Basel Committee
on Banking Supervision

Regulatory Consistency Assessment Programme (RCAP) – Report on risk-weighted assets for counterparty credit risk (CCR)

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BANK FOR INTERNATIONAL SETTLEMENTS

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Preface

Consistent implementation of the Basel framework is fundamental to raising the resilience of the global banking system, maintaining market confidence in regulatory ratios, and providing a level playing field for internationally active banks. Against this background, the Basel Committee on Banking Supervision (the Committee) is examining the consistency of the regulatory implementation of the Basel III framework and of the calculation of risk-weighted assets (RWA) by banks as part of its Regulatory Consistency Assessment Programme (RCAP).

At the end of 2014 the Basel Committee conducted a hypothetical test portfolio exercise (HPE) to examine variability in banks' modelling of derivatives, and specifically in exposure modelling.[1] This is the first HPE by the Basel Committee that focuses on Counterparty Credit Risk (CCR) RWA and so covers the Internal Models Method (IMM) and advanced Credit Valuation Adjustments (CVA) risk capital charge for "over-the-counter" (OTC) derivative trades.[2] This HPE follows two earlier exercises that focused on market risk RWA and which were published in January and December 2013.[3] Similarly as in the previous exercises, the quantitative HPE results in this study were supported by qualitative questionnaires on modelling practices.

Nineteen banks from 10 jurisdictions participated in the exercise; all banks are internationally active and have substantial trading activities. Six participating banks received an on-site visit by a team of supervisors. This allowed for a deeper understanding of the observed variability and identification of the key drivers.

The analysis used relatively simple "plain vanilla" hypothetical OTC derivative trades that allow testing for the impact of differences in modelling by controlling for portfolio composition while keeping the analysis tractable. It should be emphasised that the quantitative analysis is based on *hypothetical* portfolios only and therefore shows *potential* variation, not actual variation across banks. Also, no attempt was made to determine the appropriate or acceptable level of variation across banks. Similarly, no attempt was made to judge the appropriateness of banks' modelling choices or to assess the compliance of approaches taken in the various jurisdictions with the Basel standards.

The Basel Committee wants to thank the participating banks for their responses and willingness to engage with the analysis team in discussing the results of the exercise. The feedback and responses substantially helped to foster the Committee's understanding of the drivers of variability across banks and to identify potential areas where consistency in CCR modelling practices and supervisory approaches may be improved. This also allowed scope for highlighting observed good practice in both the IMM and CVA areas.

Chapter 1 presents the key findings and lists a number of policy recommendations and observed sound practices that the Basel Committee may consider when seeking to mitigate the variability in outcomes for the Basel capital standards.

1 It is noted that the findings are also relevant for derivative positions that are held in the banking book of banks.

2 The IMM is also applicable to securities financing transactions (SFTs), while the CVA may be applied to SFTs when the supervisor deems CVA loss exposures arising from SFTs to be material. For purposes of this first CCR HPE, however, SFTs were excluded from the scope of the exercise, but may be included in future HPEs.

3 See www.bis.org/publ/bcbs240.pdf and www.bis.org/publ/bcbs267.pdf.

Executive summary

This report covers internal models for counterparty credit risk (CCR), which constitute the last part of trading-related internal models to be studied by the Basel Committee. The report follows previous reports on internal models for market risk, including VaR and stressed VaR, and models for the incremental risk charge (IRC) and comprehensive risk measure (CRM). The objective of the report is to analyse the variability of regulatory outcomes, to highlight good practices and to identify areas where additional attention from banks and supervisors is required to mitigate unwarranted RWA variability. In this regard, an important aim of the report is to support banks and supervisors in the implementation and supervision of CCR models.

CCR models are relatively new to the Basel framework (Basel II for IMM and Basel III for CVA risk capital charge) and generally viewed as complex models that require substantial development effort and the availability of sophisticated IT systems. These models are predominantly applied to OTC derivative transactions and securities financing transactions (SFTs).

The analysis in this report shows considerable variability in the outcomes of CCR models. The variability is typically somewhat higher for CVA models than for IMM models. Overall, the level of variability is broadly similar to the variability of other market risk model outcomes observed in previous exercises. Key drivers for the variability include differences in banks' modelling choices, as well as differences in supervisory practices.

The report lists a number of observed good practices and identifies areas where banks and supervisors may seek to harmonise practices to reduce variability in outcomes. Additionally, the Basel Committee is considering whether it may be necessary to narrow down certain modelling choices for banks and/or harmonise supervisory practices to enhance consistency in outcomes. In this regard, it is expected that the fundamental review of the trading book and in particular into the review of the CVA risk capital charge, will mitigate some of the observed variability in regulatory outcomes for counterparty credit risk.

Chapter 1: Introduction and overview of results

1.1 Introduction and rationale for exercise

Previous trading book HPEs looked at banks' modelling of market risk. For instance, banks that trade in interest rates (IR), equities (EQ), foreign exchange (FX) or commodities are exposed to market risk, which is capitalised through value-at-risk models (VaR) under the current Basel framework.[4] However, OTC derivative instruments, such as options, swaps and forwards, expose banks to counterparty risk in addition to market risk. Counterparty credit risk is the risk that a counterparty will default before the final settlement of the transactions' cash flows and cause a loss to the bank if the transaction has a positive economic value at the time of default.[5]

As derivatives can fluctuate strongly in value, depending in part on changes in the value of the underlying reference instrument, the potential exposure of the bank to its counterpart can change considerably over the life of the contract. The Basel framework requires banks to estimate the expected exposure on the counterparty at different time steps for the life of the derivative contract. This time profile of expected exposure feeds into the CVA VaR and into the exposure at default (EAD), which is used for calculating the default risk capital charge for counterparty credit risk (CCR).[6]

The Basel framework offers different approaches to estimate the expected exposure for OTC derivatives and SFTs. This report focuses on the Internal Models Method (IMM), which is mainly used by large advanced banks with substantial trading activity. The IMM typically uses several market risk factors, including measures of historical or implied volatilities, to simulate market data in the future and estimate the bank's expected exposure to the counterparty.

Following the financial crisis, the Basel Committee substantially reformed the measurement of CCR, including a new risk capital charge for credit valuation adjustments (CVA). As a result, banks are required to calculate the following separate capital charges for counterparty credit risk:

1. Credit risk related to the risk of a default of the counterparty: the capital charge for counterparty default risk is based on either the Internal Ratings-Based (IRB) approach, or the Standardised Approach. Both approaches require an estimate of the exposure-at-default (EAD)

[4] Note that the fundamental review of the market risk framework proposes expected shortfall (ES) as the new metric of the capital charge for market risk.

[5] Unlike a bank's exposure to credit risk through a loan, where the exposure to credit risk is unilateral and only the lending bank faces the risk of loss, CCR creates a bilateral risk of loss: the market value of the transaction can be positive or negative for either counterparty to the transaction. The market value is uncertain and can vary over time with the movement of underlying market factors.

[6] Starting from the current market value of a trade, a number of scenarios for market risk factor developments lead to MtMs for a trade at each future time step in the simulation. Netting of the trades belonging to one netting set gives a distribution of potential exposure values of the netting set at each time step. The expected exposure (EE) is the mean (average) of this distribution at any particular future date. This is done up to the longest maturity of transactions in the netting set and provides the EE time profile of the netting set over its life time, which is used for the CVA VaR calculation.

The EEs over the one-year horizon are monotonised to derive the effective expected exposure (EE), ie the effective EE can only increase starting from t_0. The effective expected positive exposure (EEPE) is then the time-weighted average of effective expected exposure over the first year, or, if all the contracts in the netting set mature before one year, over the time period of the longest-maturity contract in the netting set.

For further information see Basel II Annex 4, paragraphs 25–33.

to calculate the risk-weighted assets (RWA). Additionally, the IRB approach requires estimates of probabilities of default (PD) and loss-given-defaults (LGD) (for advanced IRB only). For derivatives and securities financing transactions, the EAD can be calculated based on IMM, which is the focus of this report. In this regard, the analysis complements earlier work by the Basel Committee on the variability of PD and LGD estimates, published in July 2013.[7]

2. Market risk of the expected loss related to changes in creditworthiness of the counterparty: the CVA risk capital charge estimates the capital needed to cover for fair value variations of CVA stemming from changes in the creditworthiness of the relevant counterparties. Under the advanced CVA approach, time profiles of expected exposures (EE) from the IMM model are fed into the bank's specific risk VaR model. Alternatively, banks can use a standardised CVA risk capital charge which is based on a regulatory formula. Banks can use the EAD from the IMM also for the standardised CVA charge.

For many large, internationally active banks the CVA risk capital charge is a relatively new and material component of the capital requirements. A comprehensive analysis of the potential variability of CCR-related RWA therefore requires an assessment of both IMM and CVA VaR models.

1.2 Overview of the hypothetical portfolio exercise structure

The test portfolio exercise which forms the basis of the analysis in this report covered the following counterparty credit risk internal models:

- IMM model, including measures for expected exposure (EE) and effective expected positive exposures (EEPE) and their stressed measures (stress EE and stress EEPE); and
- CVA model, including both CVA VaR and stressed CVA VaR (CVA sVaR).

Different hypothetical derivative trades were constructed that were submitted to participating banks. The trades were also combined in various hypothetical netting sets, ie combinations of derivative trades with a single counterparty under which close-out netting is applicable. For some of the netting sets, assumptions were made with regard to different collateralisation practices. The hypothetical trades and netting sets were kept relatively simple to keep the analysis tractable.

Regarding the analysis of the CVA risk capital charge, banks were asked to calculate the charge for a subset of hypothetical netting sets for eight different counterparties. Banks were asked to calculate the CVA risk capital charge both using internally estimated EE profiles and a "standard" EE profile that was provided to all participating banks.

1.3 Key findings on variability – IMM

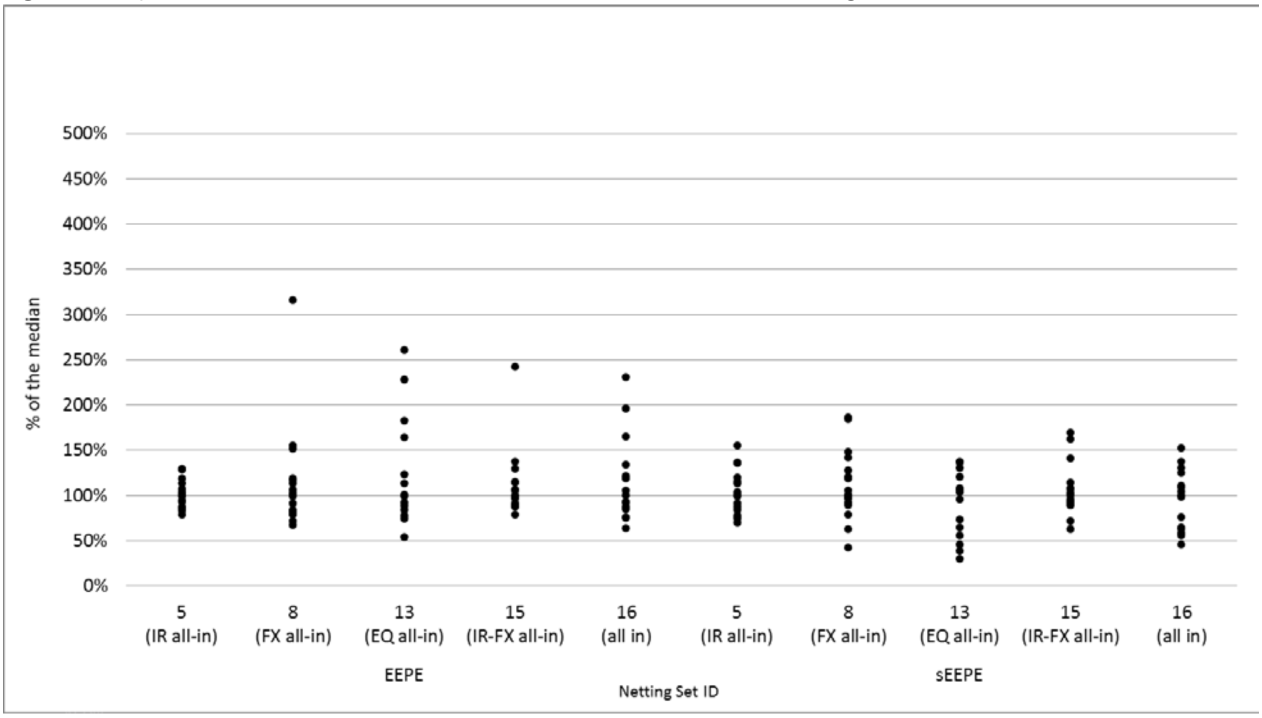
1.3.1 Key findings on the level of variability

Overall, the relative variability for IMM appears to be considerable and roughly comparable to the variability observed in previous studies for market risk models. While for individual derivative trades the variability in EEPE values can be substantial, for baskets of trades in more diversified and realistic netting sets the variability is typically lower and most banks are between 50% and 150% of the median (see figure below). This suggests that wide variation for individual trades does not necessarily compound

[7] www.bis.org/publ/bcbs256.pdf.

when trades are combined in netting sets. Rather the variability falls as idiosyncratic issues become less prominent.

Figure 1: Dispersion from the median of EEPE and stressed EEPE for all-in netting sets (each dot is a bank).



1.3.2 Key drivers of variability

It is important to emphasise that the Basel standards deliberately allow banks and supervisors some flexibility in measuring risks in order to accommodate differences in risk appetite and local practices, but with the goal of also providing greater accuracy. Some variation in EE and EEPE should therefore be expected. The following key drivers were identified for IMM models:

Drivers resulting from banks' modelling choices

- Risk factor modelling: the outputs of IMM are based on the simulation of market risk factors that drive the market values of the OTC derivatives and SFT portfolios. For this purpose, banks have to decide which risk factors to use and which probabilistic distribution to choose per risk factor. Furthermore, risk factors can be simulated on a standalone basis or simultaneously with a correlation structure between each other. Although it was not possible to conduct a comprehensive analysis on each and every modelling assumption, based on expert judgment and discussions with the participating banks, risk factor modelling is considered a key driver of variability.
- Risk factor calibration: the majority of participating banks base the calibration of risk factors on historical market data, while a minority uses a calibration based on market-implied data. From discussions with the banks, it emerged that the choice of calibration approach, particularly the use of historical vs implied volatilities, can be an important driver of variability. Furthermore, this choice can drive other modelling assumptions and characteristics of parameters (eg the drift) used in the IMM and result in further variability due to these assumptions.

- Frequency of calibration for EEPE based on current market data: the Basel framework requires banks to update the data and recalibrate the IMM on at least a quarterly basis. The majority of banks reperform the calibration for the current EEPE on a more frequent basis. The analysis shows strong statistical evidence that banks that recalibrate their model more frequently are clustered together more closely than banks that recalibrate less frequently, particularly for FX and equity trades. Recalibrating models more frequently reduces the time for model results to drift apart. Note that the frequency of calibration is related to an advanced use test interpretation that requires, for sound risk management, up-to-date model parameters, eg for volatilities and correlations.
- Determination of the stressed period to calibrate the stressed EEPE: a wide variety of practices and methodologies to derive the stressed period is observed across participating banks. The Basel framework requires that the stress period coincides with a period of increased credit spreads for a representative selection of the bank's counterparties. While the stress period can thus be different for each bank, certain stress periods appear to lead to more conservative outcomes than other stress periods. Roughly speaking, banks select – based on their counterparties – either the 2008–09 stress period or the 2011–12 stress period. In general, banks that select the 2008–09 stress period show the most conservative stress exposure. This suggests that this period of increased credit spreads coincides with a stress period for the most relevant market risk factors used typically in the IMM. Given the variety of methodologies used, this is worthy of further investigation by supervisors.
- Number of scenarios: a wide range of practices is observed across participating banks: from 1,000 up to 10,000 scenarios. The analysis shows that dispersion is typically somewhat lower when the number of scenarios is 5,000 or higher.
- Granularity for the number of time steps: the time grid used to calculate future mark-to-market values (MtMs) of the portfolio is relevant for both the EEPE calculation and the EE profile that is used to calculate the CVA risk capital charge. The former is based on the grid points over the one-year horizon, whereas the latter requires a grid of time steps over the whole time horizon up to the latest trade maturity. For the sake of simplicity, the focus of the analysis is on the EEPE calculation. The results show more variability for a denser time grid, as the higher number of time steps generates more data points with a higher possibility for more variable EEPE outputs. In this case, the more granular modelling choice leads naturally to more variable results.
- Modelling margining: overall, the introduction of margining leads to a mitigating effect on the EAD of margined netting sets as compared with the unmargined netting sets. However, when analysing the modelling of cash flows, as distinct from margin calls, during the margin period of risk (MPoR) clear evidence was found that the EEPE is more conservative when cash flow payments are modelled in the MPoR and the resulting collateral spikes feed into the EE profile. Collateral spikes are exposure spikes that occur after the settlement of large outgoing cash flows due to a delay before the offsetting margin is received.[8] The important finding is that banks apply different approaches to the modelling of MPoR and thus implement the requirements differently, leading to variability in results. The collateral spikes should be considered as part of counterparty credit risk modelling and not be treated as settlement risk,

[8] The inclusion of potential collateral spikes in IMM propagates via effective EPE (monotony operator) into a relatively high EAD, especially if the spikes occur early in the first year.

given that the variation margin payment does not belong to transaction cash flows. The Basel treatment of settlement risk therefore does not apply.[9]

- Pricing functions: the IMM engine needs to integrate a library of pricing functions to reprice the derivatives/SFT portfolios for each scenario and at each time step. Some of the banks have rebuilt or exploited existing front office pricing models. Other banks use (partially) simplified algorithms reducing the time required to run the exposure calculation. Although the implementation of different pricing functions in front office systems and the IMM does not seem to be a strong driver of variability, it is observed that most of the banks have put in place quality checks to ensure that the pricing functions under the IMM are broadly in line with front office pricing.

The exercise also found that some modelling choices lead to more conservative outcomes than others. However, in most cases, this result is due to the nature of the portfolios tested (hypothetical portfolios comprising simple long and short positions) and each choice could be aggressive or conservative for different portfolios and market conditions. The important result is to highlight areas of flexibility in rules that drive variation rather than to identify which choice is the most prudent.

Drivers resulting from supervisory practice

- Regulatory multiplier "alpha":[10] while banks are allowed to model their own alpha, most banks apply a regulatory alpha of 1.4, the default value for alpha. Three banks are subject to a higher alpha set by their supervisory authority, while only one bank is modelling and using its own alpha estimation. When aligning the alpha for all banks to 1.4, the variability across banks does not notably change. The scope for supervisors to increase alpha takes into account any weaknesses in banks' IMM and gives banks an incentive to improve the risk sensitivity and general adequacy of their internal models and processes.

1.4 Key findings on variability – CVA

1.4.1 Key findings on the level of variability

Overall, the variability for CVA also appears to be considerable and generally somewhat higher across banks than for IMM. Variability in CVA results can be attributed both to variation in exposure modelling – EE profiles that are produced by the banks' IMM models – and to variation in credit modelling – the way banks model CVA risk based on available credit spread curves, LGDs and their proxies. Variation in exposure modelling and variation in credit modelling appear to make comparably sized contributions to the overall variability of CVA VaR.

1.4.2 Key drivers of variability

Drivers resulting from banks' modelling choices

- Choice of stress period for stressed CVA: the participating banks fall broadly into two groups regarding the stress period selection: one group that applies 2008–09 data to calculate the stressed CVA VaR and one that applies 2011–12 data. The group using 2008–09 data reported

[9] The treatment of settlement risk is provided in Annex 3 of the Basel framework.

[10] When using IMM, the EAD is calculated as the product of alpha times EEPE.

generally more conservative stressed CVA VaR numbers. The Basel framework requires banks to use a stress period that falls within the stress period selected for the stress EEPE calculation. Therefore differences in stress period selection for EEPE feed into the stress period selection for CVA.

- Differences in the modelling of proxy spreads: for counterparties without CDS, or without liquid CDS, banks use proxy spread methodologies to generate times series of credit spreads required to compute the CVA VaR. Differences across methodologies result in differences in CVA outcomes. For some counterparties, banks were found to disagree on the existence of a single-name liquid CDS, resulting in some banks using a proxy methodology and other banks using a single-name CDS. But more analysis is needed to better understand how these differences in approaches might affect RWA variability.
- Modelling of basis risk in CVA VaR: some participating banks do not model the basis between a name and its corresponding proxy, while other banks take basis risk into account using simple methods.
- Differences in VaR modelling: earlier Committee reports on risk-weighted assets for market risks identified important drivers for variability in VaR model outcomes, including partial vs full repricing, historical simulation vs Monte Carlo, use of overlapping 10-day periods vs 10-day scaling.[11] In principle, such differences in VaR methodology might also lead to variability in CVA VaR. In this exercise, however, these potential drivers were not found to contribute to variability of CVA VaR.

Drivers resulting from supervisory practice

- Regulatory multiplier differences: for most banks the regulatory multiplier for CVA VaR is set at the minimum of 3. Only one bank in the sample used a different multiplier. As such, variability in regulatory multipliers does not appear to play an important role but may be a potential driver for variability of CVA results.

1.5 Observed good practice and areas for further attention

The findings highlight certain areas where banks and supervisors may focus their attention and harmonise practice to reduce variability in CCR models' outcomes. To help banks and supervisors in their implementation and supervision of these models, a number of good practices are listed below. Additionally, a number of areas were identified that the Basel Committee intends to further investigate with a view to narrowing down unwarranted variability. In this regard, the fundamental review of the trading book and, in particular, the review of the CVA risk capital charge are expected to mitigate some of the observed variability in outcomes and to enhance the consistency across banks in RWA measurement.

1.5.1 Good practice in the area of IMM

The following good practices were identified with the aim of supporting banks and supervisors in the implementation and supervision of IMM models.

[11] See www.bis.org/press/p130131.htm and www.bis.org/publ/bcbs267.htm

1. Consistency between front office pricing and IMM pricing: most of the participating banks have put in place some automatic checks to ensure that the current mark-to-market value (MtM) calculated under the IMM is consistent with the current MtM calculated by front office systems (often using thresholds based on absolute or relative notional values). It is considered good practice to look at such differences on a trade rather than netting set level, as unwarranted MtM differences may cancel inside a netting set. If a trade fails this check, the trade should be reverted to the standard approach, ie carved it out of its netting set. Although there is no strong statistical evidence that such check would lead to less variability in the RWA outcomes, it is considered good practice to ensure data quality.

2. Determination of the stressed period to calibrate the stressed EEPE: the Basel framework requires that the stressed period used to calibrate the stressed EEPE measure coincides with a period of increased CDS or other credit spreads for a representative selection of the bank's counterparties with traded credit spreads. This requirement was intended to implicitly capture wrong-way risks, ie a positive correlation between the deterioration of a counterparty's creditworthiness and the increase of an institution's exposure to this counterparty. Various practices were observed across participating banks for determining this stressed period. While the Basel framework explicitly allows some flexibility in determining the stress period, supervisors should critically review cases where banks report very low (or very high) ratios of stressed EEPE to EEPE. Illustrative benchmark ratios are provided in Section 3.4.2.4 of this report.

3. Granularity of time steps: the Basel framework does not set a minimum number of time steps for IMM. Since a wide range of choices was observed amongst participating banks, banks should demonstrate to their supervisor that the selection of time steps results in appropriate exposure estimates. This would require a check that a bank's exposure estimate closely resembles the exposure estimates obtained by a denser (or even daily) time step selection. If the bank fails this test, it should improve its time step selection process, eg by increasing the number of time points or by implementing a dynamic allocation matching maturing trades and significant intermediate cash flows.

1.5.2 Areas for further attention

The following areas highlight aspects of IMM modelling where the close attention of banks and supervisors is warranted when implementing and supervising IMM models. Additionally, the Basel Committee intends to review these areas to see whether policy recommendations may be formulated to further narrow down variability and to harmonise supervisory practices.

1. The frequency of recalibration for EEPE based on current market data: the Basel framework requires banks to recalibrate the EEPE measure based on current market data on at least a quarterly basis (see revised para 61 in Basel III). The analysis shows strong statistical evidence that banks which recalibrate their model more frequently are clustered more closely together. Therefore, increasing the recalibration frequency will result in better data quality, more exposure stability and less variability. Since most of the banks can and do reperform a calibration on a more frequent basis (sometimes daily), it is recommended that the minimum frequency of recalibration is increased to the same frequency as the EEPE recalculation and link it more closely to the regular risk management purposes as part of the use test. Additionally, it is recommended that the use of the latest available data is required.

   The IMM recalibration frequency also affects the CVA risk capital charge calculation as the CVA capital formula includes a 60-business day average (see Section 1.5.2).

