%	68.9%	117.8%	157.6%		134.2%
		2	103.7%	94.0%	83.3%	71.4%	104.1%	156.7%	130.3%		96.3%
		3	29.9%	163.8%	36.2%	536.7%	307.4%	4.2%		188.4%	1.4%
		4	100.0%	99.5%	101.5%	94.2%	133.9%	141.2%			99.2%
		5	101.2%	98.8%	87.3%	79.0%	103.5%	129.1%	113.3%		95.0%
	FX	6	88.7%	92.7%	80.5%	78.7%	146.9%	123.8%	110.1%	120.5%	100.0%
		7		147.3%		71.3%	141.4%	90.5%	100.0%	95.5%	115.1%
		8		108.7%	78.9%	80.7%	145.3%	98.3%	96.6%	114.0%	101.7%
	EQUITY	9	15.0%	75.6%		86.0%	373.5%	114.0%	121.9%	290.5%	78.3%
		10	77.9%	100.0%		91.3%	179.4%	91.6%	101.0%	157.4%	
		11	23.0%	81.5%		57.7%	266.9%	161.4%		123.1%	100.0%
		12	100.0%	92.5%	107.1%	97.3%	165.0%	109.8%	94.8%	125.3%	94.7%
		13	77.2%	83.8%		100.0%	259.2%	122.2%		163.2%	98.4%
	Diversified	14	58.8%	86.6%	100.0%	92.3%	182.0%	131.7%	103.5%	131.6%	83.0%
		15	94.0%	112.0%	88.8%	76.6%	133.3%	125.2%	97.0%		103.0%
		16	71.8%	87.7%	83.1%	86.9%	217.9%	114.9%		126.5%	112.3%
Margined	IR Ns2	17	136.8%	79.1%	77.9%	226.9%	100.3%	81.9%	439.4%		99.7%
		18	99.9%	79.3%	89.7%	88.1%	101.3%	100.1%	170.6%		101.1%
		19	1162.7%	37.6%	0.0%	18.5%	465.3%	0.0%	243204.0%		162.4%
	IR Ns1	20	150.5%	80.6%	59.9%	109.5%	90.5%	66.5%	305.8%		146.5%
		21	117.7%	90.4%	85.4%	79.6%	86.8%	114.8%	199.6%		109.6%
		22	419.4%	0.0%	0.0%	0.0%	14.0%	186.0%	333942.9%		715.2%
		23	126.1%	98.1%	90.0%	79.0%	124.6%	96.3%	190.2%		101.9%
		24	109.8%	94.9%	84.7%	78.5%	115.8%	101.4%	151.0%		98.6%
	Ns15 (all in IR F	25	222.0%	77.5%	38.0%	11.0%	302.2%	120.5%	12508.8%		79.5%

Deviation from the Median: SEEPE - *netting sets*

Unmargined	IR	1	207.0%	94.3%	67.0%	80.5%	64.8%	105.7%	157.5%		122.9%
		2	156.5%	90.5%	70.8%	90.8%	91.5%	129.3%	128.6%		108.5%
		3	20.8%	154.2%	28.8%	455.5%	264.0%	3.8%		145.8%	54.2%
		4	90.3%	92.3%	92.7%	100.0%	115.3%	122.0%			101.8%
		5	143.1%	95.3%	77.7%	88.0%	92.4%	142.4%	108.8%		104.7%
	FX	6	43.6%	74.6%	105.9%	93.7%	100.0%	107.7%	117.7%	124.3%	89.5%
		7		126.4%		94.9%	98.8%	100.0%	99.9%	109.7%	106.6%
		8		91.4%	100.7%	100.1%	99.9%	97.8%	102.4%	120.7%	93.7%
	EQUITY	9	11.8%	49.5%		129.6%	163.6%	70.4%	132.3%	285.7%	69.5%
		10	50.8%	58.9%		125.6%	100.0%	48.4%	126.6%	132.8%	
		11	15.1%	54.4%		54.4%	118.0%	101.3%		117.3%	100.0%
		12	77.8%	71.6%	106.2%	92.1%	127.3%	95.4%	100.0%	114.9%	233.8%
		13	53.1%	62.4%		130.0%	163.6%	87.6%		184.9%	100.0%
	Diversified	14	56.7%	78.4%	86.1%	100.9%	125.4%	104.6%	91.9%	113.9%	100.0%
		15	98.4%	100.5%	96.1%	95.6%	102.0%	110.1%	99.5%		106.9%
		16	63.8%	66.7%	74.3%	119.9%	143.6%	87.2%		157.3%	112.8%
Margined	IR Ns2	17	179.6%	75.6%	58.1%	212.5%	82.7%	57.3%	316.6%		117.3%
		18	122.8%	80.9%	87.8%	99.3%	100.7%	97.5%	148.0%		111.0%
		19	1062.7%	10.5%	0.0%	157.9%	42.1%	0.0%	19216.6%		178.4%
	IR Ns1	20	243.5%	81.5%	60.4%	115.9%	84.1%	52.7%	282.2%		133.7%
		21	175.5%	91.8%	84.9%	87.3%	86.9%	117.4%	203.3%		108.2%
		22	239531.1%	0.0%	0.0%	0.0%	200.0%	0.0%	4726021.6%		8874.3%
	Ns15 (all in IR F	23	127.9%	89.1%	100.4%	99.0%	99.6%	95.8%	191.7%		115.9%
		24	122.5%	90.9%	98.4%	98.4%	101.6%	96.9%	167.7%		111.4%
		25	197.9%	58.8%	103.0%	94.8%	97.0%	89.4%	5068.4%		166.1%