2. Minimum number of scenarios: the Basel framework does not set a minimum requirement for the number of scenarios under the IMM. Half of participating banks apply 1,000 scenarios and half apply a greater number of scenarios (from 2,000 to 10,000). The group of banks that use

5,000 or more scenarios appear to generate less variable results than the group using fewer scenarios. The variability also seems to depend on whether the respective netting sets are margined or not. Based on this finding, it is recommended that banks using fewer than 5,000 scenarios should demonstrate that fewer scenarios do not alter the convergence of the EEPE measure. Furthermore, it is recommended that supervisors check that increasing the number of scenarios does not come at the cost of eg simplifying the pricing methodology used for IMM or the granularity of the simulated time points.

3. Modelling of margining mechanisms: modelling margin mechanisms under the IMM is complex and will become of paramount importance once the forthcoming clearing and margining requirements enter into force. As the Shortcut Method will be removed from the Basel Accord, institutions using the IMM will all be required to model margin mechanisms with a full simulation or, if they are not permitted to do so, use SA-CCR. Banks that already model margin mechanisms with a full simulation are currently using different assumptions and approaches to model the exchange of collateral in the future and whether any settlement cash flows (different from margin cash flows) are exchanged during the MPoR. A high variability of outcomes is observed due to these different modelling assumptions. It is recommended that supervisors closely monitor the modelling of margin mechanisms under the full simulation approach. In this regard, the Basel Committee is examining if additional specification can be developed concerning the modelling of the MPoR, and the associated potential cash flows. In particular, the Basel Committee is reviewing the cash flow-driven exposure spikes that may occur in the modelling of MPoR. These spikes should be considered as part of counterparty credit risk modelling and not as part of settlement risk.[12]

Further, it is observed that the internal modelling of the "alpha" multiplier – a regulatory multiplier that is by default set to 1.4 but could be lowered to 1.2 if the bank has modelling approval – is complex and can add modelling risks to the calculation of regulatory capital requirements. Only one participating bank had supervisory approval to model alpha. The Basel Committee is considering removing the discretion to model alpha, which could decrease the complexity of the Basel framework at seemingly low cost.

1.5.3 Good practices and areas for attention for CVA

The following good practices and areas for further attention have been identified for consideration by banks and supervisors.

1. Stress period selection: various practices were observed that potentially lead to unwarranted variability in CVA VaR results. As for IMM, supervisors are encouraged to investigate cases where banks show very low or very high ratios of stressed CVA VaR to CVA sVaR – supervisors should request that banks provide adequate information on the methodology by which the stressed period is chosen, including the overall validation of this methodology. In this regard, supervisors should pay particular attention to the selection methodology when the selected period does not contain any data from Q2 2008 to Q2 2009.

2. Usage and derivation of proxy spreads: the choice to use a proxy spread and the modelling approaches for multi-name proxies can vary significantly across banks. The Basel Committee

[12] Collateral spikes resulting from settlement cash flows are not a settlement risk as the variation margin payment does not belong to transaction cash flows. The Basel treatment of settlement risk (see Annex 3 of the Basel framework) does not apply.

intends to review if further guidance and/or additional regulatory minimum requirements are needed to harmonise approaches across banks. Examples may include:

- Introduction of certain quality criteria about the liquidity of the CDS to determine if a CDS could be used directly in the VaR calculation (eg at least three contributors).
- To further clarify the acceptability of proxies depending on the degree of relationship to the counterparty (parent/child or larger) or on the difference in ratings (eg a difference of less than two notches).
- Provide additional guidance for modelling multi-name proxies (intersection, cross-section or regression methods), and provide clarity about what are the acceptable approximations for these methods (eg in case of subcategories of names with insufficient data for the intersection method).

3. Modelling basis spread: it is recommended that banks model an idiosyncratic factor in the time series for each counterparty when spreads are proxied. This idiosyncratic factor should ideally be a random variable. Tests on liquid names may be made in order to check if the multi-name proxies including basis risk give similar results as a direct approach.

1.6 Limitations of the exercise

Given the limited number of banks participating in the exercise, the statistical evidence of some findings may be challenged. To mitigate this, the quantitative analysis was supplemented by qualitative analysis and expert judgment throughout the exercise.

In order to limit the burden for banks in running the exercise, a single set of HPE results based on banks' current model settings was requested. Therefore, it was not possible to isolate the relative importance of each driver of variability, which would have required HPE results under prescribed settings that all banks would have used (eg given stressed period, given number of scenarios etc). The assessment of the importance of each variability driver may suffer from the distortion produced by observing the effects, potentially opposite, of all the variability drivers at the same time.

For the sake of simplicity and practicality, the stylised netting sets designed for this exercise include only a small number of trades. This naturally means that the results can only indicate potential levels of variability in RWAs rather than the variability of RWAs for actual netting sets held by participating banks. In addition, the section of the analysis that focuses on the variability of banks' IMM results does not integrate an analysis of the variability of banks' RWA for counterparty default risk, otherwise it would have also required risk weights for hypothetical counterparties computed by banks according to the credit risk framework. The variability of counterparty default risk RWA of banks using both the IMM and an IRB approach for credit risk could be broadly assessed by combining the results of the Basel Committee exercises on the banking book and the results of this exercise.[13]

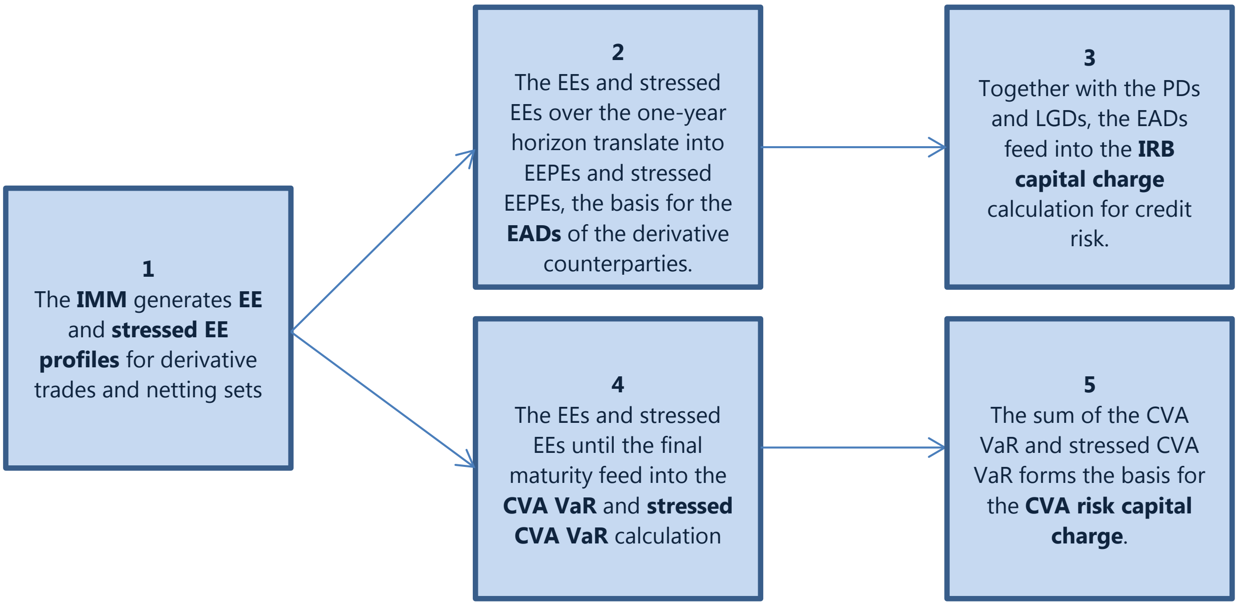
[13] For the SIGBB study see www.bis.org/press/p130705.htm.

Chapter 2: Scope of exercise and sample of banks

2.1 Scope of exercise

The exercise covers two regulatory models: (i) IMM models and (ii) CVA models. Both models generate outputs that are used in the calculation of CCR risk-weighted assets and so form building blocks of the RWA calculation.

The following flow chart provides a simplified illustration of the building block calculations for counterparty credit risk RWA. The focus of the exercise is on the IMM model (block no 1) and the CVA models (block no 4). Note that banks can also use the standardised approach for credit risk, instead of the IRB approach (block no 3).



2.2 Sample of banks

Participation in the exercise was voluntary, and was targeted at banks with significant trading books that have either already obtained or are close to obtaining approval for taking the internal models approach under Basel III for calculating regulatory capital requirements. As such, most participating banks were G-SIBs. However, some banks from countries with no G-SIBs were also included in the exercise on the basis of the materiality of their trading activities relative to that of their domestic peers. Overall, the range of banks included in the exercise provided significant coverage of the jurisdictions in which banks with large trading books operate.

Overview of participating banks per jurisdiction — Table 1

Country	Number of banks participating in EEPE exercise	Number of banks participating in CVA VaR exercise
Belgium	1	0
Canada	1	1
France	2	2
Germany	2	2
Italy	2	2
Japan	1	1
Netherlands	1	1
Switzerland	2	2
United Kingdom	2	2
United States	5	3
Total	19	16

In addition to running their models on the test portfolios and submitting results, participating banks were requested to complete qualitative questionnaires. The questionnaires have provided qualitative information on the methodology applied in banks' models to support the analysis of the quantitative results.

Following the receipt of completed questionnaires and test portfolio results, a sample of participating banks was selected to receive an on-site visit. On-site visit teams included typically six foreign supervisors in addition to a host from the home supervisor. The on-site visits provided an opportunity to gain a deeper understanding of the bank's submitted test portfolio results and associated qualitative questionnaires to help identify the key reasons for differences in results.

The test portfolio exercise ran from October 2014 till February 2015. The follow-up on-site visits included six banks and took place in March 2015.

2.3 Quality control and outlier analysis

Considerable time was spent to ensure high-quality data submissions by participating banks. High-quality data is important to mitigate any variability caused by operational errors, including misspecification of the hypothetical trades or booking errors, which could distort the analysis of key drivers. The following steps were taken for quality assurance:

1. Extensive booking instructions and trade specifications were prepared and discussed in-depth with the participating banks before the start of the exercise;
2. Banks were requested to submit the initial market values (IMVs) of the hypothetical derivative trades. Discrepancies in IMVs across banks were carefully checked and feedback to banks was provided to correct bookings where necessary;
3. A separate Q&A process was set up to promptly address questions from banks regarding the trade specifications of the hypothetical trades and nettings sets to ensure consistency in the booking of trades;

4. A second round of checks was performed based on the submitted IMV and HPE results. The preliminary HPE results were also shared with the participating banks to cross-check once more and eliminate any remaining booking errors; and,

5. Trades with IMVs more than two standard deviations away from the mean sample IMV were manually reviewed and removed from the analysis.

Overall, the resulting data set is of high quality and the observed variation in EEPE and CVA measures is considered a fair reflection of the potential variability caused by differences in internal modelling across banks. The variability caused by operational errors or inadvertent mistakes in the booking of trades is considered minimal due to the extensive efforts in analysing trade bookings and data quality control.

Chapter 3: IMM – Analysis of exercise results

3.1 Analysis methodology

The analysis focused on identifying the possible key drivers of IMM variability, and on assessing the impacts of these drivers in terms of risk measure. The analysis is based on three data sources: the IMM HPE results, the information from qualitative questionnaires provided by the participating banks about the assumptions and the settings of their IMM, and on-site visits to a number of banks to discuss the results in more detail.

Nineteen banks participated in the HPE. Participating banks provided non-stressed and stressed EEPE results for different trades and netting sets. The HPE include seven stylised interest rate trades, four stylised FX trades, and seven stylised equity trades. These were used to form 13 stylised single asset class unmargined netting sets, three stylised multi-asset class unmargined netting sets and nine stylised margined netting sets. The hypothetical trades were designed to reflect simple and common structures used by market participants. Simple trades are useful to isolate key drivers of variability across banks and to keep the analysis tractable, but do not necessarily reflect realistic derivatives portfolios that are often much more complex. The results therefore indicate potential variability across banks and not actual variability.

Throughout this chapter, results are presented as anonymised scatter plots and, unless stated otherwise, results have been normalised so that the plots represent the dispersion from the median value for each trade or netting set (ie the median value of each vertical plot area is 100%). Data points which are beyond the scale of the graph are highlighted in red and their values listed below the graph.

3.2 Test portfolio description

3.2.1 Test trade description

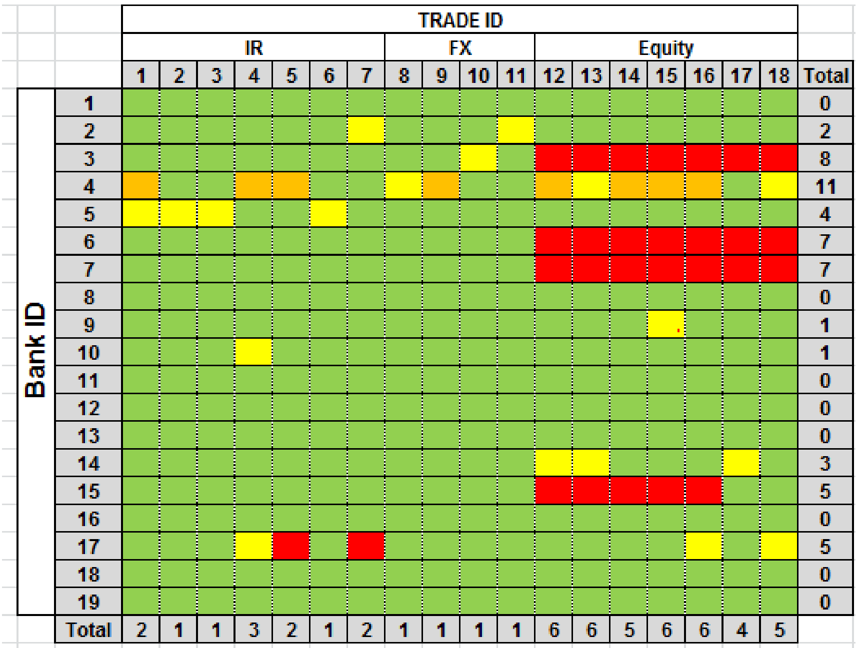
There were 18 stylised trades in the IMM part of the HPE. All the trades are based on a one million notional, expressed in the currency of each trade,[14] except for trade number 8 which is based on a two millions notional, expressed in the currency of this trade (see Annex 1).

As indicated in Section 2.3, extensive data quality checks were performed to ensure that participating banks consistently booked the stylised trades and netting sets. Some submissions were removed from the analysis based on the following criteria:

- Obvious booking errors (eg use of wrong base currency),
- Initial market values of the trades that lie beyond two standard deviations of the median value IMV (after removing the obvious booking errors). Note that this criterion was not applied to trade no 10, for which the median value was very close to zero.

The following table provides a granular breakdown of the resulting data used for the analysis. It shows for each trade which data points were removed and for what reason.

[14] For interest rate or FX swaps denominated in two currencies (eg basis swaps, cross-currency swaps), the one million notional is expressed in one of the two currencies, used as the reference currency. The notional of the other leg is corresponding to this amount converted into the currency of this leg.



Breakdown of trade data used in HPE — Table 2

	Data included in analysis
	No results submitted
	Data excluded from the analysis because obviously wrong base currency
	Data excluded from the analysis because beyond two standard deviations

3.2.2 Test netting set description

There were 25 stylised netting sets in the IMM part of the HPE. Each netting set was structured as a combination of two or more of the stylised trades that have been defined for the exercise. The netting set submissions have been requested in different "base currencies" into which all the stylised trades contained in the netting sets should be converted (see Annex 2).

Similarly as with the stylised trades, and using the same exclusion criteria, extensive data quality checks were performed to ensure that the netting sets were booked correctly. A granular breakdown of the data used for analysis can be found in the following table. It shows for each netting set which data points were removed and for what reason.

	Netting Sets																									
	IR					FX			Equity					Diversified			Margined									
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	Total
Bank ID 1																										0
2																										1
3																										8
4																										14
5																										5
6																										15
7																										9
8																										0
9																										1
10																										0
11																										0
12																										0
13																										0
14																										2
15																										4
16																										1
17																										14
18																										3
19																										0
Total	1	1	2	3	2	1	2	1	5	5	5	4	5	1	2	4	3	3	5	3	3	5	3	3	5	

Breakdown of netting set data used in HPE — Table 3

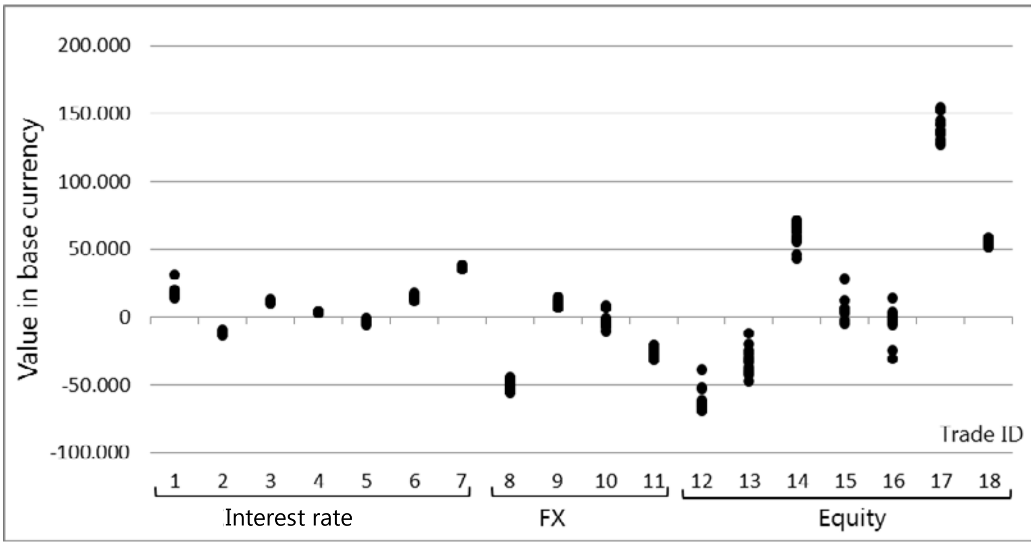
(green)	Data included in analysis
(red)	No results submitted
(yellow)	Data excluded from the analysis because beyond two standard deviations
(blue)	Data excluded from the analysis because incorrect margin features

3.3 Comparison of variability across the portfolios

3.3.1 Comparison of variability across trades

The figure below shows the absolute dispersion of initial market value for each of the stylised trades, expressed in their respective base currency. Overall, IMV variability is relatively low for all three asset classes, with the lowest variability for interest rate trades. The variability for equity trades is somewhat higher and may be the result of differences in the pricing convention for equity forwards, which tend to be less commonly traded by banks.

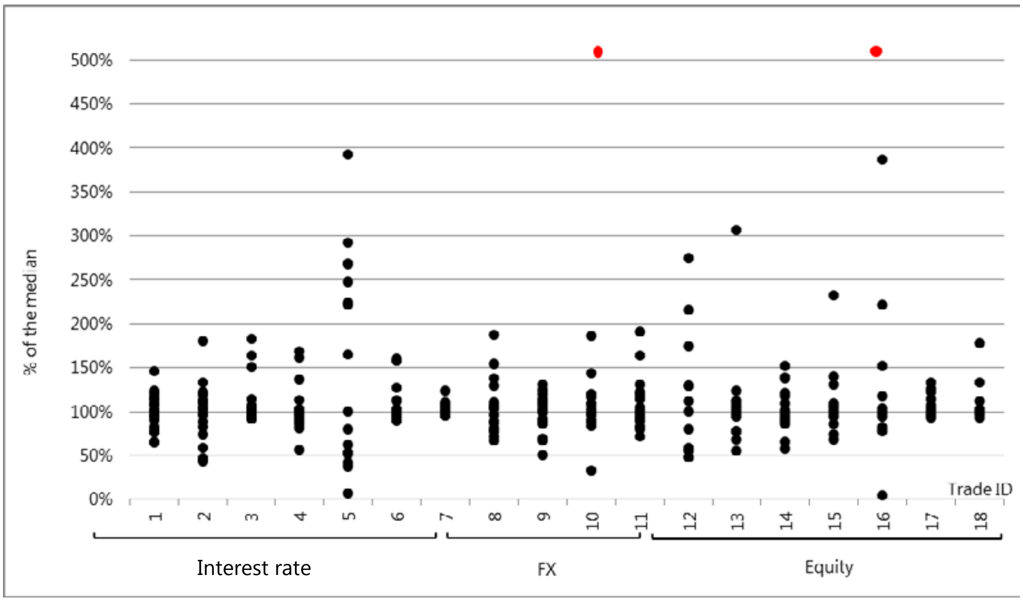
Figure 2: Absolute dispersion of IMV for all individual trades.



The following graph shows the range of reported non-stressed EEPEs as a percentage of the median for each trade. It is important to note that trades with a median EEPE close to zero can show relatively high dispersion due to the denominator effect, even when the absolute dispersion is limited.

The majority of submissions lie between 50% and 150% of the median value. Variability is noticeably higher for trade 5 (OIS swap) but this is partly explained by the very low median EEPE in absolute terms. The same is true for trades 10, 11 (cross-currency swaps with resettable notional) and trade 12 (equity forward). These derivatives also tend to be more complex and less frequently traded.

Figure 3: Dispersion of EEPE for all individual trades as proportion of median.



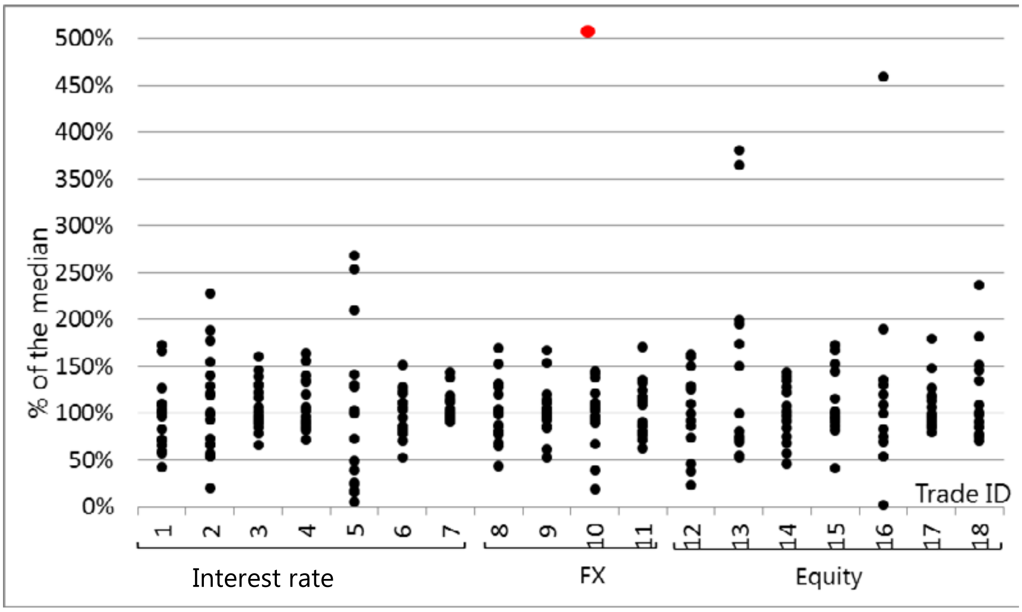
Beyond scale of graph (in red)

Trade 10 – 926%

Trade 16 – 769%

The following graph shows the reported stressed EEPE values for each trade as a percentage of the median. The dispersion is slightly lower compared with the EEPE values. This could be explained by the higher absolute stressed EEPE values indicating proportionately lower variation in relative terms.

Figure 4: Dispersion of stressed EEPE for all individual trades as proportion of median.



Beyond scale of graph (in red)

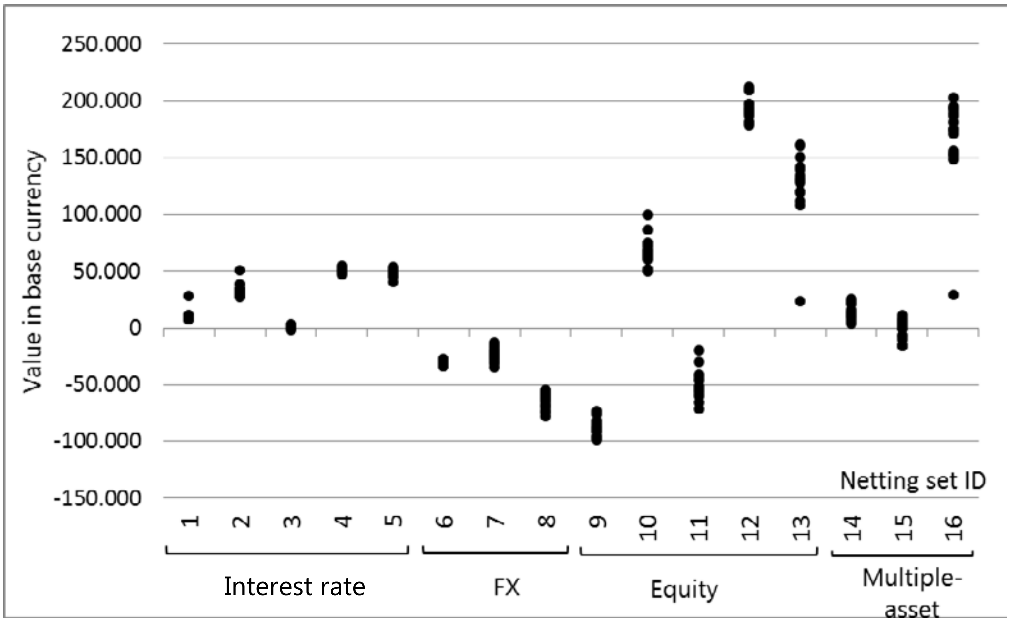
Trade 10 – 552%

3.3.2 Comparison of variability across netting sets

3.3.2.1 Comparison of IMV variability across netting sets

The following graph shows, in absolute terms, the dispersion of initial market values for the netting sets included in the HPE. The equity and multi-asset netting sets show the largest dispersion – this may be due to the level of IMV variability for the individual trades included in these netting set.

Figure 5: Absolute dispersion of IMV for netting sets.



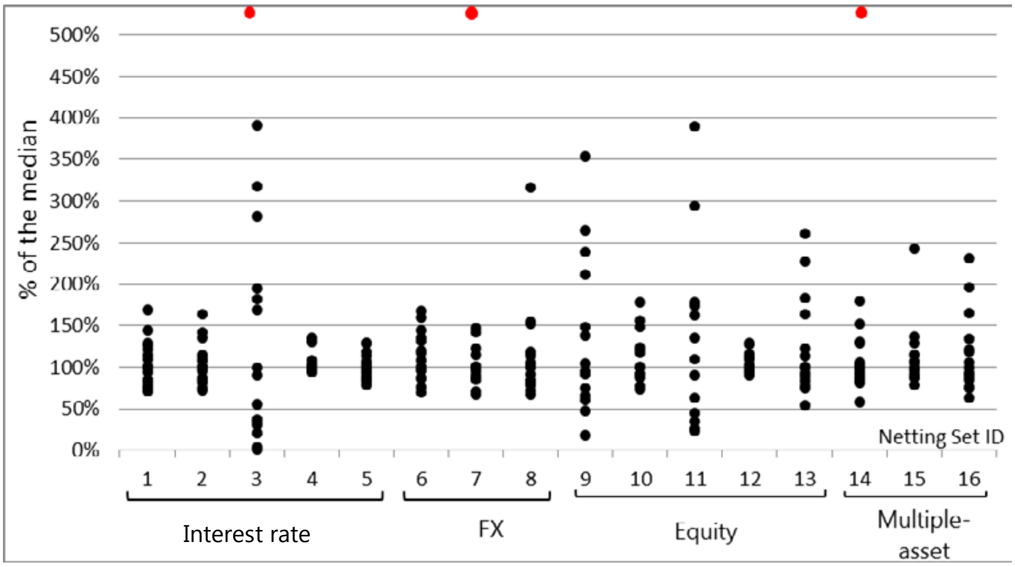
3.3.2.2 Comparison of variability across unmargined netting sets

The following graph shows the relative dispersion for the unmargined netting sets. In particular, there is high dispersion for the following netting sets:

- Netting set 3 (OIS-LIBOR) – potentially driven by the low absolute values.
- Netting set 7 (cross-currency swap) – potentially driven by the low absolute values and the high variability of trade 10.
- Netting sets 9, 11 (equity forwards) – potentially driven by high variability at trade level.

The diversified netting sets (5, 8, and 13) show less dispersion.

Figure 6: Dispersion from the median of EEPE for all unmargined netting sets.



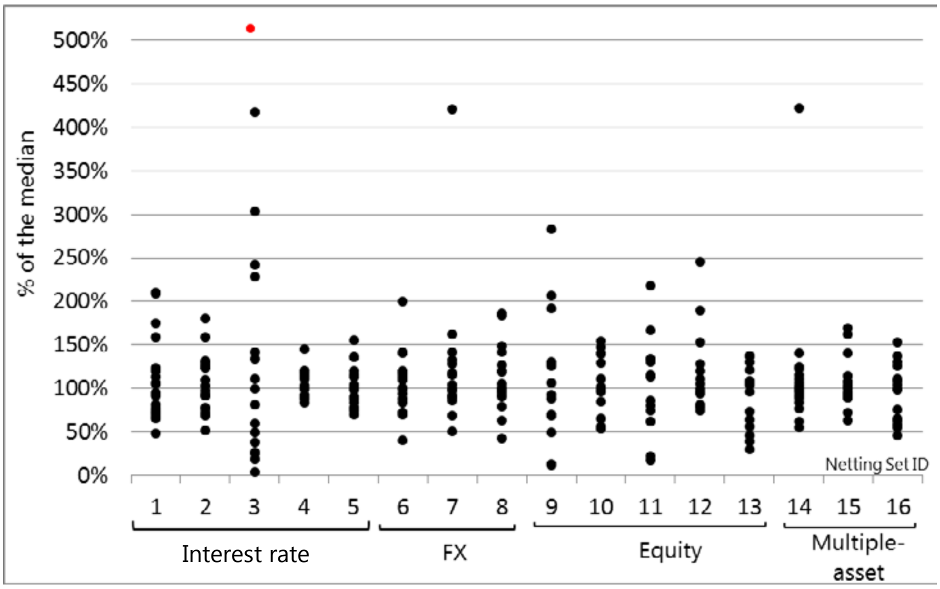
Beyond scale of graph (in red)

Netting set 3 -554%, 1136%

Netting set 7 - 666%

Netting set 14 – 621%

Figure 7: Dispersion from the median of stressed EEPE for all unmargined netting sets.



Beyond scale of graph (in red)

Netting set 3 – 848%

3.3.2.3 Comparison of variability across margined netting sets

The current and future regulatory environment is contributing to an increased use of margin, for example the BCBS margining requirements rules that will be implemented in the near future. The following graphs compare (in absolute and relative terms) the unmargined netting sets with the following three corresponding margined netting sets:

- Netting set with variation margin.
- Netting set with variation margin, a minimum transfer amount and a minimum threshold amount.
- Netting set with variation margin, a minimum transfer amount and an independent amount.

Overall, margining reduces the absolute variability across banks (see figure below). For the margined netting sets with variation margin, the EEPE is on average around 20–40% of the exposure for the uncollateralised netting set (see Section 3.4.4). Exposure and dispersion appear to increase with the introduction of a minimum threshold amount, and sharply decrease for those netting sets incorporating an independent amount. Notably, there also appears to be more dispersion in stressed EEPE values than in the respective non-stressed EEPE values.

Figure 8: Absolute dispersion of EEPE and stressed EEPE for all margined netting sets; the first netting sets of each block (ie netting sets no 2, 1 and 15) are unmargined. The three following netting sets are margined as per the specifications mentioned above.

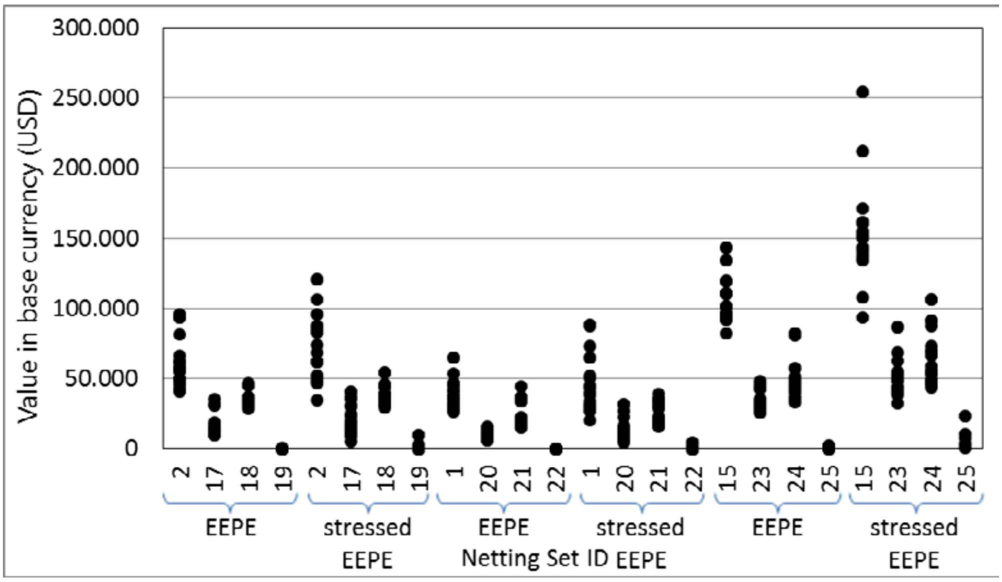
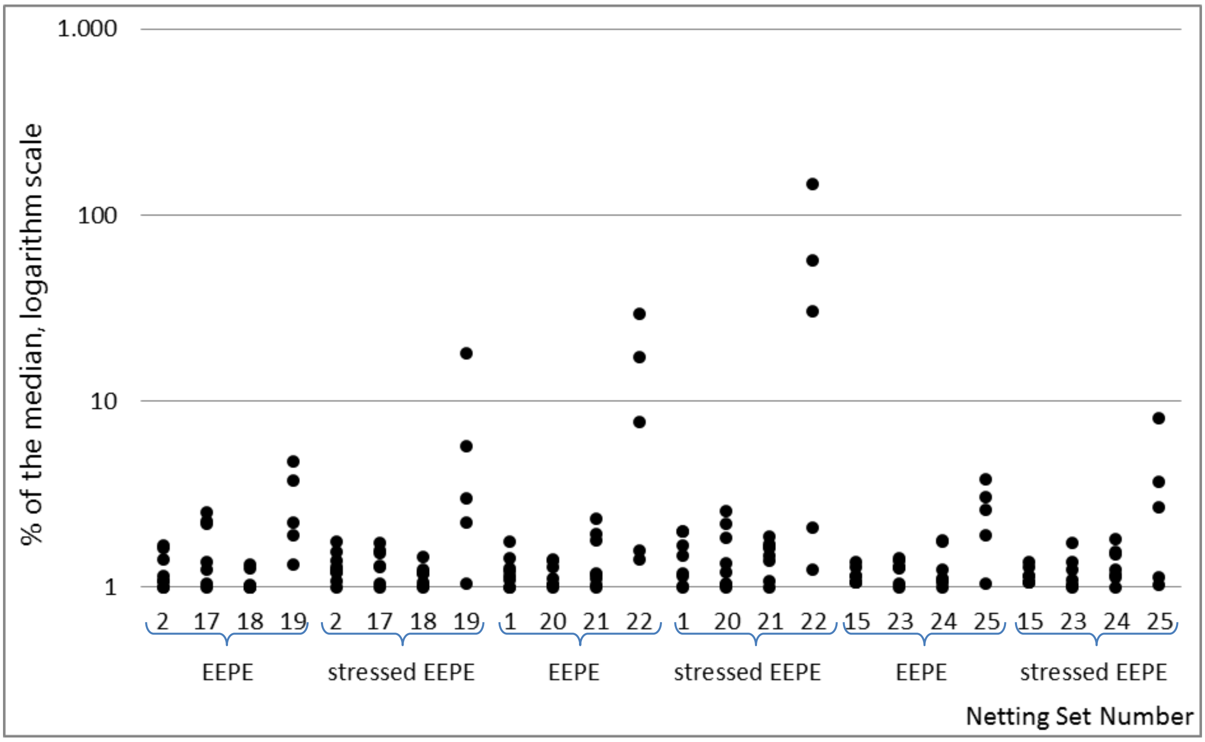


Figure 9: Dispersion of EEPE and stressed EEPE for all margined netting sets as a proportion of the median using a logarithmic scale.



3.3.3 Comparison of variability across EE profiles of netting sets 15 and 24

Participating banks were asked to provide the full EE profiles (non-stressed and stressed) of the all-in netting sets 15 and 24.[15] In order to isolate the variability stemming from the estimation of the EE profile on the CVA risk charge, an average EE profile was generated by averaging and interpolating over the submissions at each time step and banks were asked to recalculate the CVA HPE based on this fixed EE profile (see Section 4.3 Comparison of variability across portfolios – Fixed EE profiles).

The non-stressed EE profiles of netting sets 15 and 24 submitted by banks are provided below. Each line in the graphs indicates a different firm involved in the exercise, with the black line being the modified average EE profile. The colours are consistent across graphs.

Banks were provided with both the EE profiles up to the longest maturity in the netting sets (20 years) and the same profiles up to a one-year horizon, respectively relevant for the CVA risk charge and the EEPE risk measure. Note that all the trades included in both netting sets 15 and 24 are still live over the first year, and start to expire at the end of the first year, second year, fifth year, tenth year and twentieth year respectively (the maturing of the trades can clearly be observed in the 20-year profiles by a change of their shape at each of these time steps).

A wide range of shapes was observed for the EE profiles up to 20 years, highlighting the varying conservativeness of the EE profile but also the granularity of the chosen time steps.

[15] Netting set 15 – Unmargined netting set including all interest rate and FX trades.
Netting set 24 – Netting set with minimum transfer amount and threshold amount including all interest rate and FX trades.

Figure 10: Dispersion of the 20-year EE profiles for netting set 15.

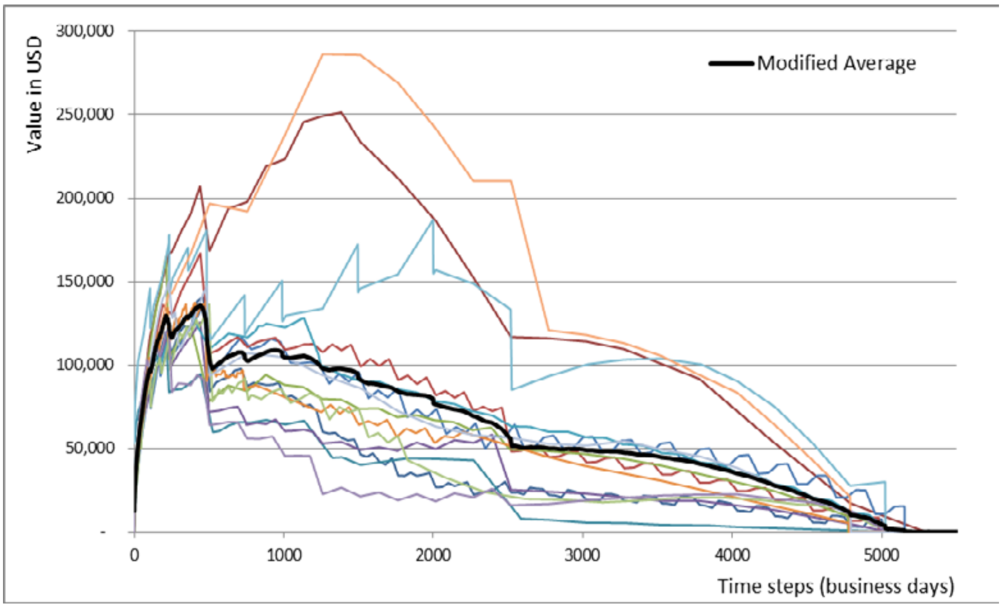
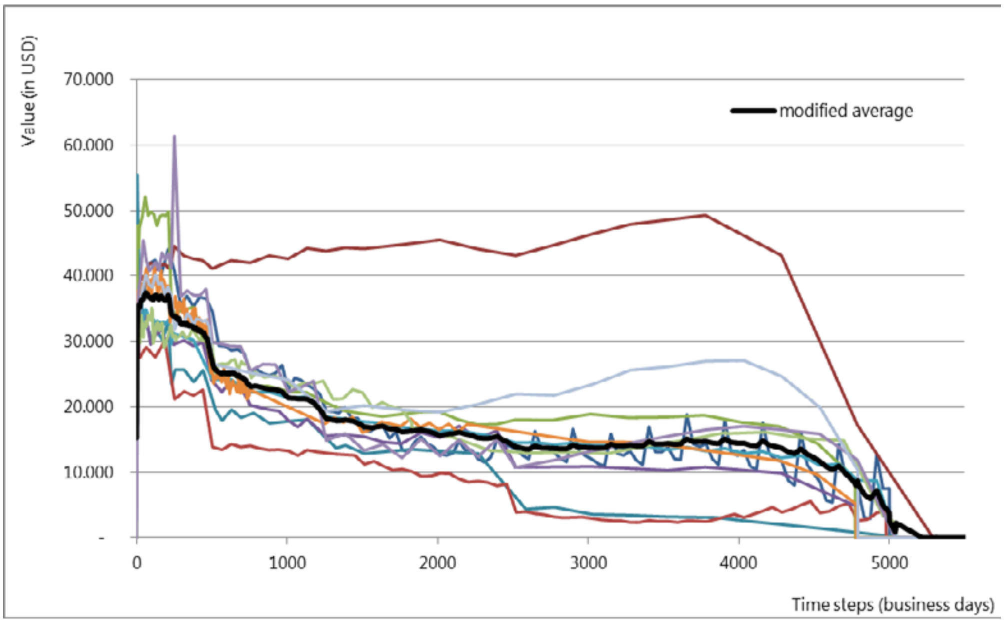


Figure 11: Dispersion of the 20-year EE profiles for netting set 24.



This dispersion is however significantly lower when observed over the first year. This could be explained by a "size effect" (all the trades are still live over the first year), but also because differences in the stochastic processes used to generate risk factors scenarios (probability distributions, calibration of drifts and volatilities) may lead to a more pronounced effect over a longer time horizon only.

Figure 12: Dispersion of the one-year EE profiles for netting set 15.

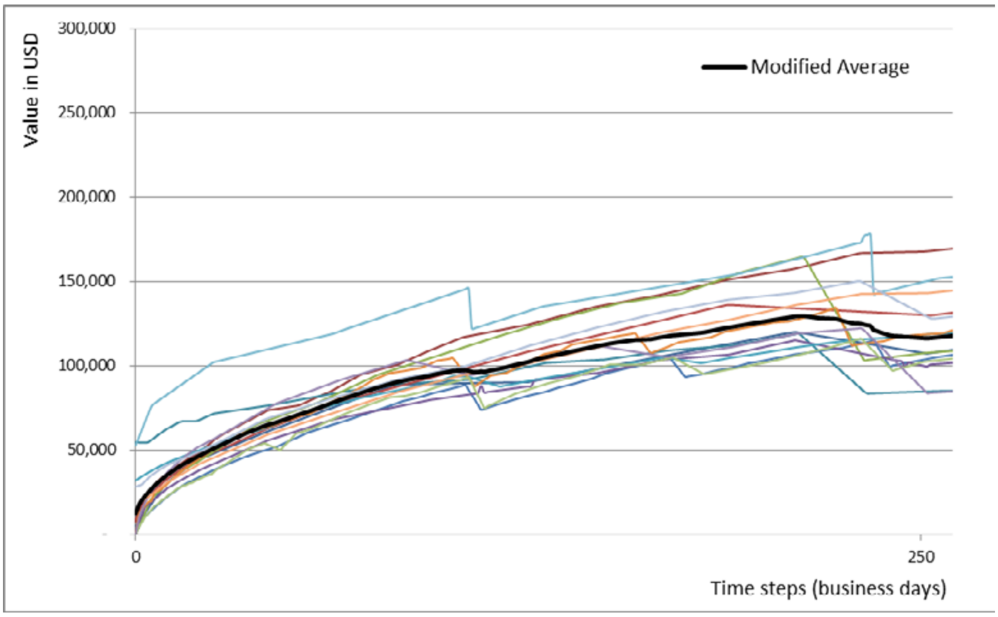
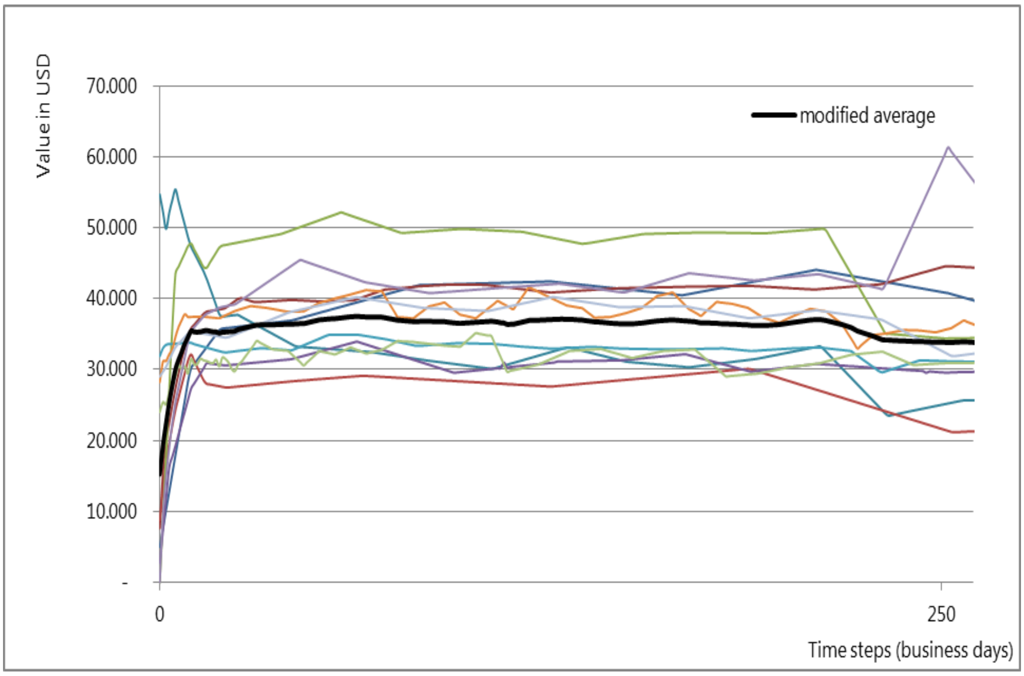


Figure 13: Dispersion of the one-year EE profiles for netting set 24.



3.4 Main drivers of variability

3.4.1 Variability coming from pricing of trades

3.4.1.1 Variability coming from the IMV

The IMV of a trade is the starting point from which its future market values are generated under the IMM. Therefore, variability in IMV across banks may to some extent explain variability in their EEPE measures.

The two figures below try to assess the importance of this source of variability for trades with positive or negative IMV separately. Since the EEPE measure is only based on scenarios for which the market value of the trade (or a netting set) is positive, this dependency may vary when many scenarios would be excluded. For each trade, the figures display the dispersion of the IMVs from their median value in the x-axis to the dispersion of the EEPEs from their median values in the y-axis. A more pronounced dependency between the IMV variability and the EEPE variability will be observed for data points located along the diagonal of each figure.

Figure 14: Dispersion of trade IMVs and trade EEPEs expressed as % of their median value for each trade with negative IMV.