CVA

For CVA only ratios below 60% are highlighted

Table 16: Deviation from the median for CVA VaR and CVA S-VaR under fixed EE profile

Deviation from the Median: *CVA VAR (Fixed EE)*

Count. 1	79.6%	100.0%	142.6%	85.7%	82.7%	62.4%	143.6%	161.4%	132.0%
Count. 2	96.9%	88.6%	100.0%	152.6%	131.2%	87.8%	123.7%	141.5%	91.8%
Count. 3	67.2%	104.0%	113.5%	74.9%	45.7%	104.2%	100.0%	201.0%	95.6%
Count. 4	92.7%	104.9%	90.0%	105.2%	70.5%	64.3%	103.7%	117.1%	100.0%
Count. 5	104.5%	100.0%	99.3%	168.1%	91.8%	17.1%	161.2%	50.3%	163.9%
Count. 6	124.8%	100.0%	210.3%	102.2%	79.0%	50.5%	57.9%	124.4%	99.1%
Count. 7	348.0%	112.9%	192.1%	99.8%	55.5%	100.0%	99.0%	48.3%	401.3%
Count. 8	109.1%	118.5%	43.6%	100.0%	92.2%	70.5%	151.8%	136.6%	95.4%
All in	107.6%	116.1%	90.9%	119.2%	94.9%	63.9%	105.0%	100.0%	76.7%
Sub all in	91.6%	107.7%	99.6%	168.5%	113.1%	77.3%	100.0%	126.2%	76.5%

Deviation from the Median: *CVA Stress VAR (Fixed EE)*

Count. 1	38.3%	91.6%	152.4%	54.0%	307.1%	151.1%	100.0%	330.6%	49.6%
Count. 2	85.5%	100.0%	85.8%	85.0%	137.8%	115.3%	92.6%	185.0%	109.7%
Count. 3	36.5%	64.1%	100.0%	39.7%	301.2%	283.6%	101.4%	189.8%	83.2%
Count. 4	75.1%	111.1%	46.9%	97.2%	193.6%	113.9%	100.0%	183.9%	49.2%
Count. 5	104.5%	67.5%	100.0%	95.8%	103.1%	53.7%	47.8%	110.2%	162.5%
Count. 6	83.5%	100.0%	183.4%	29.8%	488.7%	48.7%	111.9%	147.2%	49.9%
Count. 7	192.6%	54.4%	173.9%	82.9%	100.0%	138.8%	68.1%	65.1%	160.4%
Count. 8	90.4%	100.0%	59.8%	85.9%	231.5%	102.5%	194.8%	326.6%	56.3%
All in	102.7%	99.9%	101.1%	68.4%	154.4%	97.3%	100.0%	138.3%	62.4%
Sub all in	76.3%	101.1%	100.0%	87.4%	190.5%	97.0%	103.0%	133.2%	67.1%

Table 17: Deviation from the median for CVA VaR and CVA S-VaR under free EE profile