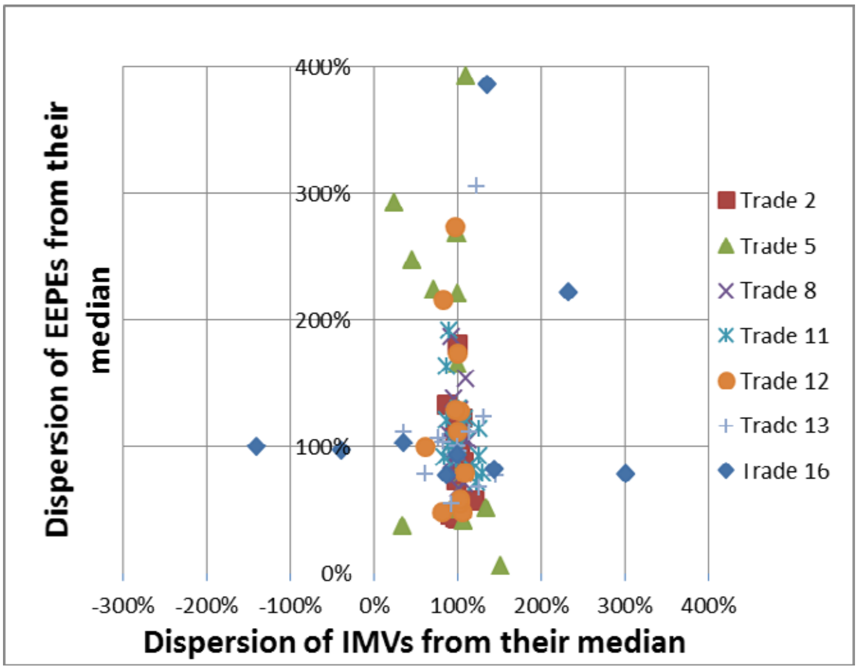
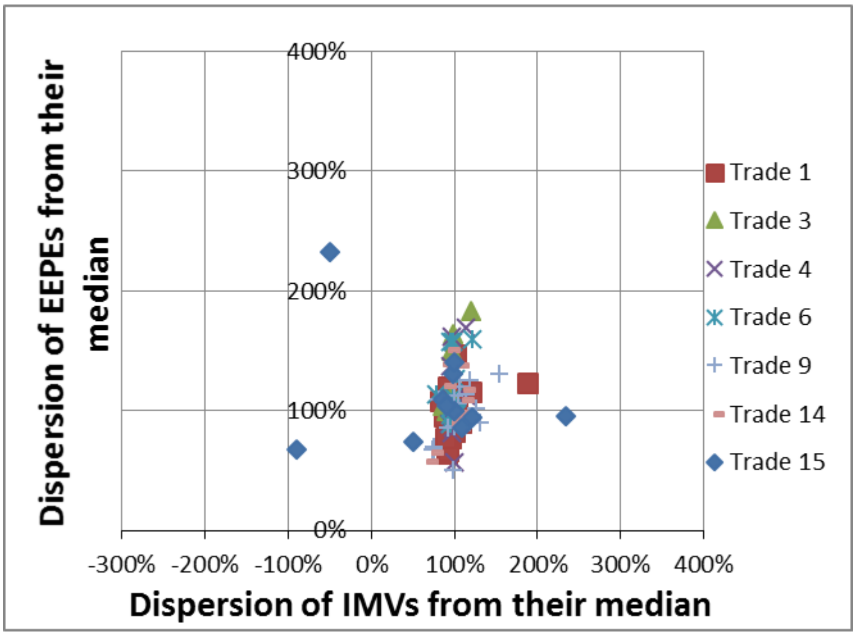


Figure 15: Dispersion of trade IMVs and trade EEPEs expressed as % of their median value for each trade with positive IMV (excluding options).



The variability of the IMVs across banks is low for most of the trades and therefore does not explain the higher variability observed for the EEPEs of the same trades. In addition, the higher variability of the IMVs observed for trades with IMV close to 0 (trades 15 and 16) does not necessarily lead to higher variability in the corresponding EEPE. However, it is noted that trades with negative IMV demonstrate more variability in their corresponding EEPE.

This result might be driven by the construction of the HPE and of the analysis itself. In a possible follow-up exercise it could be considered to perform such analysis separating the trades according to their IMVs being close to or far from zero.

3.4.1.2 Consistency between front office pricing and IMM pricing

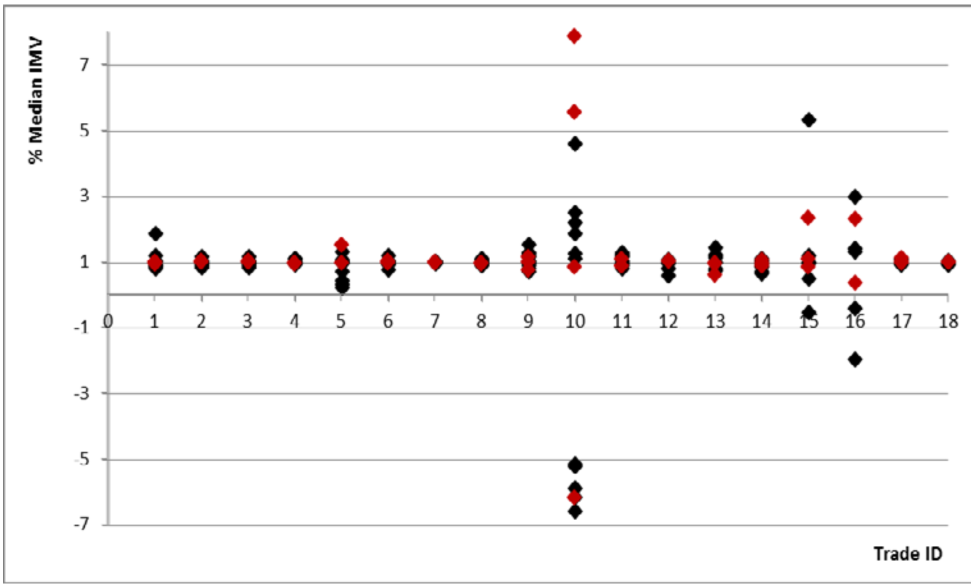
Under the IMM, banks have to reprice their derivative/SFT portfolios for each scenario and at each future time step. Therefore, the IMM engine needs to integrate a library of pricing functions that will take as input the entire set of simulated or non-simulated market data at each future time step.

These pricing functions can be rebuilt for the purposes of the IMM or simply exploit the existing Front Office pricing libraries used to provide quotes, mark positions in the books and hedge the relevant risks. As shown in the table below, this is the case for a small number of banks in the sample (four out of 16). The other banks use simplified pricing functions under the IMM. In fact, the large number of repricings required for generating the EE profiles up to the maturity of the transactions means that banks cannot re-use very sophisticated pricing algorithms which require a lot of time to run. As common pricing simplifications used by participating banks under the IMM, the following is observed:

- No skew for options;
- No use of multi-curves for IR products (ie calibrated to OIS, basis spreads, CCY spreads); and
- Finite difference or regression-type algorithm for callable/exotic products instead of plain Monte-Carlo/American Monte-Carlo.

The variability of the HPE trades initial market value (IMV) of banks using FO pricing functions is higher than at banks that do not use FO pricing functions. FO pricing functions in the IMM also lead to a higher mean of IMV. Both results could be explained by a higher degree of sophistication of the FO pricing functions, which may differ from one bank to another, especially when the trades or the modelling of the underlying risk factors gets more complex, whereas the simplified pricing functions used under the IMM are nearly similar for all banks.

Figure 16: Dispersion of trade IMVs expressed as % of their median value for each trade.



The red dots represent banks which IMM pricing is aligned with Front Office pricing, the black ones banks which do not.

Statistics on trade IMVs expressed as % of their median value for each trade — Table 4

	All samples	Is pricing in IMM consistent with FO pricing?	
		No	Yes
Sample size	16	12	4
Mean across trades	99%	87%	138%
Stdev/Mean across trades	169%	145%	185%

Most of the banks using the IMM have put in place control checks to ensure that the pricing functions used under the IMM are broadly in line with FO pricing. Although these checks are not explicitly required under the Basel Accord, they are very important to ensure the accuracy of the risk metrics measured by the IMM.[16]

These control checks usually compare the differences between the IMV from FO and IMM pricing functions against predefined thresholds defined in relative terms of the trade notional (eg 5% of trade notional) and/or in absolute amounts of currency (eg $500,000). When a difference exceeds these thresholds, banks usually investigate where the difference comes from, attempt to adjust the pricing

16 Some banks in the sample check the difference between FO and IMM pricing on netting set level only, others do not perform such checks.

under the IMM to reduce this difference and, when the difference persists, remove the trade from the scope of the IMM and capitalise it under a standardised approach (Current Exposure Method or Standardised Method) or add a capital add-on to the RWA.[17]

Additionally, it has to be noted that, when trades with an IMV exceeding the thresholds are capitalised under one of the standardised approaches, this usually leads to a higher capital requirement for the respective trade. As a result the corresponding exposure values are less comparable to the ones of trades staying in the IMM. This leads to a higher variability in the RWA for the respective bank over time.

Although there is no statistical evidence that such control checks lead to less variability in the RWA across banks, it is a good practice to conduct such checks. Furthermore, a clarification to the Basel rules which make such regular checks an approval requirement would lead to greater harmonisation across different jurisdictions.

3.4.2 Variability coming from fundamental modelling choices

3.4.2.1 Risk factors modelling under the IMM

The outputs of IMM are based on a number of simulated potential future values of the market risk factors that drive the market value of banks' derivatives (and SFTs) portfolios. The generation of these scenarios require that banks choose some probabilistic distributions for those market risk factors at different future dates, ie some stochastic processes.

As the IMM depends on complex internal models based on a significant number of modelling assumptions, the way that banks model different risk factors and the choice of risk factors itself could be an important source of variability in the results. It proved too challenging to conduct a comprehensive analysis of modelling choices to assess the importance of this source of variability in the HPE outputs. In particular, it would have required a visit to each participating bank to discuss thoroughly their modelling choices due to the limitations inherent in collecting information via questionnaires.

Nevertheless, a basic analysis was performed of risk factor modelling choices under the IMM based on the answers provided by participating banks in the questionnaires and during the on-site visits.

The three tables below provide a list of main risk factors used by participating banks in its IMM for the asset classes relevant for the HPE trades. The tables also show whether a drift assumption is made for the stochastically modelled risk factors. But not all risk factors are modelled in each bank; some are assumed to be deterministic, ie a time-dependent function or constant over time.

[17] At least one bank systematically applies a shift to the IMV under the IMM to bring it back to the FO IMV for trades that do not exceed the control check thresholds. This practice may lead to operational issues if the shift is kept for each instance of repricing until the maturity of the trade.

Main risk factors used for interest rate products and the underlying modelling assumptions

Table 5

Interest rate risk factors	Yield curve	Implied volatility	FX spot	Basis spread	CCS spread	OIS swap
Stochastic without drift	2	1	2	1	0	0
Stochastic with drift	13	0	11	1	1	1
Deterministic	2	13	0	2	1	0
	17	14	13	4	2	1

Main risk factors used for foreign exchange products and the underlying modelling assumptions

Table 6

FX risk factors	FX spot	Yield curve	CCS spread	Basis spread	Implied volatility
Stochastic without drift	3	4	0	0	0
Stochastic with drift	14	10	0	1	0
Deterministic	0	2	4	1	1
	17	16	4	2	1

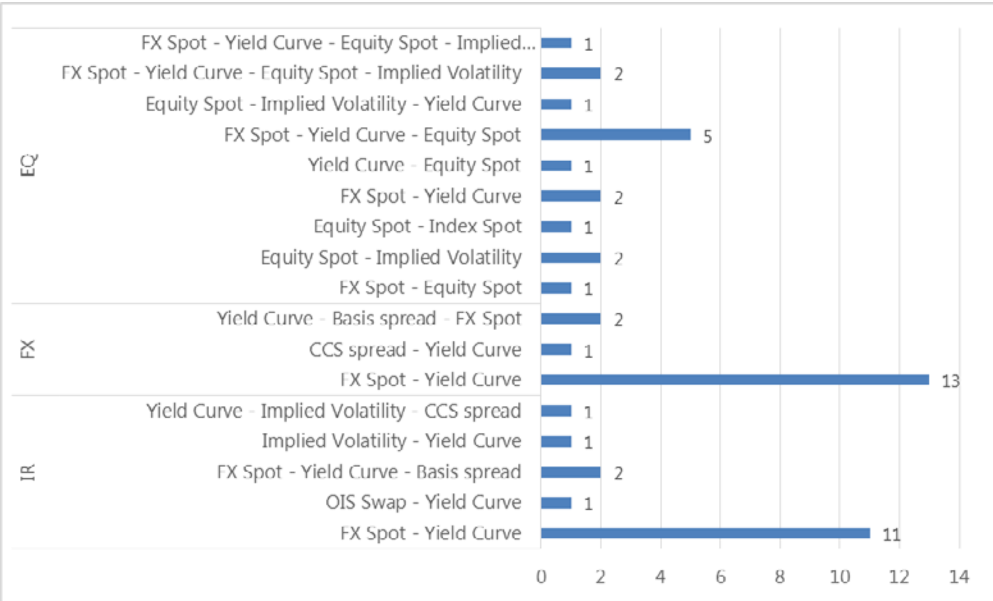
Main risk factors used for equity products and the underlying modelling assumptions

Table 7

Equity risk factors	Equity spot	Yield curve	FX spot	Implied volatility	Dividend yields	Index spot
Stochastic without drift	4	6	3	2	0	1
Stochastic with drift	11	6	8	3	0	0
Deterministic	0	1	1	6	3	0
	15	13	12	11	3	1

When looking at risk factor modelling choices, not only the modelling of single risk factors should be considered, as risk factors modelled with a stochastic process may be simulated on a standalone basis or simultaneously with a correlation structure between each other. The figure below provides an overview of those risk factors modelled with a stochastic process and simulated jointly with other risk factors.

Figure 17: Risk factors per asset class which are simulated simultaneously by banks, with total number of banks.



3.4.2.2 *Choice of calibration under the IMM*

According to the Basel Accord, banks can use either historical market data or market-implied data to calibrate the parameters of the risk factor's probability distribution (eg interest rate curves, volatilities, correlations, dividends, drift etc). Historical market data calibration is based on statistics inferred from the historical time series of market data. Market-implied data calibration is based on current prices directly derived from market quotes.

Based on answers provided by the banks in the questionnaire, only one bank calibrates the IMM based on market-implied data for all risk factors and product types, five banks use a hybrid approach differentiating according to risk factors and/or product types (eg drifts calibrated on market-implied data and volatilities calibrated on historical market data). The majority of participating banks calibrate IMM completely on historical market data.

Below is a high-level comparison of the possible impacts of the two types of calibrations in the exposure outputs. This is relevant since the interviewed banks indicated that, in their opinion, using either market-implied or historical calibration may lead to significant differences in exposure values. In addition, a link between this potential exposure variability driver and other exposure variability drivers is made, as the choice for either of these options could drive the choices for other modelling assumptions in the IMM:

1. Stability of model parameters: historical volatilities are usually more stable than market-implied volatilities, since they are calculated over a longer time horizon. Consequently, the most significant moves average out to some extent. Market-implied volatilities are based on a single day's observation, ie daily changes in market prices and thus cause high variability in market-implied volatilities. This might contribute to exposure variability in banks' normal EEPE figures that varies over time, and potentially in the HPE results, which are a single-date observation.

2. Recalibration frequency: banks that have implemented market-implied calibration have an incentive to recalibrate their parameters more frequently since the market can change significantly on a daily basis. For banks that have implemented historical calibration, this incentive is lower, as a few new observations would not change the estimated model parameters significantly.

3. Magnitude of model parameters under stressed calibration: stress-implied volatilities are generally larger than historical stress volatilities, even when the IMM is calibrated from a period of financial stress to the market risk factors. Particularly when the stress-implied volatility is chosen from a day with the highest observed implied volatility, this might contribute to exposure variability in banks' stress EEPE figures, even in the HPE. Consequently, this item might be related to the observation that the stress period selection seems to contribute to the exposure variability.

Due to the construction of the HPE, it was not possible to separate the effects stemming from one or the other choice as regards calibration. For example, the exercise did not allow the impact of drift to be analysed under the two approaches. The drift under the risk-neutral probability and under the historical probability approach may differ significantly, also depending on the time horizon, and the impact on modelling outcomes may be significant. Furthermore, a differentiation of overlaying effects resulting from this basic choice and driving the other above-mentioned model assumptions could not be analysed. But based on the judgment of team members and supported by the banks' opinions, this choice is believed to be a main driver of variability in EEPE results and further analysis will be considered for a future exercise.

Since there are a number of variability drivers and, for the time being, there is no indication that predefining either calibration method significantly decreases overall variability in the CCR RWA, there is intentionally no recommendation with respect to this item.

3.4.2.3 Frequency of calibration of non-stressed EEPE

The Basel rules require banks to update the data used for the calibration of the IMM based on current market conditions at least quarterly, and more frequently if necessary, to reflect changes in those market conditions. The updating of these data should naturally be followed by a recalibration of the IMM parameters (eg volatilities, correlations etc) used in the stochastic processes defined to generate future scenarios of risk factors (see Section 3.4.2.1 on modelling of risk factors). The current value of the risk factors at which the IMM simulation starts, corresponding to a reporting date of regulatory data, should be extracted from that date.

According to the answers provided in the questionnaire, the majority of participating banks reperform the calibration of the IMM on a more frequent basis than quarterly for all asset classes. However, in some banks the frequency varies across the parameters (eg volatilities are recalibrated more frequently than correlations). Some banks perform a daily recalibration, at least for certain parameters. Nevertheless, two banks of the panel only perform the recalibration of the parameters on a yearly basis.

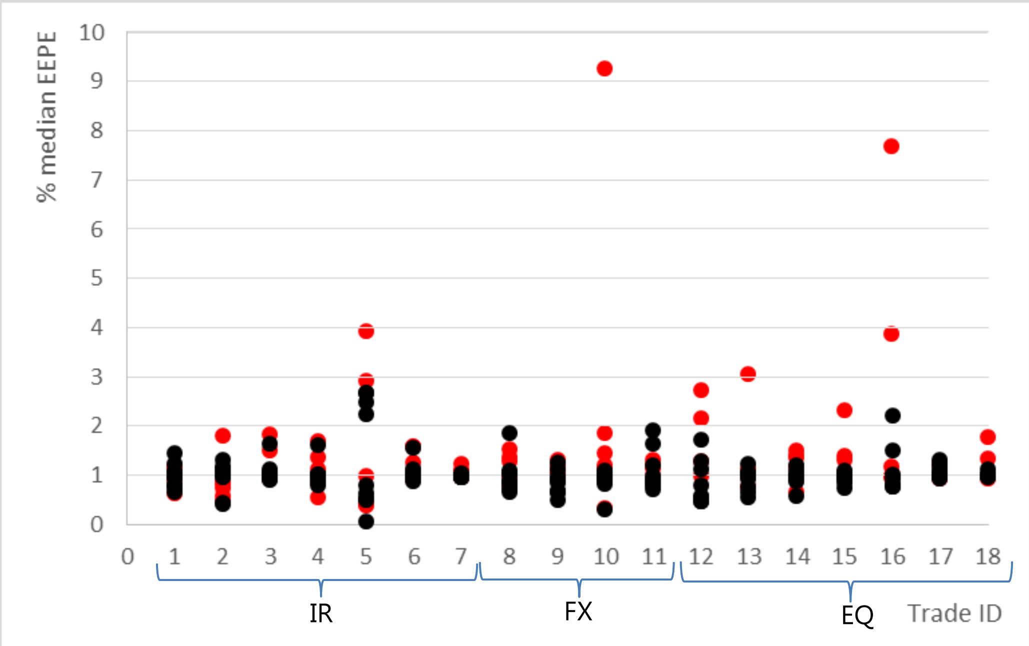
Since the exercise was performed by banks as of 31 October 2014, which is not a regulatory reporting date, it is likely that banks with less frequent recalibration used older data to run the exercise than banks with a more frequent recalibration. For the analysis of the influence of the choice of recalibration frequency on the HPE trades' results, the banks were divided into two subsamples: one group performing the recalibration more frequently than quarterly and the other group with less frequent recalibration (quarterly up to yearly).

As can be observed in the figure and table below, different frequencies of recalibration of the IMM do not lead to high variability in the non-stressed EEPE of the interest rate HPE trades: for these trades the dispersions of the two groups of banks are very close to each other. Regarding the "conservativeness" of results, both groups' results deviate only to a minor degree.

There is clearly more variability in the results of equity and FX HPE trades for the group of banks performing the recalibration quarterly or less frequent, as the observed dispersion is significantly higher compared with that of the other group of banks or even the interest rate trades. However, the mean of the banks performing less frequent recalibration is higher.

For the group of banks recalibrating the IMM more often, dispersion and mean are close to each other for all three asset classes.

Figure 18: Dispersion of trade EEPEs dependent on the frequency of data recalibration.



The red dots represent banks which recalibrate the IMM quarterly or less often, the black ones banks which do the recalibration more frequently.

Statistical breakdown of the different calibration frequencies for the non-stressed EEPE

Table 8

	All samples	IR		FX		EQ	
		Quarterly or less frequent	More frequent than quarterly	Quarterly or less frequent	More frequent than quarterly	Quarterly or less frequent	More frequent than quarterly
Sample size	17	7	10	7	10	5	10
Mean across trades	115%	115%	107%	145%	97%	161%	99%
Stdev/Mean across trades	70%	55%	42%	109%	32%	80%	28%

From the outcomes of the HPE exercise, the frequency of recalibration of the IMM is a driver of variability in the non-stressed EEPE, with different degrees across the asset classes. A possible explanation for this observation is that interest rate risk factors are usually less volatile than FX or equity risk factors. Therefore, less frequent recalibration of interest rate stochastic processes may not fundamentally affect the outputs of the non-stressed EEPE.

According to the Basel requirements, all banks with an IMM have to demonstrate that the IMM is used for internal purposes, too. Therefore, banks usually compute the IMM exposures more frequently than quarterly to set trade lines or to calculate credit limit utilisation for each counterparty. Hence more frequent recalibration will have a more significant impact on the outputs of the use test than on the regulatory capital, which is only required to be reported on a quarterly basis.

However, the requirement to maintain a minimum ratio for regulatory capital is continuous and banks need to be able to calculate their own funds requirements at all times. Thus, from a supervisory perspective, in certain cases it may be appropriate to recalibrate risk factors of the IMM more frequently than quarterly to better align with the minimum capital requirements, as well as with use test requirements.

Furthermore, there is an overlaying effect between the choice for the frequency of recalibration and the choice whether to use historic market data or market-implied data, which might influence the observations and should be considered. In particular, banks using implied volatilities from market-implied data need to update more frequently, as explained in Section 3.4.2.2 above.

3.4.2.4 Choice of stress period for stressed EEPE

Under the Basel III framework, banks are required to use the greater of the portfolio-level capital charge based on EEPE using current market data and the portfolio-level capital charge based on EEPE using a stressed calibration. Banks must demonstrate for the chosen stress period at least quarterly that it coincides with a period of increased CDS or other credit spreads of its counterparties. For calculating the stressed EEPE, the model parameters inherent to the IMM (eg volatilities, correlation, and dividend yields) are calibrated to this stress period. When those parameters are estimated with statistics based on historical time series (ie "historical calibration"), three years of stressed market data should be used.

In line with the Basel framework, the determination of the stress period is disconnected from the banks' portfolios composition. That is, the stress period should not be chosen with respect to the stress to the market risk factors driving the IMM outputs but should be dependent on the bank's counterparty composition.

The majority of banks determine this stressed period around the recent financial crisis.[18] As shown by the figure below, this period leads to a more conservative calibration of the stressed EEPE at a bank level, which is illustrated by the ratio between the stressed and non-stressed EEPE of banks' real portfolios.[19] Thus, the recent financial crisis seems to offer stressed market data for most of the risk factors included in banks' portfolios.

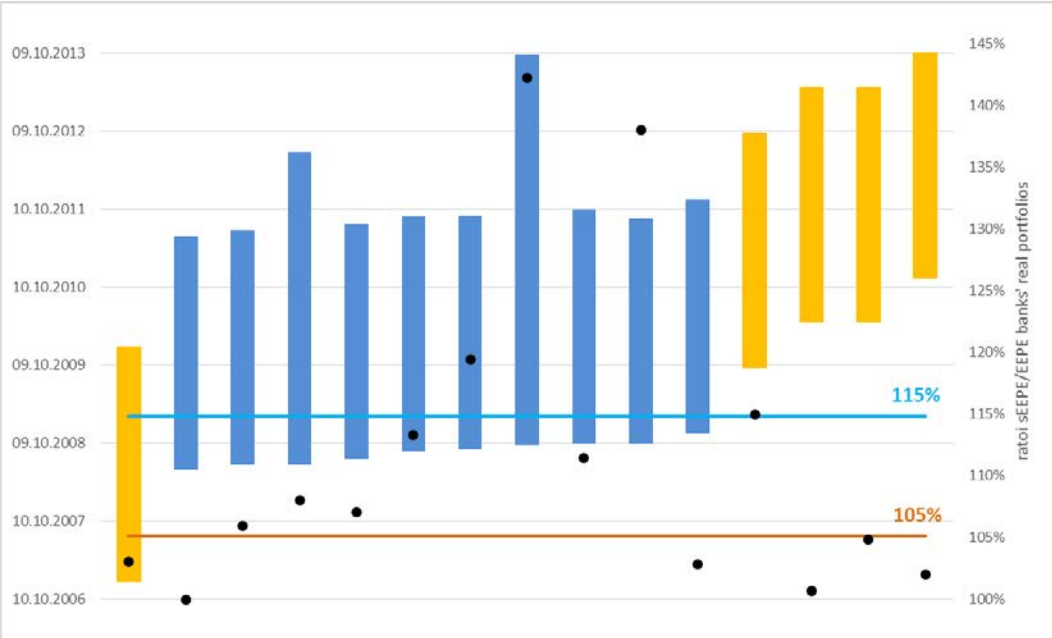
Clearly, when the stressed period deviates from the recent financial crisis, these ratios are lower: a mean of the ratio of stressed EEPE to non-stressed EEPE of 105% across the banks belonging to this group compared with 115% for the group of banks calibrating the stressed parameterisation to the financial crisis.

Two banks in the sample use more than a three-year time window for the stress period to calibrate the stressed EEPE, but there is no strong statistical evidence that this has an impact on the level of conservativeness of the stressed EEPE at bank-level.

18 As distinct from the sovereign debt crisis.

19 The ratio of banks' real portfolio stressed EEPEs to non-stressed EEPEs was used as a proxy for this exercise. Actually, banks have to compare RWAs resulting from both stressed and non-stressed calibrations. Using EEPEs allows for simplification of the analysis, and neglects "only" the portfolio effects as netting set EEPEs have to be summed up. The risk-weighting applied is mostly linear as it is the same for each counterparty irrespective of stressed or non-stressed calibration under the IMM.

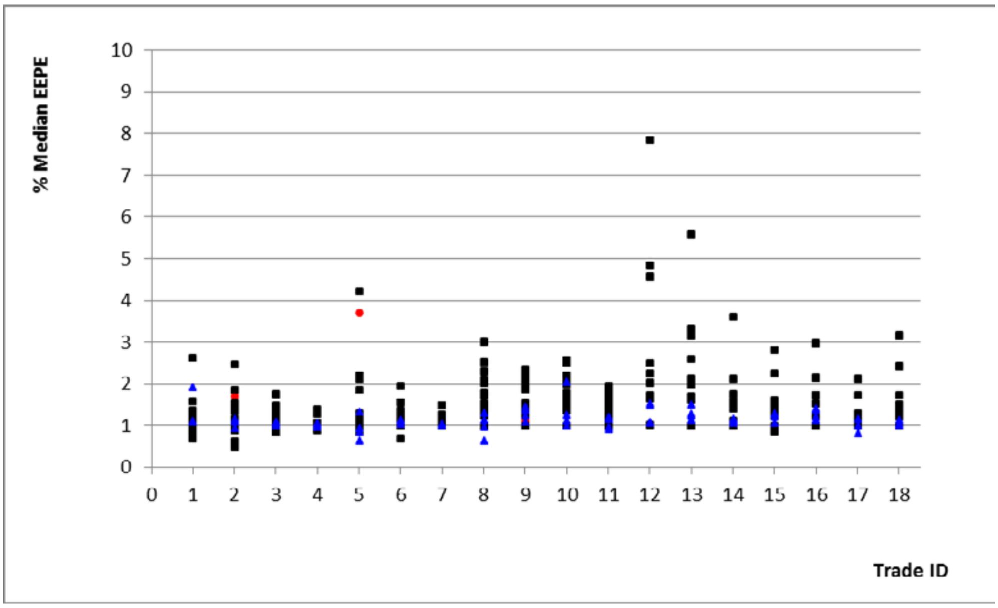
Figure 19: Comparison of banks' stressed period used to calibrate the stressed EEPE measure ranked by start date of the stressed period. For each bank, the black dots represent the ratio between the stressed EEPE and the non-stressed EEPE at bank level.



Irrespective of the choice of the stress period, the ratio of stressed EEPE to non-stressed EEPE on the real portfolio lies between 100% and 120% for most banks, which is not a wide range of variability. If a bank shows significantly deviant ratios, it might be meaningful for supervisors to further investigate the choice of stress period and the validity of reasons for using that period.

To confirm the above finding, ie the fact that the recent financial crisis coincides with a global period of higher volatilities for different asset classes, the figure below compares the ratio between the stressed EEPE and the non-stressed EEPE for each HPE trade across banks. As can be observed in the figure and table below, banks that selected the start of the stressed period during the peak of the financial crisis (August 2007–March 2009) experience more conservative stressed EEPE measures for the trade HPEs.

Figure 20: Ratios between stressed EEPE and non-stressed EEPE for each trade HPE.



The red dots represent banks for which the stressed period for stressed EEPE starts before August 2007; the black dots those with stress periods between August 2007 and March 2009 and the blue dots those with stress periods after March 2009.

Statistics on the dispersion of ratio stressed EEPE/non-stressed EEPE dependent on the start of the stress period

Table 9

	All samples	Start of stressed period for stressed EEPE		
		< Aug-07	>Aug-07;<March-09	>March-09
Sample size	19	1	14	4
Mean across trades	146%	138%	157%	114%
Stdev/Mean across trades	52%	55%	53%	19%

The mean of the ratio of stressed EEPE to non-stressed EEPE is higher for the HPE trades compared with the banks' real portfolios, which is a result of the construction of the exercise, meaning that the HPE trades are not necessarily representative for banks' real portfolios. No credit risk trades were included in the exercise's hypothetical portfolio, which would probably influence the overall outputs given the banks' chosen stress periods.

Looking at each asset class separately, the finding of more conservative results is particularly pronounced for FX and equity trades and slightly less pronounced for the interest rate trades, as can be seen in the table below. However, the dispersion of the ratios is not very high across all asset classes but is slightly higher for the sample of banks with the start of stress period at the peak of the financial crisis.

Statistics on the dispersion of ratio stressed EEPE/non-stressed EEPE dependent on the start of the stress period. Breakdown per asset class of the HPE

Table 10

	Start of stressed period for stressed EEPE								
	< Aug-07			>Aug-07;<March-09			>March-09		
	IR	FX	Equity	IR	FX	Equity	IR	FX	Equity
Sample size	1	1	1	14	14	14	4	4	4
Average across trades	157%	105%	-	124%	168%	192%	107%	118%	118%
Stdev/Mean across trades	57%	4%	-	39%	27%	62%	19%	25%	14%

Since the Basel rules do not specify how the stressed period should be determined, banks have developed various methodologies to identify their stress period. Most banks base their methodology on a time series of credit spreads for a selection of representative counterparties. Others base their methodology on a bank-specific composite credit spread index. Some banks seek to maximise the non-stressed EEPEs/EADs or the RWAs of selected counterparties to find the stressed period, while others search for the time period that is the most volatile for the credit spreads of the selected counterparties or the composite credit index. The banks that seek to maximise EEPE/EADs will either try all the possibilities in the available history for selected counterparties or select a limited number of time periods in the entire history. Banks that search for the most volatile period can typically automate the search, in which case all the possibilities in the entire history available for the time series are tested, or, rarely, this is done manually, eg by graphing the time series of the selected counterparties or the composite credit index.

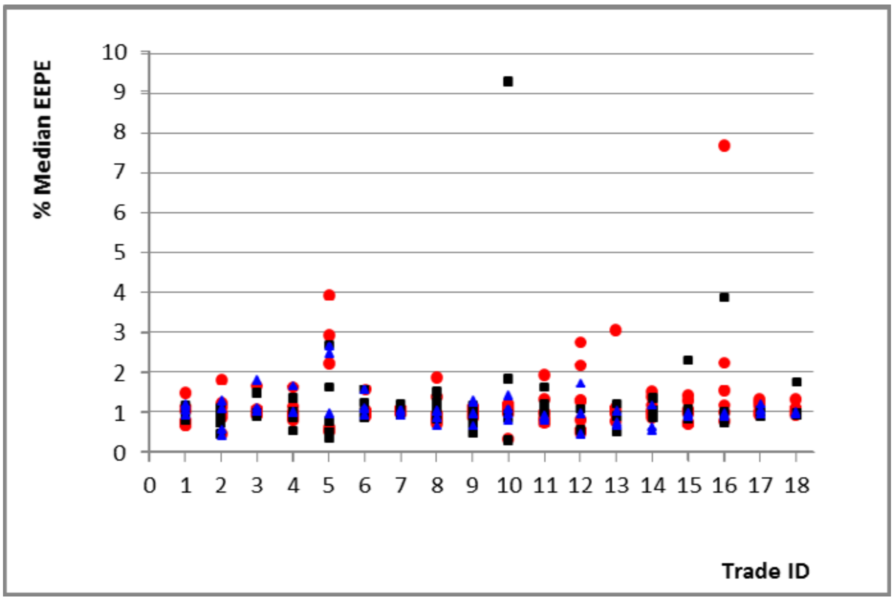
3.4.3 Features of the IMM engine

3.4.3.1 Number of simulations

Under the Basel framework, banks that use the IMM can choose the number of scenarios that they will generate to compute the expected exposure values at each time step. This number varies widely across the participating banks. It starts as low as 1,000 simulation paths and goes up to 10,000. Some banks do not choose a fixed number of scenarios for all transactions covered under the IMM but rather a number that varies depending on the nature of the transactions, which can and sometimes does exceed 10,000 scenarios.

The figure below shows that the group of banks using 5,000 or more scenarios has slightly less variable results. Conversely, the dispersion of outputs for banks with a number of scenarios between 1,000 and 5,000 is the highest of the three groups. Overall, the results provided by the banks are not far away from each other, as evidenced by the mean across trades.

Figure 21: Dispersion of EEPE dependent on the number of scenarios chosen.



Red dots represent banks using 1,000 scenarios, the black dots banks using more than 1,000 and fewer than 5,000 scenarios, and the blue dots represent banks with 5,000 or more scenarios.

Statistics on dispersion of EEPE dependent on the number of scenarios

Table 11

	All samples	Number of scenarios		
		=1000	>1000;<5000	>=5000
Sample size	19	8	7	4
Mean across trades	114%	116%	114%	108%
Stdev/Mean across trades	68%	66%	82%	36%

In theory the expected exposures computed under the IMM should converge to their theoretical values more quickly than other risk measures (such as variance, peak exposure etc), although this also depends on the shape of the underlying portfolios. To test this, some banks perform regular statistical tests to ensure the convergence of the expected exposures to their theoretical value. The results of these tests led some banks to increase the number of scenarios or demonstrate that a higher number of scenarios does not improve the convergence of the expected exposures. However, these convergence tests do not seem to be a widespread practice.

Although it seems logical that increasing the number of scenarios would improve results, this may not be the case for two reasons. First each scenario is based on the bank's choice to use historical or market-implied data. As referenced in Section 3.4.2.2, this choice will create differences, which may be compounded by adding more scenarios. Secondly, the complexity of the banks' pricing functions can also limit the chosen number of scenarios as banks balance the trade-off between complexity and computational burden. Hence, when expecting banks to raise the minimum number of scenarios, supervisors should consider that this may lead to an unwanted simplification of the IMM-implemented pricing models.

3.4.3.2 Granularity of grid points

To derive the EE time-profile, banks must evaluate the market values of the trades/netting sets at various points of time to calculate their expected exposures. Due to constraints in computational power, it is not feasible for banks to calculate market values for every day over the full time horizon through the longest maturity in the portfolio. Therefore banks choose a grid of discrete time steps. The Basel framework has no clear requirements on the density of this grid and it allows banks to choose static or dynamic grid points.

Static grid points mean that the time steps in the IMM have a fixed grid of business or calendar days for each trade or netting set, notwithstanding the occurrence of cash flows for a certain trade or netting set. Some banks have different fixed grids for margined and unmargined netting sets or for different counterparties. Dynamic time steps mean a bank will set the grid points dependent on, for example, the cash flows of the trades/netting sets. The grid is not only likely to be different for different netting sets but also varies over time for the same netting set.

While the vast majority of participating banks use only static grid points, one of the banks in the panel complements the static time steps with dynamic ones, and another one uses only dynamic time steps.

The number of static grid points over the full time horizon varies significantly, with a range of 55 through 404. Furthermore, the number of grid points is not necessarily dependant on the total time horizon as more grid points are concentrated in the short term. This could be due to the fact that EEPE only depends on the number of grid points within the first year.

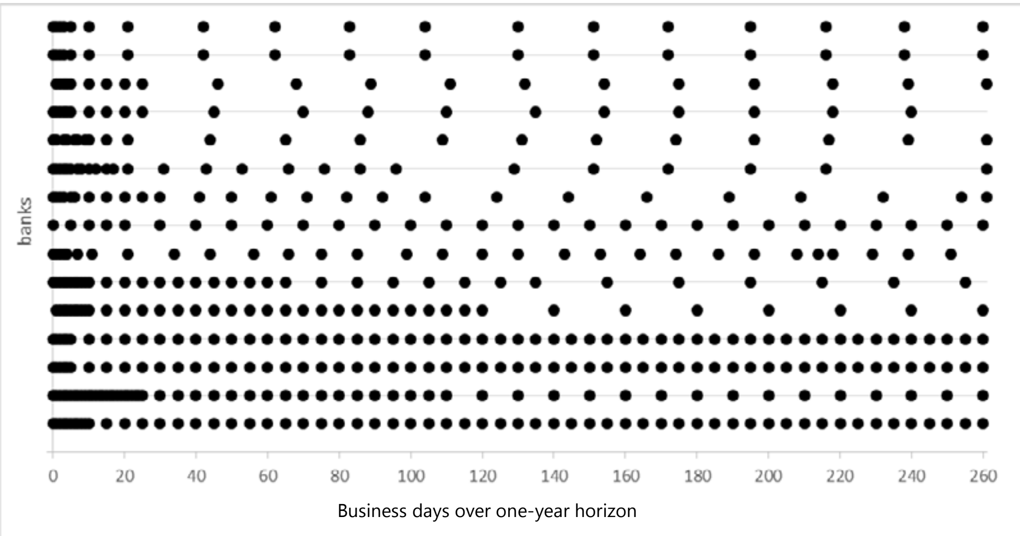
However, the number of grid points up to the maturity of all trades is relevant for the use test of the IMM and for the CVA charge.[20] In this exercise, the longest trade maturity was 20 years, and the table below shows the number of time steps used by the banks to calculate the EE profiles of trades and netting sets in the exercise. It varies significantly across the participating banks, but gets less dense for longer maturities at all banks.

20 Some banks in the panel indicated that they keep the expected exposure constant, ie equal to the expected exposure at the latest grid point, when a trade matures after the maximum horizon of the IMM simulation.

Number of grid points used by the different banks over different time horizons					Table 12
Bank	Number of time steps up to the respective horizon of simulation				
	1Y	2Y	5Y	10Y	20Y
A	9	12	20	34	62
B	17	22	36	48	58
C	18	20	23	28	37
D	18	20	29	32	39
E	20	22	29	35	42
F	20	24	33	41	51
G	21	23	35	46	66
H	26	29	35	41	47
I	26	22	36	48	54
J	29	32	44	64	84
K	30	46	82	131	197
L	35	45	54	60	68
M	39	50	53	58	64
N	57	66	102	162	282
O	57	59	71	90	129
P	58	71	92	104	116
Q	61	105	156	171	178
Median	26	29	36	48	64

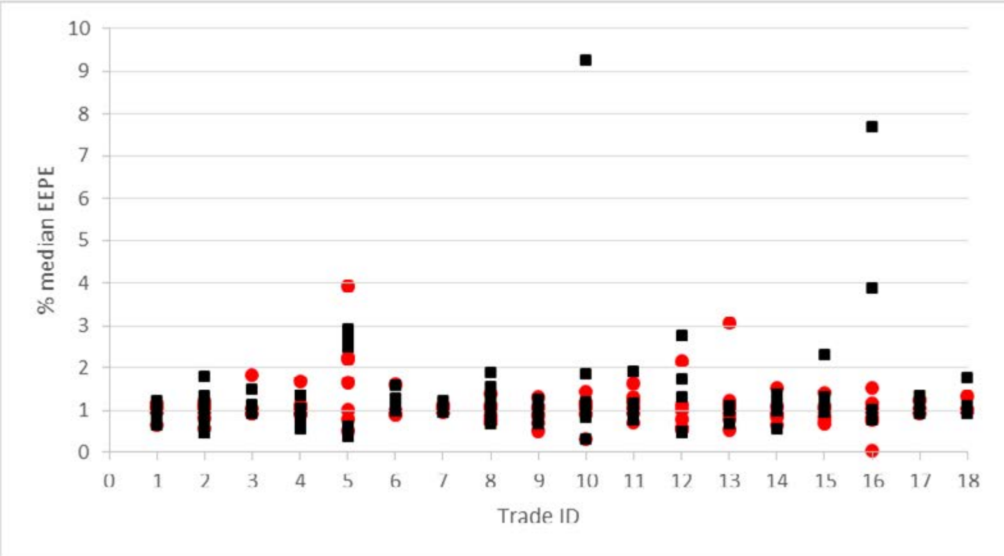
Looking at the granularity of grid points over the first year, which is relevant for the calculation of EEPE, one can see that the number of grid points varies significantly across banks, with a range between nine and 61 time steps. Additionally it can be seen from the figure below that, for most banks, the grid is denser in the first two weeks and gets more scattered the further the view goes into the future. Most banks start with daily time steps. At the end of the one-year horizon, the time steps are chosen between weekly and monthly.

Figure 22: Static grid points of banks in business days for one-year horizon.



To analyse if more or less dense grid points would alter the variability of the exercise outcome, the banks in the panel were separated into two groups: one with a number of time steps less than or equal to the median of 26, and a second group that had more time steps than the median. The figure below shows that the first group of banks produced on average less conservative non-stressed EEPEs for the HPE trades, but also that they showed less dispersion than banks that had more time steps.

Figure 23: Comparison of dispersion of EEPE dependent on the number of grid points used over the one-year horizon.



The red dots represent banks using less grid points over the first year than the median of the panel, and the black ones show the banks with more grid points than the panel's median.

Statistics on dispersion of EEPE dependent on the number of grid points over one-year horizon.

Table 13

	All samples	Number of grid points for relevant horizon (maturity of trade)	
		Less than or equal to the median of the panel	More than the median of the panel
Sample size	19	10	9
Mean across trades	114%	107%	121%
Stdev/Mean across trades	69%	42%	84%

It was of interest to analyse if the results were the same, when distinguishing between HPE trades with shorter (less than two years) and longer maturities (10 years or more). This is done in the table below. The average across the trades and the dispersion confirm what was previously already shown above, namely less conservative and less dispersed EEPEs.

Statistics on dispersion of EEPE dependent on the number of grid points over one-year horizon differentiated for trades with short and long maturities Table 14

	Trades with maturity less than two years		Trades with maturity of 10 years or more	
	Less than or equal to the median of the panel	More than the median of the panel	Less than or equal to the median of the panel	More than the median of the panel
Sample size	10	9	10	9
Mean across trades	109%	122%	105%	134%
Stdev/Mean across trades	47%	76%	26%	117%

At first sight, these results are counterintuitive, as one would expect less dispersion in case of the more sophisticated methodology. However, taking a look at what the grid of time steps means for the calculation of exposure values, there are two possible explanations. First, since the expected exposures as basis for the EEPE are calculated at each time step, a lower number of time steps picks up fewer data points. When this low number of time steps also corresponds with the choice for static grid points, it is likely that time points at which the exposure of the netting sets changes are not captured by the grid. It is more probable that exposure peaks lie between two time steps. Therefore, the whole EE profile is expected to be flatter than in the case where more time steps are used. This flatter profile might lead to a lower mean for EEPEs. Second, not all banks with a number of time steps above the median use the same grid, ie the results vary because the calculation is based on different time points and therefore different exposure values for the netting sets. Hence, the dispersion is higher than in the case of a lower number of time steps, as exposure changes are better met, but at different points in time.

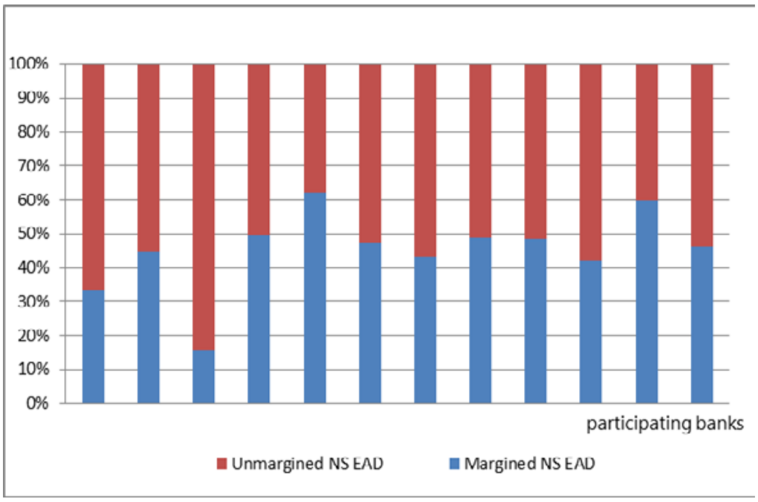
Furthermore, the construction of the HPE trades accounts for only a few cash flows, and therefore significant deterministic exposure jumps, in the first year. This could also have an impact on the outputs.

Among banks that have implemented more than 26 time steps, some indicated that it makes no material difference for the EEPE results of their real portfolio if the number of grid points is increased significantly over the one-year horizon. Although it does not seem to be a widespread practice to exceed the number of time steps over the one-year horizon significantly (sometimes up to daily) for the purposes of model validation, supervisors should require such a validation to ensure appropriate exposure estimates.

3.4.4 Modelling of margin mechanism

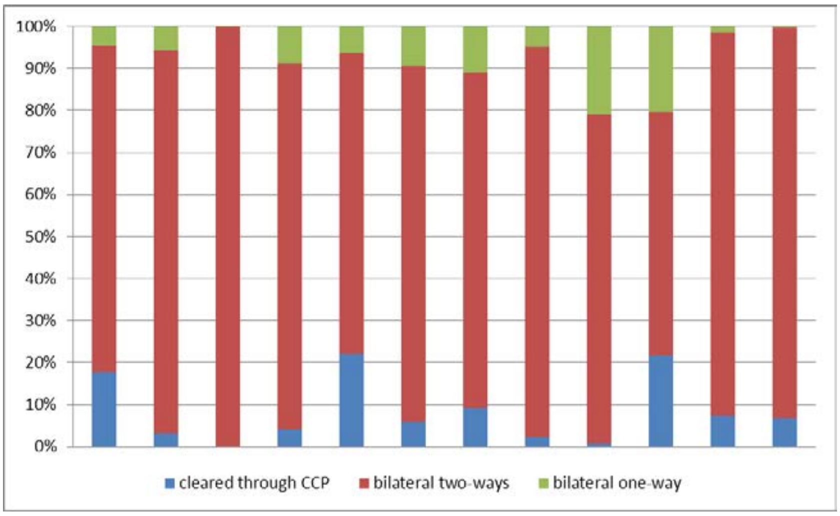
The portion of netting sets under a margin/collateral agreement (thereafter “margined netting sets”) and netting sets without a margin/collateral agreement (thereafter “unmargined netting sets”), as expressed in terms of EAD, is broadly similar for the participating banks: on average 55% of the total EAD comprises unmargined netting sets and 45% margined netting sets (see the figure below). However, since the EAD of margined netting sets under IMM are usually much lower than their unmargined equivalent, one is led to believe that margined netting sets are much more important when expressed in terms of trade count rather than of EAD. This portion will surely increase once the forthcoming clearing and margining requirements enter into force.

Figure 24: Margined/unmargined netting sets as expressed in % of total banks' IMM EAD.



The margin/collateral agreements in the banks' portfolios are clearly dominated by the bilateral margin agreements, which themselves are significantly dominated by two-way agreements (ie when both the banks and the counterparty post collateral) expressed in terms of EAD (see figure below). It is difficult to assess how much this breakdown would change if expressed in terms of trade count. The portion of centrally cleared netting sets is rather small compared with the bilateral agreements.

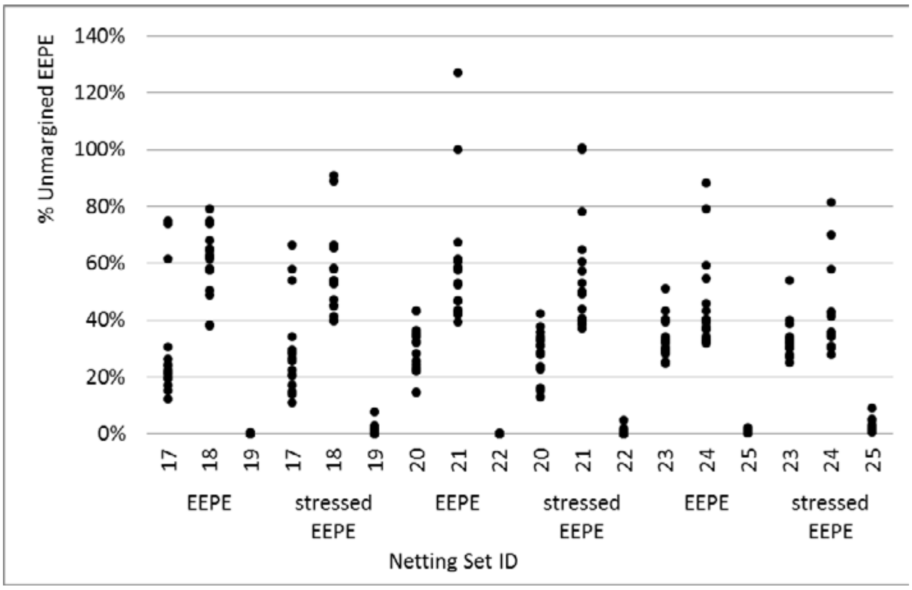
Figure 25: Type of margining as expressed in % of banks' total IMM margined EAD.