Deviation from the Median: *CVA VAR (Free EE)*

Count. 1	56.3%	109.5%	112.9%	81.6%	122.7%	97.6%	186.0%	81.3%	100.0%
Count. 2	40.5%	100.0%	78.6%	113.1%	247.4%	184.5%	187.8%	84.4%	88.7%
Count. 3	56.3%	130.3%	100.0%	73.3%	89.9%	291.8%	201.2%	118.1%	86.5%
Count. 4	92.1%	111.9%	82.1%	101.2%	100.0%	126.4%	129.8%	88.4%	97.9%
Count. 5	81.0%	100.0%	77.5%	138.9%	110.2%	12.2%	229.3%	27.1%	133.4%
Count. 6	43.1%	116.6%	110.9%	79.4%	136.0%	100.0%	129.6%	66.3%	85.8%
Count. 7	115.5%	92.3%	105.6%	49.5%	68.2%	130.1%	100.0%	18.3%	235.7%
Count. 8	51.1%	151.2%	38.2%	87.5%	178.5%	154.0%	268.8%	97.4%	100.0%
All in	59.5%	135.8%	75.6%	100.0%	182.2%	137.6%	166.3%	61.6%	75.7%
Sub all in	35.2%	100.0%	63.2%	110.9%	171.2%	135.9%	126.2%	60.1%	60.7%

Deviation from the Median: *CVA Stress VAR (Free EE)*

Count. 1	51.9%	100.0%	95.4%	54.9%	325.8%	217.0%	134.6%	253.1%	43.3%
Count. 2	67.4%	100.0%	54.6%	82.5%	159.4%	151.2%	99.8%	147.6%	106.1%
Count. 3	70.1%	99.6%	91.0%	56.2%	481.2%	590.0%	173.4%	197.3%	100.0%
Count. 4	94.8%	99.9%	40.2%	100.0%	180.3%	193.5%	102.2%	169.3%	47.6%
Count. 5	155.0%	84.3%	82.1%	111.8%	140.7%	37.6%	85.8%	100.0%	165.5%
Count. 6	72.4%	125.4%	109.2%	35.2%	691.4%	81.1%	180.3%	100.0%	50.8%
Count. 7	117.1%	55.5%	100.0%	74.7%	119.6%	180.2%	75.1%	46.7%	136.7%
Count. 8	72.6%	100.0%	37.1%	82.8%	260.0%	143.5%	245.6%	283.2%	54.3%
All in	78.5%	100.0%	57.5%	65.2%	175.3%	128.9%	112.8%	104.0%	49.9%
Sub all in	61.6%	100.0%	53.8%	81.7%	221.4%	131.1%	114.8%	104.0%	52.8%