When the forthcoming clearing and margining requirements enter into force, the portion of one-way bilateral agreements will certainly decline, since the bilateral margin requirements for the vast majority are based on two-way agreements.

The graph below is intended to clarify the mitigating effects of margin agreements on derivative netting sets. For each participating bank, the graph displays the ratio between the EAD of a margined netting set from the HPE exercise and its unmargined equivalent,[21] for each of the three hypothetical two-ways margin agreements, ie (i) variation margin only; (ii) threshold amount[22] and variation margin; and (iii) independent amount[23] and variation margin.

Figure 26: Comparison of unmargined and margined netting set EEPE and stressed EEPE for three margin agreements.



The mitigating effect of a given margin agreement on the EAD of its unmargined equivalent is broadly stable across the three netting sets tested and does not seem to depend on their composition. On average, the EAD of the stylised margin agreement with variation margin represents only 34% of its unmargined equivalent, the stylised margin agreement with threshold amount and variation margin 59% of its unmargined equivalent and the stylised margin agreement with independent amount and variation margin 0.3% of its unmargined equivalent.

3.4.4.1 Comparison between Shortcut Method and Full simulation

In March 2014, the Basel Committee agreed to remove the Shortcut Method from the Basel framework to promote better risk modelling and to simplify the Basel framework. This change becomes effective as of 1 January 2017.

Four banks in the sample still use the Shortcut Method to compute the EEPE of margined netting sets under IMM. As can be observed in the table below, the Shortcut Method provides on average less conservative results than a full simulation across all the three stylised margin agreements. While the outputs of the Shortcut Method appear less variable than the outputs of full simulation, the

21 The margined netting sets 17, 18, 19 are based on the same portfolio as unmargined netting set 2 (interest rate offsetting netting set), margined netting sets 20, 21, 22 on unmargined netting set 1 (interest rate directional netting set), and margined netting sets 23, 24, 25 on unmargined netting set 15 (all-in interest rate and FX).

22 The threshold used was adapted to each netting set to reflect its composition.

23 The independent amount used was adapted to each netting set and based on estimates of the initial margin that would be required for each of them.

Shortcut Method omits important features of a margin agreement, which can result in inadequate risk modelling.

Statistics for dispersion of EEPE depending on method used to derive EEPE for margined netting sets Table 15

	All banks in the sample	Sorted by method used for margined netting sets	
		Shortcut Method	Full simulation
Sample size	16	4	12
Mean across margined NS	139%	112%	147%
Stdev/Mean across margined NS	211%	60%	224%

A known drawback of the shortcut method is the limited recognition of various features that may exist within margin agreements, other than the variation margin. As observed in the table below, this can cause the outputs of the shortcut method to deviate significantly from the outputs of full simulation.

Statistics for dispersion of EEPE differentiated by the margin features of the HPE and depending on method used to derive EEPE for margined netting sets Table 16

	Margin NS with VM only		Margin NS with VM and TH		Margin NS with VM and IA	
	Shortcut method	Full simulation	Shortcut method	Full simulation	Shortcut method	Full simulation
Sample size	4	12	4	12	4	12
Mean across netting sets	108%	106%	135%	96%	71%	238%
Stdev/Mean across netting sets	36%	37%	34%	19%	155%	234%

3.4.4.2 Modelling of cash flows during the margin period of risk

The modelling of cash flows during the margin period of risk (MPoR) is fundamentally linked to the point in time the bank chooses the MPoR to start as well as the default time of the counterparty within the MPoR. Among the participating banks, seven banks assume that the MPoR starts just after the last margin call whereas 11 banks assume that MPoR starts after the last successful settlement of collateral. Regarding the counterparty default, 10 banks assume that the counterparty defaults at the beginning of the MPoR, seven banks assume the default to happen somewhere within the MPoR and one bank assumes that the counterparty defaults at the end of the MPoR. The combinations of banks' choices are summarised in the following table:

Number of banks per combination of begin of MPoR and point in time when counterparty defaults

Table 17

	start of MPoR after last settlement	start of MPoR after last margin call	
default at beginning of MPoR	5	5	10
default within MPoR	5	2	7
default at end of MPoR	1	-	1
	11	7	

Generally, banks which assume that the default happens at the beginning of the MPoR also assume that there is no exchange of cash flows (eg coupon payments, exercise of options, exchanges of collateral) during the MPoR. In contrast, a bank that assumes the default occurs at the end of the MPoR also assumes that any cash flows are exchanged during MPoR.

The following table provides an overview of banks' assumptions with respect to the exchange of cash flows within different periods of the MPoR. It shows how the modelling assumptions for cash flow exchanges within the MPoR vary significantly.

Number of banks per combination of cash flow modelled during different periods of MPoR

Table 18

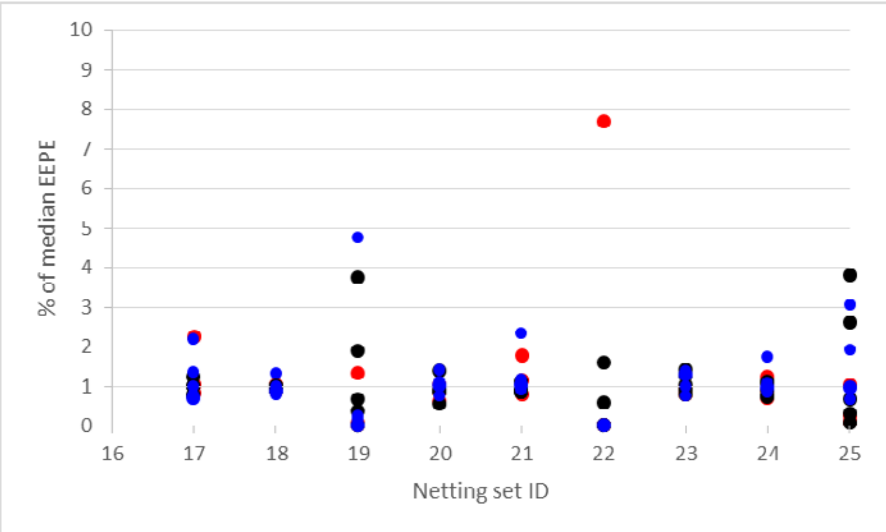
	None	Some cash flows (mostly settlement and coupons)	All (settlement, coupons payed and received, margin)
Before start of ISDA grace period (or similar)	4	2	10
During the grace period	10	3	3
After the default trigger is confirmed	16	0	0

Other than for stochastic changes of the market value of a netting set, not all banks consider the effect of deterministic sharp changes in the value of a netting set within the MPoR following or around the counterparty default. Such deterministic jumps are triggered by settlement events, particularly payments (eg because a large contract matures or a large payment is due under a swap contract). As a result the netting set value increases suddenly and persists until the margin balance is readjusted, ie by the end of the MPoR. This may result in substantially higher estimates of EAD because EEPE, due to its monotonic function, measures one-off exposure peaks due to settlement events that occur within the first year. Furthermore, differences in the modelling assumptions with regard to the time a counterparty defaults and settlement payments could have a significant impact on RWA variability across banks for margined derivative trades.

During the on-site visits, six participating banks were asked for more details about how they account for cash flows in the MPoR. Based on this feedback, banks can be grouped into two categories: banks that take cash flows into account and banks that show no spikes. The latter group does not show spikes for various reasons: (i) treatment as settlement risk; (ii) assumption of default at beginning of MPoR; and (iii) do not model precisely enough (eg Brownian Bridges substituting missing time grid points). Particularly banks in the last group sometimes assume that the default happens in the MPoR and that cash flows can occur in the MPoR, so that their modelling simply shows no spikes.

As outlined above, accounting for cash flows could lead to much higher exposures than at banks that do not account for cash flows within the MPoR. This expectation is confirmed by the HPE results of the margined netting sets. These banks demonstrate that accounting for some cash flows in any period of the MPoR shows more conservative results than those banks which consider no cash flows (see the table below). The dispersion for these two subsamples is much higher than for the other ones.

Figure 27: Dispersion of margined netting set EEPE dependent on the cash flows taken into account during the MPoR.



The red dots represent banks which do not take into account any cash flows; black dots represent banks which account for cash flows only before the start of ISDA grace period (or similar) and blue dots are banks' results where cash flows until the end of the grace period are considered in the IMM.

Statistics for the dispersion of EEPE or margined nettings sets dependent on the modelling assumptions for the margin period of risk — Table 19

	All samples	Are exchanges of cash flows modelled during the MPoR?			
		No	Only before the start of grace period	Until the end of the grace period	Until the end of the grace period and after default is triggered
Sample size	13	3	5	5	0
Mean across margined NS	147%	109%	166%	151%	-
Stdev/Mean across margined NS	218%	129%	258%	174%	-

The observed increase in variability when using a more granular modelling of cash exchange during the MPoR could also be related to differences in setting the grid points and to the sort of cash flows taken into account in the MPoR.

3.5 Other drivers leading to variability

3.5.1 Alpha parameter

To convert EEPE risk measures into EAD, banks have to apply the multiplier alpha which has a default value of 1.4. The alpha value may be adjusted under two circumstances:

- A discretion allows supervisors to increase alpha based on the compliance with qualitative criteria for counterparty credit risk management;
- Upon approval from supervisors, firms are permitted to model their own alpha taking into account the diversification of their portfolios across counterparties. In this situation, alpha cannot be lower than 1.2.

Four firms in the sample reported an alpha value different from 1.4: one firm uses an alpha lower than 1.4 and three firms use an alpha higher than 1.4.

The following test was used to determine whether an alpha different from 1.4 increases the variability of the IMM outputs. To consider a more realistic scenario, the variability is examined for the maximum between the stressed and non-stressed EEPEs for all the all-in netting sets, ie netting sets 5, 8, 13, 15, 16, 23, 24 and 25, by applying each bank's prevailing alpha in one case and 1.4 to all banks in the other case.

The resulting "EADs" show significantly less dispersion for the banks with an alpha different from 1.4, although it is important to note that the sample sizes are much smaller, which at least partly explains this result. The mean of EADs across the all-in netting sets is lower for banks with different alphas. This suggests that variability of RWA is higher for the (larger) sample of banks with an alpha of 1.4, given same PD and LGD for the counterparties across all banks. At the same time these banks show on average more conservative RWAs.

Statistics on the impacts of alpha in the dispersion maximum between non-stressed and stressed EEPE for the all-in netting sets — Table 20

	All samples	Bank's prevailing alpha		
		<1.4	1.4	>1.4
Sample size	19	1	15	3
Mean across all-in NS	164%	71%	177%	132%
Stdev/Mean across all-in NS	201%	29%	209%	48%

Case 1: Using banks' prevailing alpha.

Replacing banks' prevailing alpha by 1.4 for those banks with alphas different from 1.4 seems to better align the results of those banks to the median values of the other banks. It may be noticed that the bank which uses its own alpha estimation was overall less conservative than the other banks, even before the application of their own lower alpha. The same holds true for the banks with a higher alpha, for which the results are certainly less conservative when applying the lower default value for alpha.

Statistics on the impacts of alpha in the dispersion maximum between non-stressed and stressed EEPE for the all-in netting sets

Table 21

	All samples	Bank's prevailing alpha set to 1.4		
		<1.4	1.4[24]	>1.4
Sample size	19	1	15	3
Mean across all-in NS	168%	85%	184%	122%
Stdev/Mean across all-in NS	206%	28%	212%	48%

Case 2: Setting alpha to 1.4 for all the banks.

Since the sample of banks with alpha of 1.4 consists of the majority of banks, the results in this analysis are likely affected by other drivers of variability as well. Nevertheless, the analysis gives a first impression of the possible relative effect of different alphas, particularly when comparing the results of the two tables above. Furthermore the choice of alpha different from 1.4 will naturally lead to more variability of RWAs in addition to the variability stemming from the IMM itself.

The scope for supervisors to increase alpha takes into account weaknesses in banks' IMM. This option is in line with the multiplicative factor for VaR models in the market risk framework and can help encourage banks to improve internal models and processes and make them more risk-sensitive.

3.5.2 Conversion of risk measures into given base currency

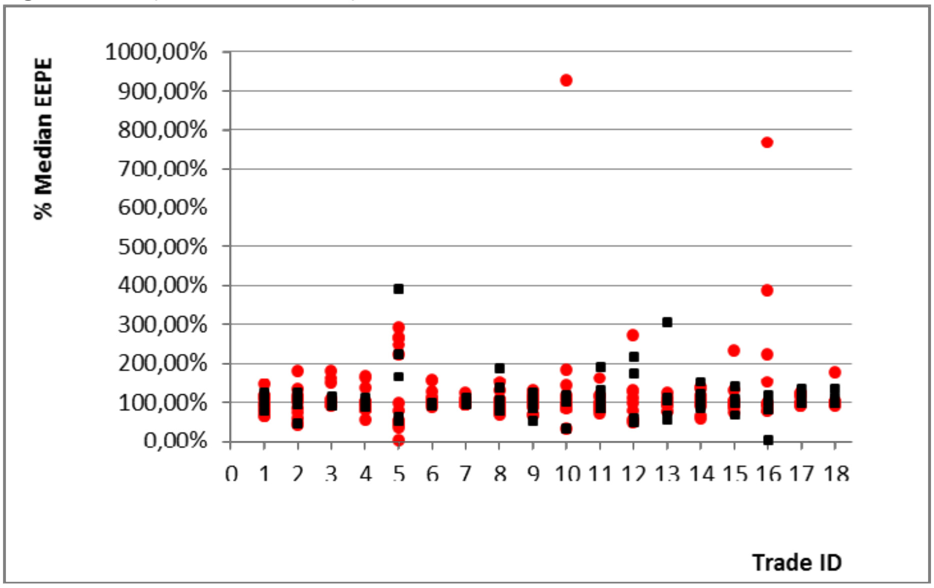
The outputs of the IMM are expressed in a single currency which generally matches the bank's reporting currency. Banks therefore need to convert trades in different currencies into this "IMM currency" during the simulation of their future market values at each time step. To do this, the majority of banks use simulated values for FX rates, jointly modelled under the IMM with the other asset classes. Few banks use forward values for the FX rates as implied by the domestic and foreign interest rate curves of each FX rate.

For the sake of the exercise, banks were asked to provide the IMM outputs of trades and netting sets in a given base currency which may have been different from the IMM currency. For some banks, this constraint created an additional risk because these banks could not change the currency under which the IMM outputs were generated into the required base currency.

As shown by the figure below, the trade EEPE results of the former group of banks, which were obliged to apply the additional conversion using spot rates, are slightly more conservative and dispersed than the EEPE results of the latter group of banks, which directly calculated the IMM outputs in the required currency.

24 The results shown in this table differ from those in the table above, even for the banks with an alpha of 1.4, because the median EAD of each netting set changes when all banks' (stressed) EEPEs are multiplied by 1.4 instead of by the prevailing alpha. Since the outputs are translated into a percentage of median EAD, ie the respective EAD as ratio of the median EAD, for the analysis the results shown are different in the two cases for each bank.

Figure 28: Dispersion of EEPE dependent on the conversion of market values of trades in a given base currency.



The red dots represent banks which generated outputs in IMM currency and then convert to base currency using spot rates. The black dots represent banks which generated the outputs directly in the required base currency.

Statistics on dispersion of EEPE dependent on the conversion of market values of trades in a given base currency

Table 22

	All samples	How market values are converted in a given base currency?	
		Outputs directly generated in required base currency	Outputs generated in IMM currency, then converted to base currency using spot rates
Sample size	18	6	12
Mean across trades	114%	109%	117%
Stdev/Mean across trades	69%	46%	76%

This source of variability is, however, inherent to the exercise and may not reflect real variability of banks' IMM outputs stemming from currency conversion. In fact, banks report only in one currency and therefore should convert the market values of trades expressed in different currencies only into this currency. The majority of the banks in the panel already stochastically model FX rates, jointly with the other asset classes, and use the simulated values of the FX rates to convert the market value of their trades in the relevant currency.

Chapter 4: CVA – Analysis of exercise results

4.1 Analysis methodology

The analysis focused on identifying the possible key drivers of CVA-VaR variability, and on assessing the impacts of these drivers in terms of absolute risk level and identifying sources of greater variability. It is based on two data sources: the CVA VaR HPE results and qualitative information provided by the participating banks on their CVA VaR methodology.

Of the 19 participating banks to the HPE, 15 banks with IMM approval are using the advanced CVA approach and have submitted data on CVA VaR. Therefore, the HPE results did not need to be pooled into two groups of banks using the standardised or advanced approach for the CVA VaR capital charge under Basel III, and the differences induced by these regulatory approaches have therefore not been analysed. The methodology for excluding erratic data used for the IMM results was not necessary for the CVA VaR exercise.

Fixed EE profiles have been used to isolate the variability resulting from the IMM models (ie variability due to differences in EE profiles) and the variability due to CVA VaR modelling. Accordingly, the analysis has consisted of two steps. Participating banks provided CVA VaR and CVA stressed VaR results, together with the EEPE results based on their IMM models, for two netting sets and eight real counterparties. They also recalculated CVA VaR and CVA stressed VaR using fixed EE profiles (for the same reference date), determined using an average of the banks' internal EE profiles.

4.2 Test portfolio description

Eight counterparty portfolios and two netting sets were considered in the CVA VaR exercise (Annex 3).

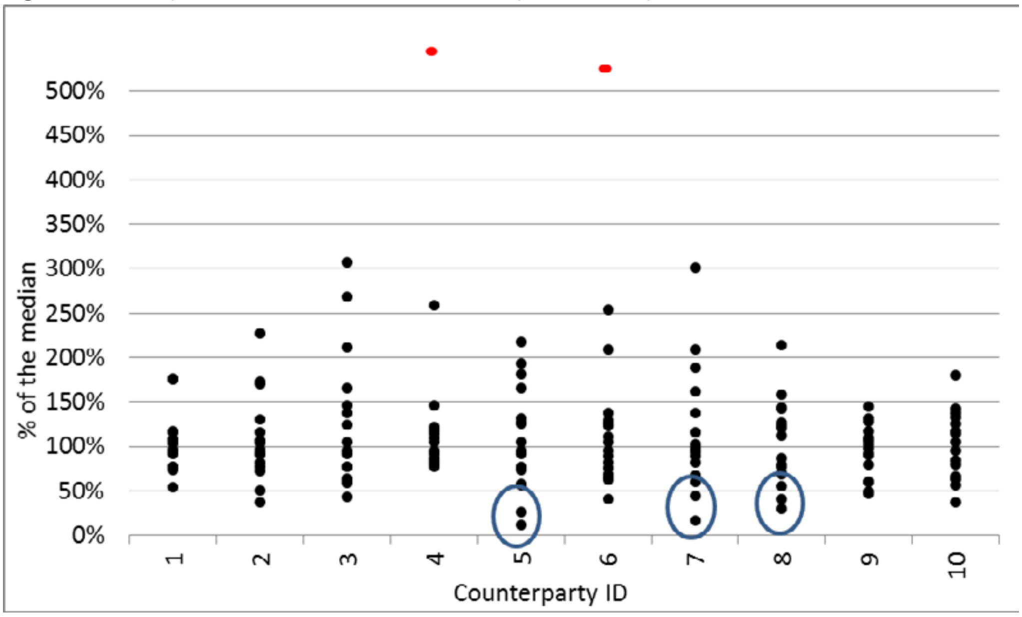
Half of the counterparties (non-financial) are associated with the netting set #15 of the CCR benchmarking exercise (with IR+FX all-in unmargined netting set) while the other counterparties are associated with the netting set #24 (the same netting set but margined). The netting sets only comprise simple derivatives. Both financial and non-financial counterparties were selected from different sectors, countries and ratings, and the sample contained counterparties without traded CDS.

4.3 Comparison of variability across portfolios

4.3.1 Participating banks' EE profiles

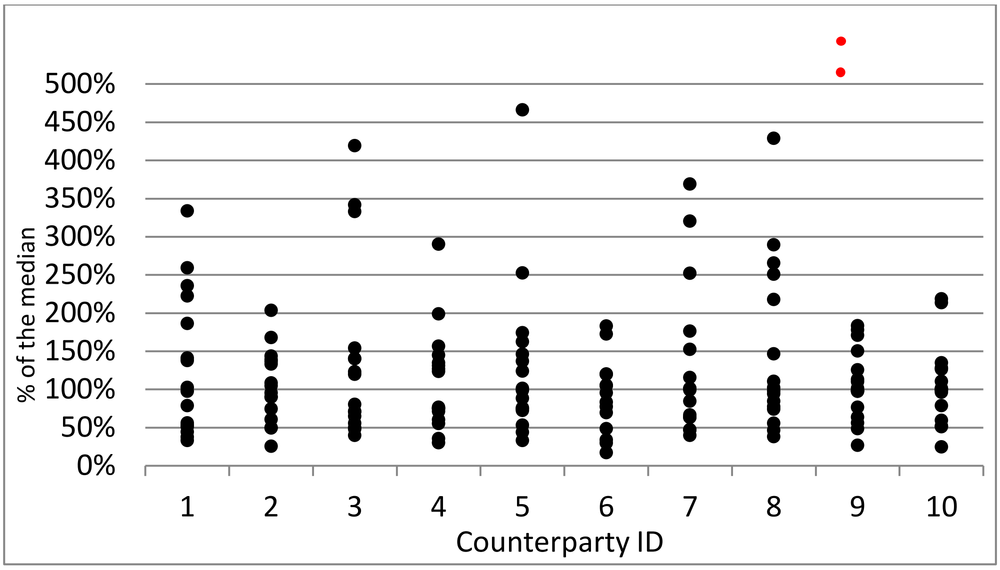
The graphs below show the dispersion of CVA VaR and CVA sVaR results with respect to the median values for all counterparty portfolios. Although some data points are very far away from the median, the results for many participating banks are between 50% and 150%. The dispersion of CVA sVaR results is greater than for the CVA results. CVA VaR results for counterparties without traded CDS are more likely to be below 50% of the median (blue circles). However, this distinction is reduced for CVA sVaR.

Figure 29: Comparison of CVA VaR – All counterparties – Dispersion from the median.



Beyond scale of graph (in red)
Counterparty 4 - 782%
Counterparty 6 – 558%

Figure 30: Comparison of CVA stressed VaR – All counterparties – Dispersion from the median.

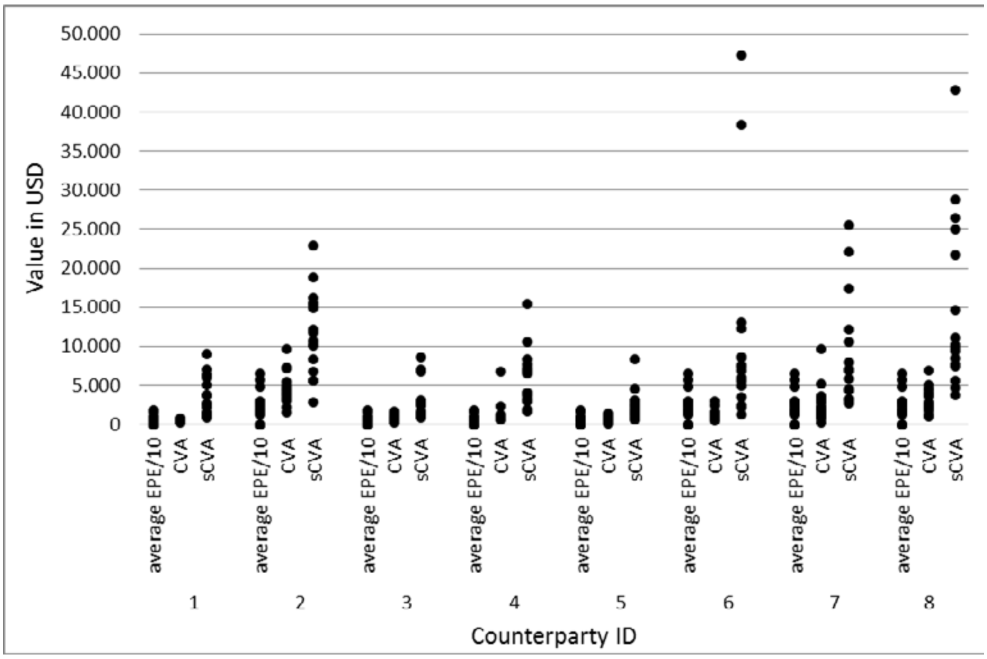


Beyond scale of graph (in red)

Counterparty 7 - 537%, 661%

The graph below shows similar results in terms of absolute values:

Figure 31: Variation of average EEPE, CVA VaR and CVA stressed VaR in absolute numbers.



4.3.2 Fixed EE profiles

The use of a fixed EE profile allows the impact on CVA variability stemming from differences in EE profiles to be disentangled from differences in CVA VaR and CVA sVaR modelling techniques across participating banks. Fixing the EE profile reduces the variability somewhat:

Figure 32: CVA VaR and CVA stressed VaR using the banks' internal EE profiles in absolute numbers.