7.7 CVA VaR levels and ranking

Figure 29: CVA VaR and S-VaR by counterparties under fixed EE profile

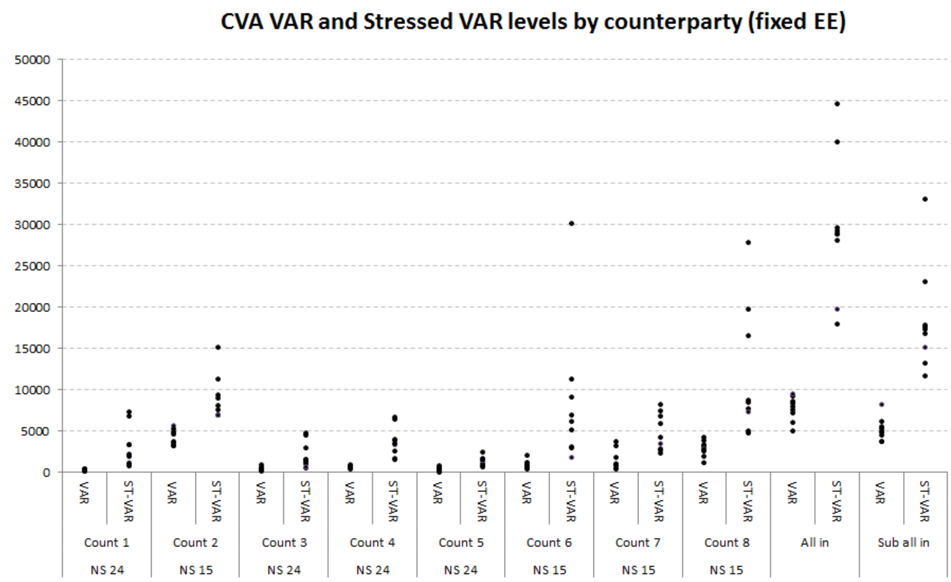


Figure 30: CVA VaR and S-VaR by counterparties under free EE profile

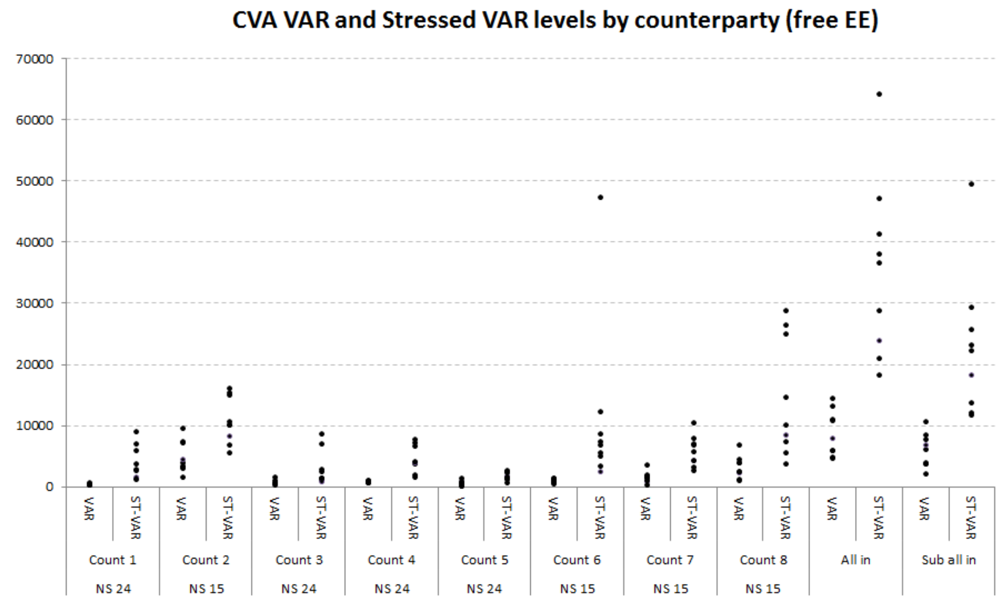
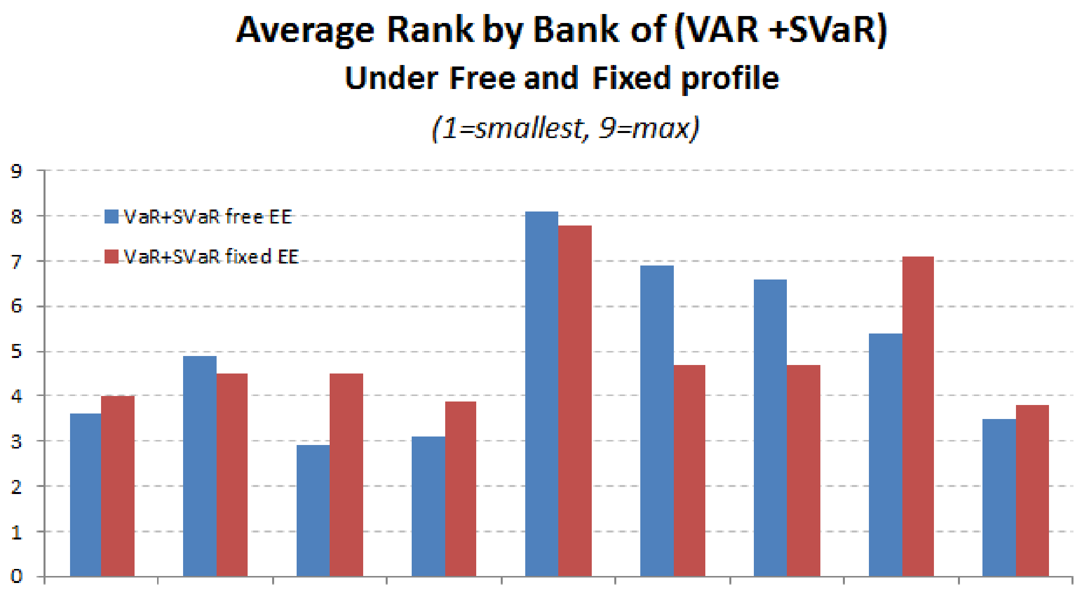


Figure 31: Rank analysis for CVA fixed vs. free EE profile



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