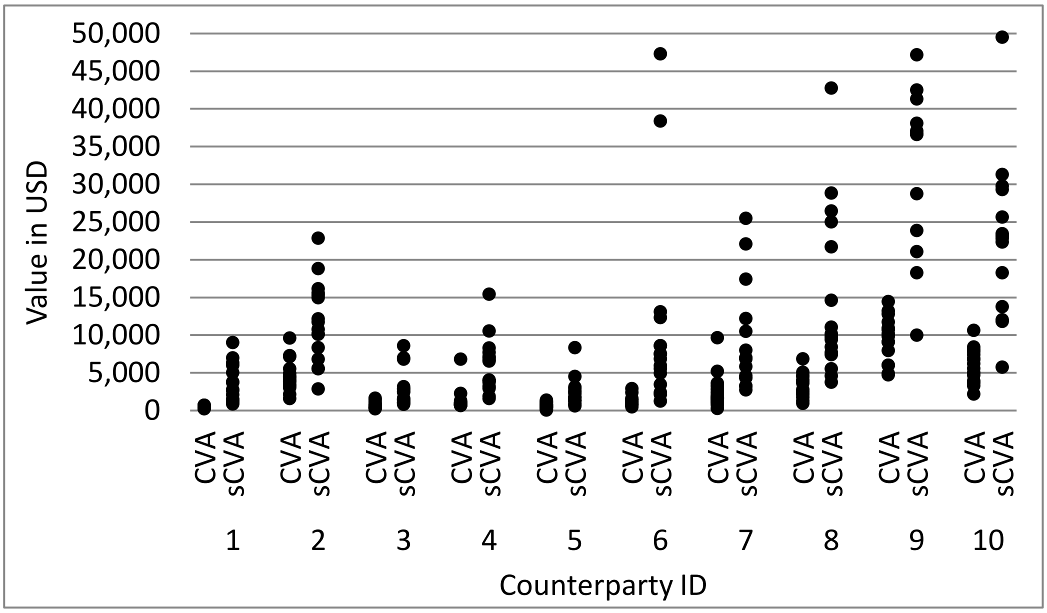
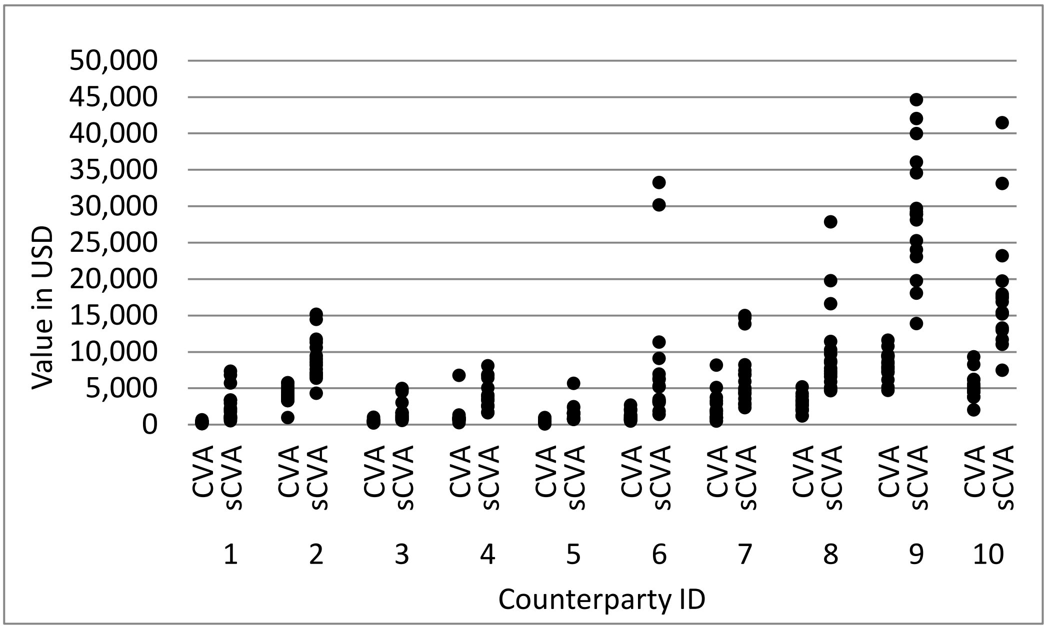
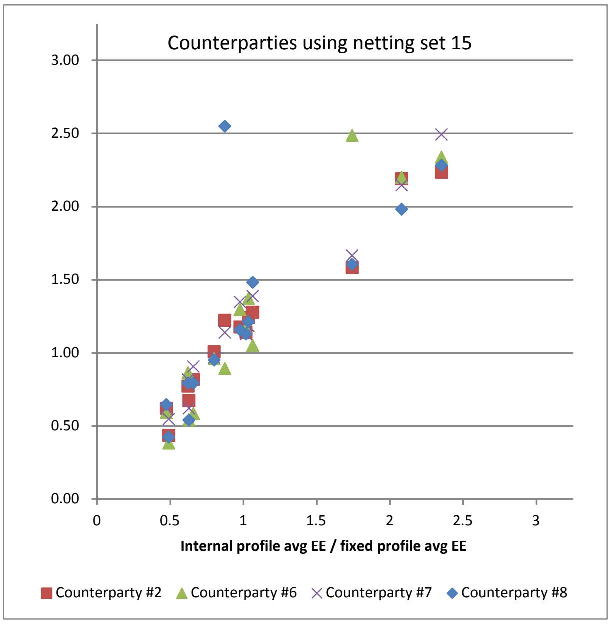


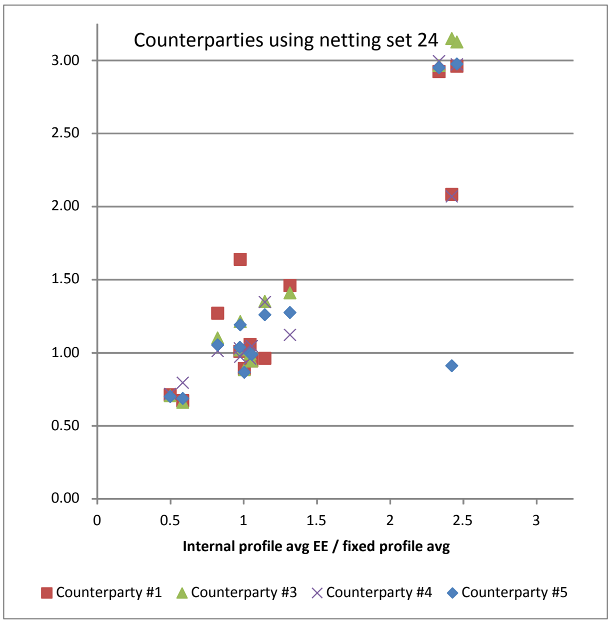
Figure 33: CVA VaR and CVA stressed VaR using the fixed EE profiles in absolute numbers.



The CVA sVaR results remain more dispersed than CVA VaR results, even when based on fixed EE profiles. The level of the EE profile scales the level of CVA VaR in a fairly proportional fashion. This can be seen in the figure below where the vertical axis is the size of CVA VaR when based on the internal calculation of EE profile (relative to CVA VaR under the fixed profile) and the horizontal axis is the size of that internal EE profile (relative to the fixed EE profile). This is broken out for the counterparties for which the HPE specified use of unmargined netting set #15 and counterparties for which margined netting set #24 was used. The proportional relationship is strong for the unmargined netting set, and weaker for the margined netting set.

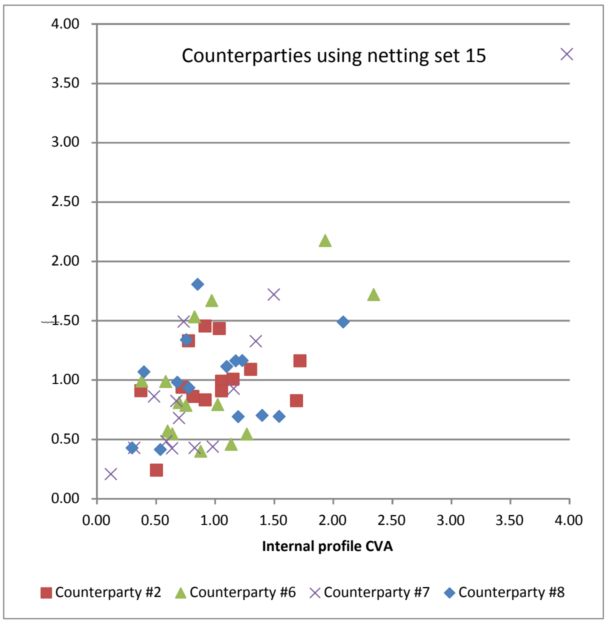
Figure 34: Changing EE profile has a roughly proportional effect on CVA VaR.

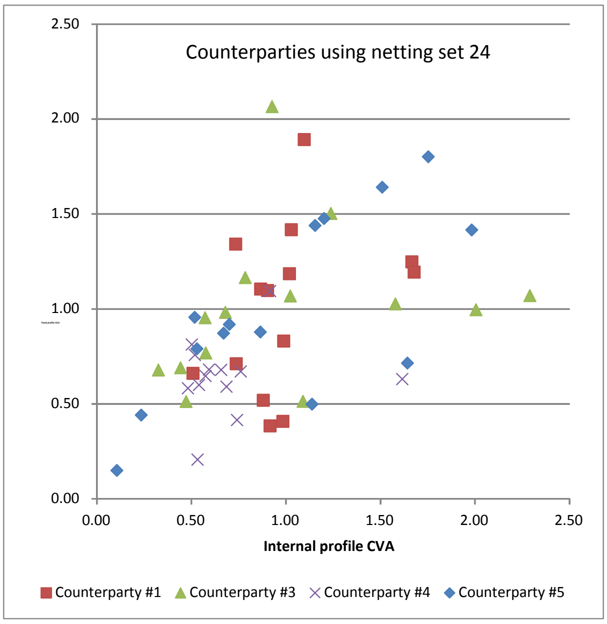




Moreover, as can be seen in the figure below, there is no clear relation in the order of the banks' CVA VaR results between the internal EE profile and the fixed EE profile. This is an indication of the relative importance of differences in exposure modelling as a driver of variation. If exposure modelling were not an important driver of variation, then the bank with the highest CVA VaR under the fixed profile would also be the highest under its internal profile. The second highest would remain the second highest etc. In the extreme case of exposure modelling being an insignificant source of variation, the relationship between internal profile CVA VaR and fixed profile would be one to one and the points in the figure below would lie on the 45-degree line. Instead, the highest CVA VaR under the fixed profile is not the highest under internal EE modelling. The factors that make CVA VaR high or low from one bank to another when exposure modelling is "turned off" under the fixed profile, eg differences in credit modelling and VaR methodology, are to some extent overwhelmed when variation in exposure modelling is "turned on". This finding varies by counterparty. Counterparty #5 preserves a fairly linear relationship between internal and fixed. Counterparty #4 is completely scrambled – its points on the graph resemble an unstructured cloud.

Graph 35: Does variation due to EE profile overwhelm other sources of variability?





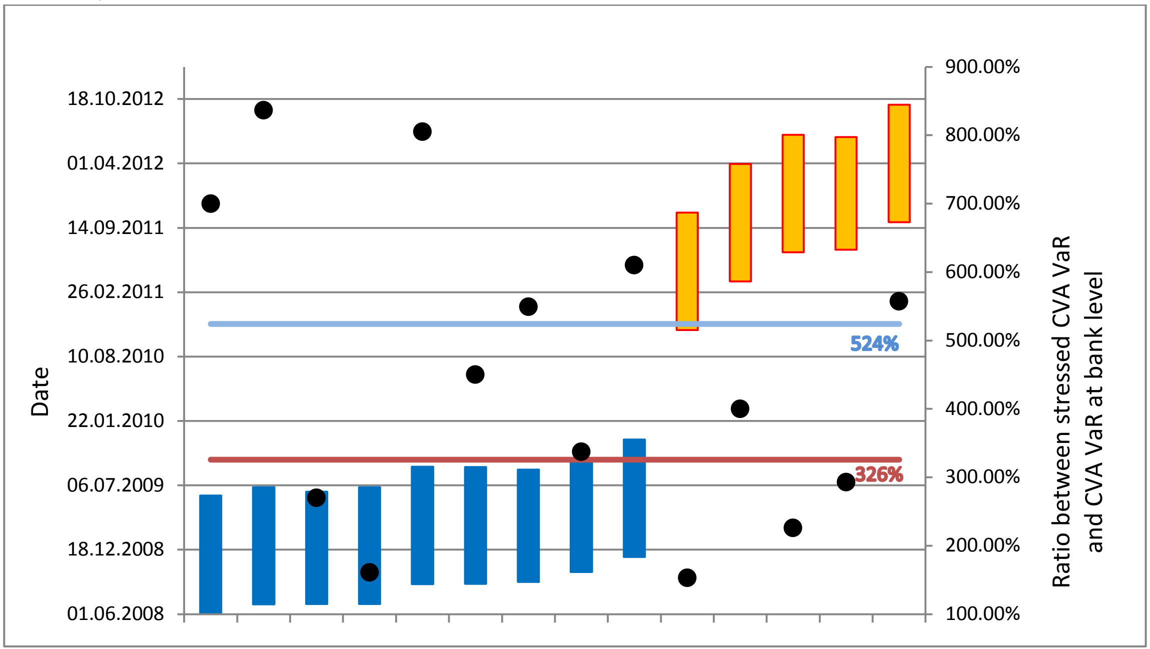
4.4 Main drivers of variability

4.4.1 Choice of stress period for stressed CVA

The CVA stress period of all participating banks is included within the three-year period for stressed EEPE. The majority of participating banks (nine) have an EEPE stress period starting in mid-2008 and a CVA stress period with the same starting date. The other participating banks have used a 2011–12 period.

The CVA sVaR depends heavily on the CVA stress period. The graph below connects these ratios (black marks based on the banks' own portfolio, right scale) with the one-year CVA stress period used (left scale). The banks using 2008–09 have an average CVA sVaR/CVA VaR ratio of 524% and the other banks an average ratio of 326%.

Figure 36: Comparison between CVA sVaR/VaR ratios and CVA stress period used, ranked by start date of the stressed period.



The use of a 2008–09 stress period leads therefore to more conservative CVA sVaR results for the HPE portfolios. Some participating banks use 2011–12 stress CVA periods due to the regulatory rules correlating the choice of the stress EEPE and CVA periods. These banks situate their stress EEPE period after the Lehman Brothers crisis before choosing the CVA stress period based on credit spread volatility.

The majority of banks first decide which period to choose for the stressed calibration of EEPE and then, within this three-year period, choose a one-year stress period for CVA purposes. However, during the on-site visits, one bank explained that it chooses the stress period for CVA first and then moves a three-year sliding window around that CVA stress period to find the period for EEPE stress calibration. Another bank chooses both stress periods independently from each other and then checks that the CVA stress period is located within the period for EEPE stress calibration.

4.4.2 Volatility modelling and use of proxies

As described in Section 3.4.2.2, the differences in banks' volatility modelling choices induced significant variability in the EEPE calculations and EE profile term structures. Because the CVA VaR time buckets can vary significantly across banks, this variability is further increased by the mapping of the EE profiles to the risk factors and time buckets in the CVA VaR calculation engines. However, the impacts of these variations are difficult to isolate due the variety of volatility levels used in the CVA VaR in connection with credit spread risk factors and time buckets.

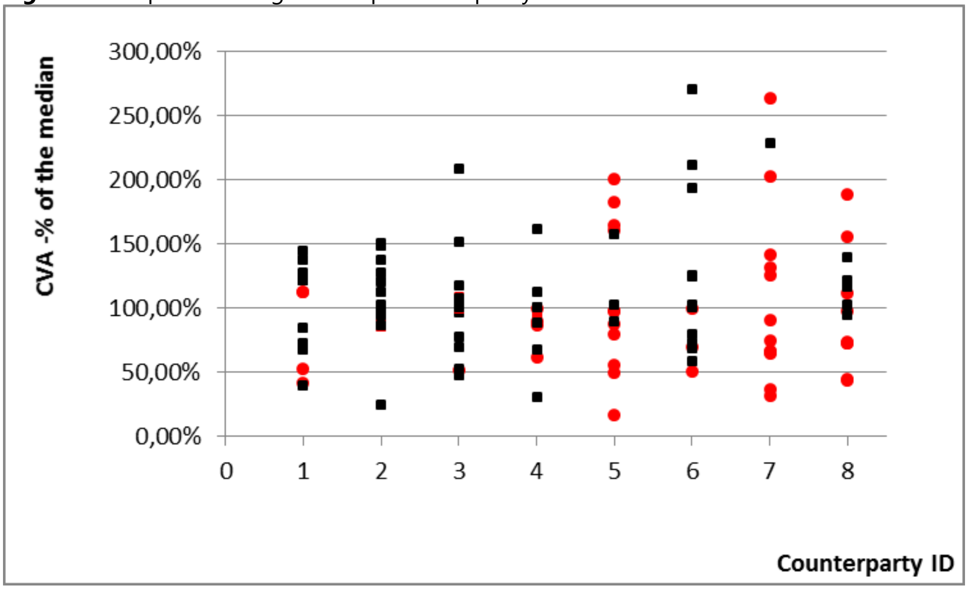
4.4.2.1 Variability induced by single-name CDS and proxy spreads

When counterparties do not have a quoted CDS, or when the series of the CDS spreads are not of sufficient quality, institutions use proxy spreads instead. Proxies are chosen taking into consideration the counterparty's rating, industry and region. Institutions may use single-name proxies, substituting the CDS spread of another individual name, often the counterparty's parent company. All institutions in the panel except one occasionally use single-name proxies. Alternatively, or if no acceptable single-name proxy exists, institutions may construct proxies based on quoted CDS spreads from multiple names.

When asked about a specific counterparty, most participating banks agreed whether or not a CDS for that counterparty is quoted. However, there was not a full consensus in the HPE as to whether quality spread data on the counterparties or acceptable single-name proxies were available. The most disagreement arose over counterparties #1 and #4, for each of which nine banks used a specific CDS spread and four used a multi-name proxy, and counterparty #8, where five used a specific CDS and nine used a multi-name proxy. Moreover, which banks used a multi-name proxy differed from counterparty to counterparty.

The graph below compares the CVA VaR from banks that use specific CDS spreads (in black) against the CVA VaR from banks that use multi-name proxies (in red). By visual inspection, the multi-name proxy banks appear to be more dispersed as a group for counterparties #5 and #8. The banks using specific CDS curves appear more dispersed for counterparty #4. Using Kendall's tau rank correlation analysis, this apparent relationship is only statistically significant for counterparty #8, where the use of a multi-named proxy is associated with a more dispersed CVA VaR.[25]

Figure 37: Impact of using name-specific or proxy CDS curves.



The red dots represent banks using a proxy (multi or single-name) for the counterparty and the black dots represent banks using a name-specific CDS curve.

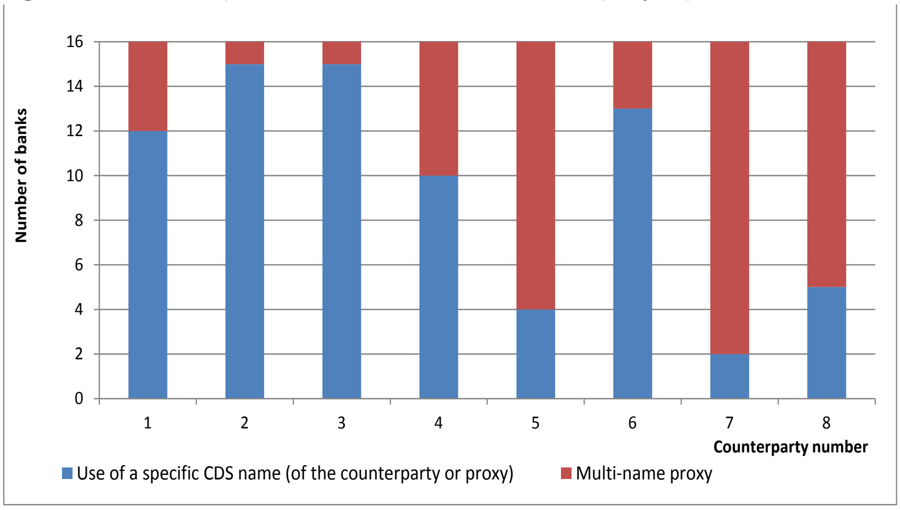
Statistics on impact of using name-specific or proxy CDS curves			Table 23
	All	Multi-name proxy	Specific CDS curve
Mean across counterparties	102%	96%	109%
Stdev/Mean across counterparties	45%	54%	40%
% of occurrence	100%	41%	59%

25 Absolute deviation from the median is greater, p-value of 0.04 for the two-tailed test.

These results might be expected as the different ways of calculating a multi-name proxy can be a significant source of variability. The following figure shows the percentage of use of a specific CDS name (initial counterparty or single-name proxy) for the HPE counterparties. It translates both:

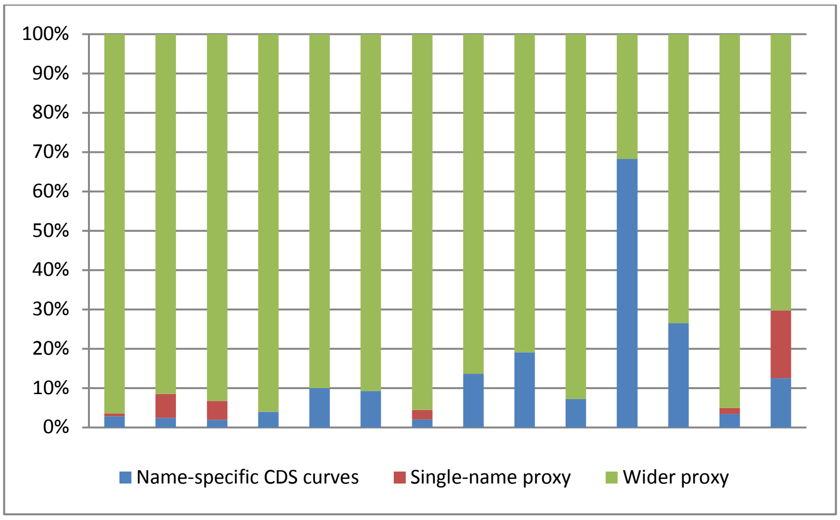
- the variability of the conditions for accepting a single-name proxy between the participating banks (eg regarding the degree of relationship between parent and child) and the difference in ratings (eg a difference of less than two notches between counterparty and proxy); and
- the variability when judging the quality of the CDS spread series (for the counterparty or a single-name proxy). For example, the liquidity is often considered through the number of contributors but the thresholds for deciding whether to use a CDS spread or a proxy often differ.

Figure 38: Use of a specific name CDS for a HPE counterparty expressed in total number of participating banks.



The use of counterparty name-specific CDS curves in the real portfolios of banks is limited (less than or equal to 10% of their counterparties for most participating banks). Although name-specific curves may be quoted, quality checks performed on the spread data (eg limited Markit contributors, data history missing, flat CDS curve, name not belonging to a main index) often influence this choice. For the vast majority of counterparties, banks use a multi-name proxy in their real portfolios.

Figure 39: Use of a name-specific CDS or a proxy expressed in % of participating banks' total number of counterparties.



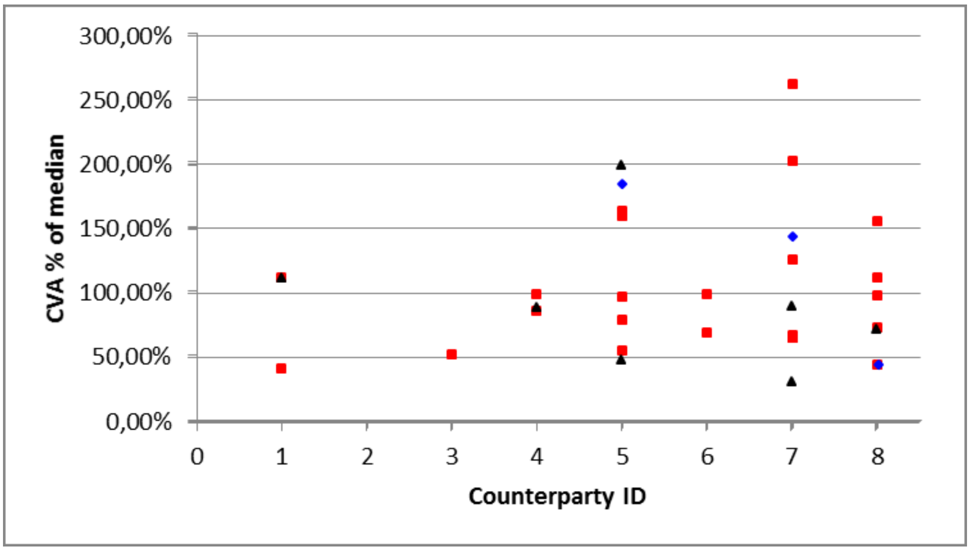
X-axis shows the participating banks. Y-axis reflects the share of banks' counterparties that is modelled using a name-specific CDS curve, a single-name proxy or a wider proxy.

4.4.2.2 Variability induced by different multi-name proxy spread methodologies

The HPE sample is too small to perform an impact analysis on the multi-name methodology, but three different approaches to building multi-name proxies have been noted:

- intersection method (five participating banks): for each rating, region, and sector categories, liquid CDS are chosen and a metric – often the average or median – is calculated. The difficulty of this method lies in dealing with subcategories where data is insufficient.
- cross-section method (two participating banks) based on a multi-dimensional regression across rating, region and industry sector.
- regression of spreads on index (less sophisticated method) chosen by one participating bank.

Figure 40: Dispersion of CVA VaR depending on the multi-name proxy methodology.



The red dots represent banks using an intersection proxy methodology, black dots those using a cross section methodology, and blue ones represent banks using others.

Statistics for dispersion of CVA VaR depending on multi-name proxy methodologies				Table 24
	all	method for modelling multi-name proxy		
		Intersection	Cross section	Others
Mean across counterparties	102%	104%	92%	123%
Stdev/Mean across counterparties	45%	51%	55%	48%

The participating banks use proxy spreads based on multiple names for the majority of the HPE counterparties, built according to rating, industry segments and regional criteria, and some banks mentioned additional characteristics such as currency and counterparty seniority.

As the choice whether to use a proxy spread, and the modelling approaches for multi-name proxies vary significantly across banks, further guidance and additional regulatory minimum requirements may need to be introduced to harmonise approaches across banks.

4.4.3 Other variability sources in the CVA VaR models

4.4.3.1 General VaR variability drivers

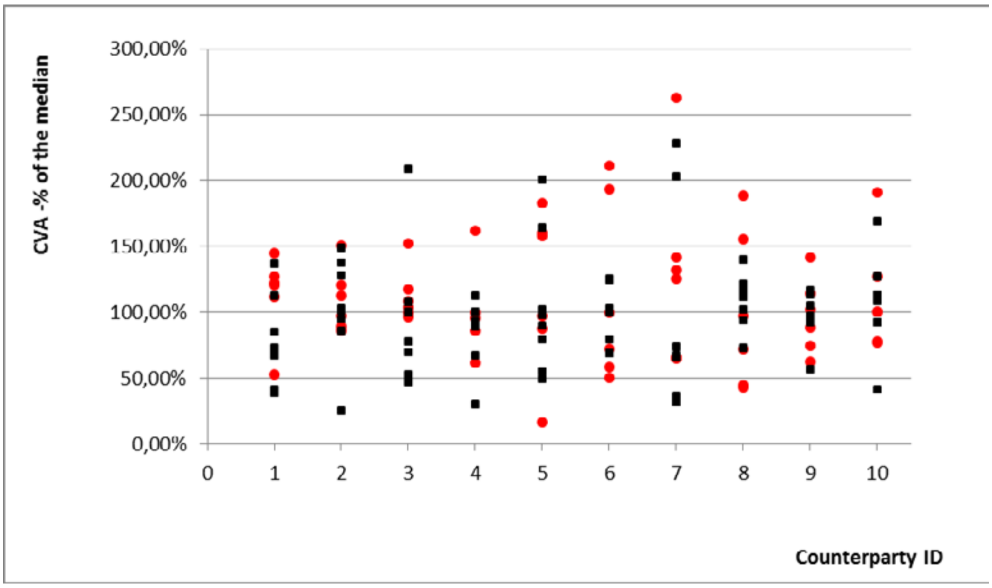
All observations of the phase 2 of market risk HPE concerning the significant variability of the VaR results due to the diversity of methodological choices made by the banks also apply to the CVA VaR.

Accordingly, the figures below summarise the risk levels (mean) and variability (standard deviation divided by mean) when grouping the HPE portfolios based on main known VaR variability drivers: full vs partial repricing, scaling to 10 days and length of calibration period.

Although it is not possible to isolate the impacts of these variability drivers nor extrapolate observations based on the limited HPE sample, it was observed that:

- Slightly more dispersion of CVA VaR results when using full repricing (black dots) and higher probability of observed to low or to high results based on partial repricing (red dots).

Figure 41: Impact of full versus partial repricing on the dispersion of CVA VaR results.

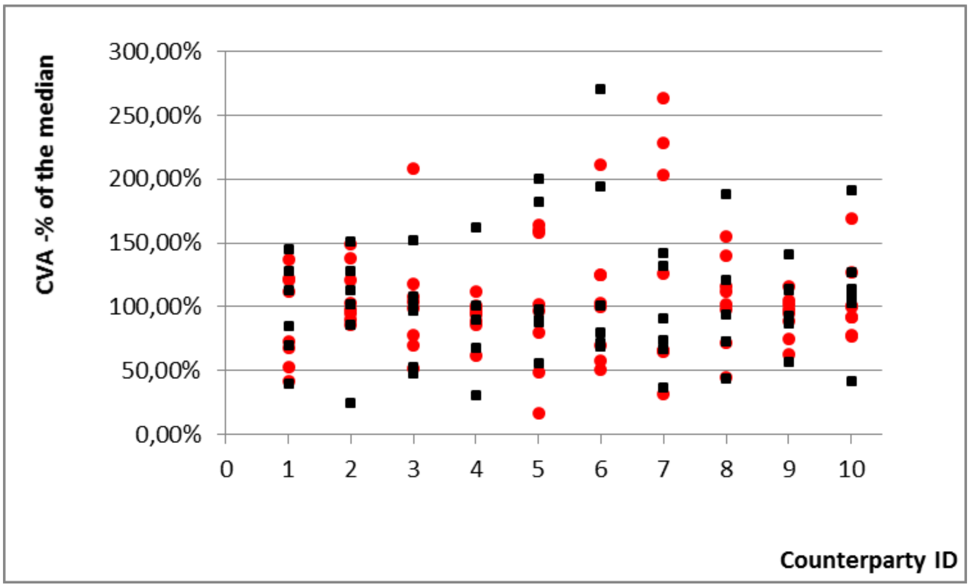


The red dots represent banks with partial repricing, black dots those full repricing.

Statistics for impact of full vs partial repricing on the dispersion of CVA VaR results			Table 25
	All	Full repricing	Partial repricing
Mean across counterparties	102%	98%	111%
Stdev/Mean across counterparties	43%	45%	41%
% of occurrence	100%	43%	57%

As regards the impact of the method used to derive the 10-day VaR, using the square root of 10 days as scaling factor (seven participating banks, red dots) vs calculating directly a 10-day VaR (eight banks, black dots) no conclusion can be drawn. The mean is the same for the two groups of banks and the variability for banks using no scaling factor is only slightly higher.

Figure 42: Impact of scaling the one-day CVA VaR.

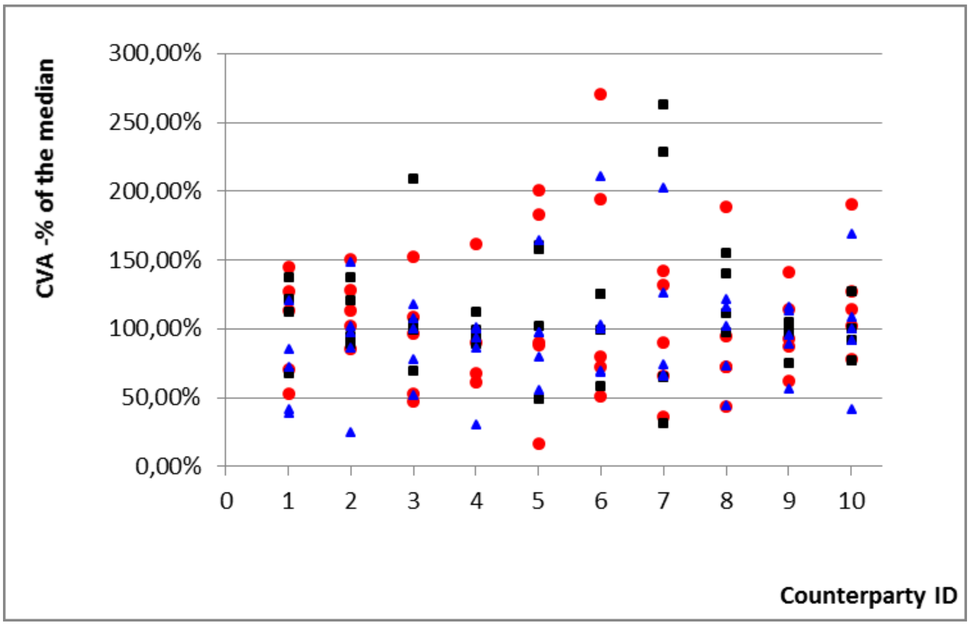


The red dots represent banks using the square-root-of-10-rule, whereas black dots represent banks calculating the 10-day VaR directly.

Statistics for impact of scaling the one-day CVA VaR			Table 26
	All	Method for deriving 10-day VaR	
		√10 scaling factor	No scaling factor
Mean across counterparties	102%	104%	104%
Stdev/Mean across counterparties	43%	42%	46%
% of occurrence	100%	57%	43%

The same holds true for the scaling to the 10-day VaR concerning the impact of the length of the historic data used to calibrate the CVA VaR. The results for the two groups of banks do not vary much. Among the 14 banks, the length varies between one and eight years (black = more than two years, blue = two years, red = less than two years). Four banks adopt a weighting scheme model.

Figure 43: Impact of using different lengths of time series.



The red dots represent banks using a time series longer than two years, black dots those using less than two years, and blue ones represent banks using a time series equal to two years.

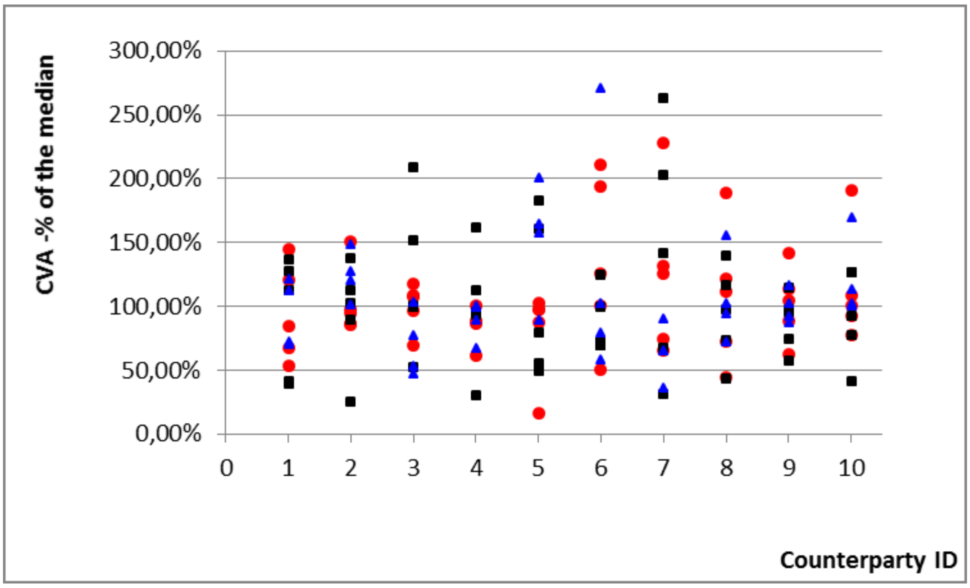
Statistics for impact of using different lengths of time series				Table 27
	All	Length of time series used		
		Less than two years	Two years	More than two years
Mean across counterparties	102%	113%	94%	106%
Stdev/Mean across counterparties	43%	40%	41%	47%
% of occurrence	100%	29%	36%	36%

4.4.3.2 Specific CVA VaR variability drivers

The modelling of idiosyncratic factors in relation to the use of proxy methodologies is also expected to be a significant variability driver of the CVA VaR results. Some participating banks do not model these factors between the counterparty names and their corresponding proxies. Other banks take it into account via more or less sophisticated methods.

The figure below shows the dispersion (from the median) of the CVA VaR results that differentiate banks' choices in modelling idiosyncratic risks. Six banks model an idiosyncratic basis between a given name and the proxy for the subcategory to which it is mapped (black dots). Four banks rely on add-ons or multipliers (blue dots). Three participating banks do not include this risk (red dots).

Figure 44: Impact of modelling of idiosyncratic factors in CVA VaR.



The red dots represent banks not taking basis risk into account, black dots represent banks taking into account idiosyncratic risk, and blue dots those using add on/ratio.

Statistics for impact of modelling of idiosyncratic factors in CVA VaR — Table 28

	All	How is basis risk taken into account?		
		No basis	Idiosyncratic	Add-on/ratios
Mean across counterparties	102%	105%	102%	105%
Stdev/Mean across counterparties	43%	40%	48%	42%
% of occurrence	100%	36%	36%	36%

As might be expected, the group of banks that model an idiosyncratic basis risk exhibit more variability of CVA VaR (standard deviation of 49% against 43% for the whole sample). However, no clear impact can be observed based on the mean values.

For the sake of consistency, the idiosyncratic risk modelled here should match the basis in the specific risk models of the market risk VaR.

4.4.4 Variability induced by credit ratings and LGD inputs

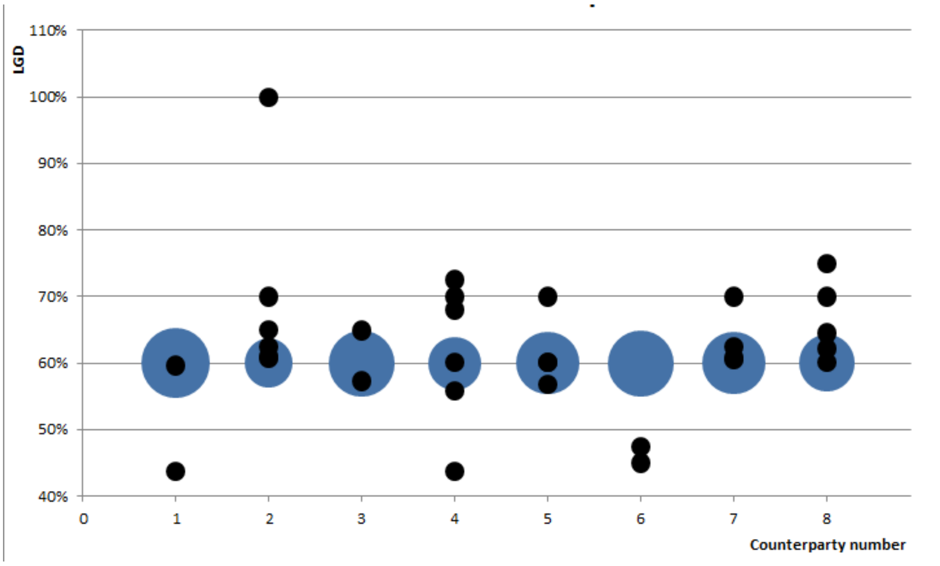
This review did not cover the banks' credit rating methodologies and their impacts. The participating banks generally highlighted their consistent use of credit ratings in their IMM and regulatory market risk frameworks. However, various approaches were observed concerning their rating mapping process for proxy spreads and CVA VaR calculations, the granularity of their rating grids, their preference for external or internal credit rating sources and their default values used for unrated names.

The diversity of loss-given-default (LGD) inputs used by the participating banks has a more straightforward impact on the variability of the CVA VaR results. Indeed, the $\mathrm{LGD_{mkt}}$ input is present in two parts of the CVA formula:

$$\mathrm{CVA} = \mathrm{LGD_{mkt}} \sum_{i=1}^{T} \max\left\{0, \exp\left(-\frac{s_{i-1} \cdot t_{i-1}}{\mathrm{LGD_{mkt}}}\right) - \exp\left(-\frac{s_i \cdot t_i}{\mathrm{LGD_{mkt}}}\right)\right\} \frac{\mathrm{EE}_{i-1} \cdot D_{i-1} - \mathrm{EE}_i \cdot D_i}{2}$$

The significant variability across the HPE counterparties observed for these LGDs – which should be based on the spread of the market instruments of each counterparty – is due both to the multi-name methodologies and to the LGD mapping process for single-name CDS. In the figure below, the circles are proportional to the number of participating banks using a particular LGD:

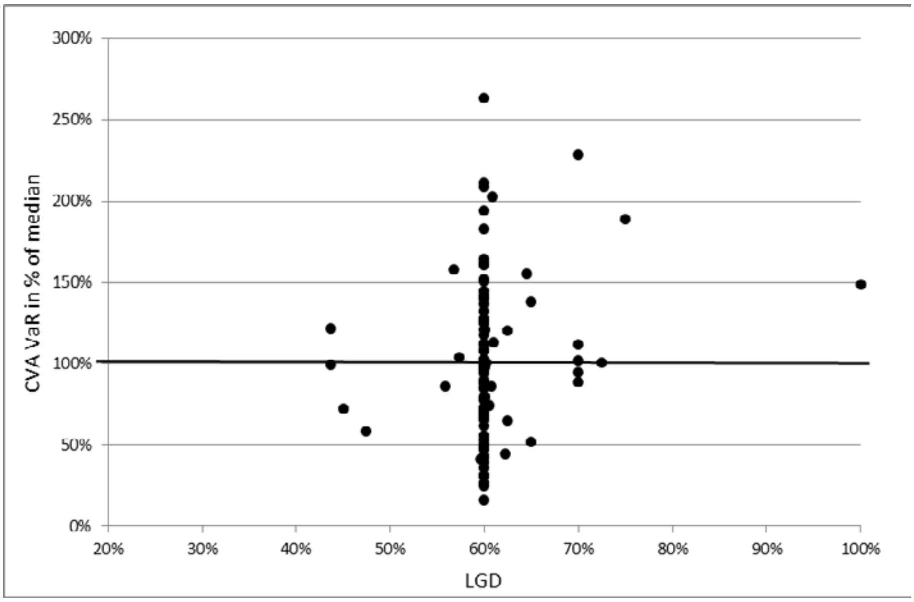
Figure 45: Dispersion of LGDs across counterparties.



In most cases, $\mathrm{LGD}_{\mathrm{mkt}}$ is a market convention and is worth 60%. Accordingly, some banks always use a 60% LGD, regardless of the CDS market convention. However, in some cases, the market convention is different and when proxy methodologies are used, both spreads and LGDs may be estimated through the same methodology. Other banks added a conservative mark-up, eg for seniority reasons.

The figure below shows the dispersion of the CVA VaR results across all counterparties and participating banks. The highest dispersion is observed around the 60% LGD, where most data results are located. A positive correlation between LGD and CVA VaR levels supports the expectation that CVA VaR is an increasing function of LGD:

Figure 46: Dispersion of CVA VaR compared with LGDs.



4.5 Other drivers leading to variability

4.5.1 Variability due to supervisory adjustments

The supervisory multipliers CVA VaR and sVaR are set to three for all participating banks except for one. Thus, the multipliers do not appear as a source of variability in the HPE.

4.5.2 Scope of the CVA charge

The discretions for competent authorities to include SFTs in the scope of the CVA charge as well as counterparty exemptions in a number of jurisdictions were observed during the HPE. Overall, nine out of 15 participating banks have IMM positions which are not included in their advanced CVA calculations. Also nine out of 15 participating banks include non-IMM positions in their advanced CVA calculations, the range of transactions covering SFT products, equity swaps, dividend swaps, exotic products, hybrid derivatives, as well as exchange traded derivatives.

4.5.3 Market risk CVA hedges

In total, 12 banks who responded to the questionnaire hedge the risks associated with the accounting CVA. Among these banks, seven banks take into account the basis between an individual counterparty spread and the spread of an index CDS. Nine banks have hedges which are not recognised for RWA purposes. It could be hedges on exempted counterparties, if any, or hedges with non-credit instruments (interest rate, change or equity instruments). In the Basel framework, these hedges will appear as naked positions in the general market risk VaR [reference to be added to Basel Committee CVA review].

Annexes

Annex 1: Trade detail specification

Description of HPE trades — Table 29

Trade number	Description
1	20y Interest rate swap receiver on 6M Euribor
2	5y Interest rate swap payer on 3M USD LIBOR
3	5y Interest rate swap receiver on 3M USD LIBOR
4	2y Interest rate swap receiver on 6M GBP LIBOR
5	2y OIS swap payer on SONIA
6	10y Interest rate swap receiver on 3M USD LIBOR
7	5y long swaption on 5y interest rate swap – 3M USD LIBOR vs fixed
8	1y FX forward contract – Sell USD/Buy JPY
9	2y FX forward contract – Sell EUR/Buy USD
10	10y Cross-Currency Basis Swap – Receive USD 3M LIBOR vs Pay EUR 3M EURIBOR
11	2y Cross-Currency Basis Swap – Pay USD 3M LIBOR vs Receive JPY 3M LIBOR
12	1y Equity forward contract – AXA
13	1y Equity forward contract – Metlife
14	6M Equity forward contract – Volkswagen AG
15	1y Equity index forward contract – DAX index
16	1y Equity index forward contract – FTSE 100 index
17	1y long call on Google OTM
18	1y long put option S&P 500 Index

Annex 2: Netting set specification

Description of HPE netting sets — Table 30

Netting set number	Trade Number	Description
1	1	20y Interest rate swap receiver on 6M Euribor
	2	5y Interest rate swap payer on 3M USD LIBOR
2	1	20y Interest rate swap receiver on 6M Euribor
	3	5y Interest rate swap receiver on 3M USD LIBOR
3	4	2y Interest rate swap receiver on 6M GBP LIBOR
	5	2y OIS swap payer on SONIA
4	6	10y Interest rate swap receiver on 3M USD LIBOR
	7	5y long swaption on 5y interest rate swap – 3M USD LIBOR vs fixed
5	(1–7)	All interest rate trades: all the individual IR trades of the exercise
6	8	1y FX forward contract – Sell USD/Buy JPY
	9	2y FX forward contract – Sell EUR/Buy USD
7	10	10y Cross-currency basis swap – Receive USD 3M LIBOR vs Pay EUR 3M EURIBOR
	11	2y Cross-currency basis swap – Pay USD 3M LIBOR vs Receive JPY 3M LIBOR
8	(8–11)	All FX trades: all the individual FX trades of the exercise
9	12	1y Equity forward contract – AXA
	13	1y Equity forward contract – Metlife
10	14	6M Equity forward contract – Volkswagen AG
	15	1y Equity index forward contract – DAX index
11	12	1y Equity forward contract – AXA
	16	1y Equity index forward contract – FTSE 100 index
12	17	1y long call on Google OTM
	18	1y long put option S&P 500 Index
13	(12–18)	All equity trades: all the individual equity trades of the exercise
14	10	10y Cross-currency basis swap – Receive USD 3M LIBOR vs Pay EUR 3M EURIBOR
	6	10y Interest rate swap receiver on 3M USD LIBOR
15	(1–11)	All interest rate and FX trades: all the individual interest rate and FX trades of the exercise
16	(1–18)	All trades: all the individual interest rate, FX and equity trades of the exercise
17	Netting Set 2	No initial margin, independent amount, minimum transfer amount or threshold amount
18	Netting Set 2	No initial margin or independent amount, but fixed minimum transfer amount and threshold amount
19	Netting Set 2	No initial margin or threshold amount, but fixed minimum transfer amount and independent amount
20	Netting Set 1	No initial margin, independent amount, minimum transfer amount or threshold amount

21	Netting Set 1	No initial margin or independent amount, but fixed minimum transfer amount and threshold amount
22	Netting Set 1	No initial margin or threshold amount, but fixed minimum transfer amount and independent amount
23	Netting Set 15	No initial margin, independent amount, minimum transfer amount or threshold amount
24	Netting Set 15	No initial margin or independent amount, but fixed minimum transfer amount and threshold amount
25	Netting Set 15	No initial margin or threshold amount, but fixed minimum transfer amount and independent amount

Annex 3: Counterparty portfolio specification

Counterparty portfolios and netting sets — Table 31

Counterparty		Exposures profiles[26]
1.	Prudential Global Funding LLC	Internally modelled profile for netting set #24
2.	British Airways PLC	Internally modelled profile for netting set #15
3.	Industrial Bank of Korea	Internally modelled profile for netting set #24
4.	Fiat Finance North America INC	Internally modelled profile for netting set #24
5.	Groupama GAN VIE	Internally modelled profile for netting set #24
6.	General Electric Company	Internally modelled profile for netting set #15
7.	Louis Dreyfus Commodities Suisse SA	Internally modelled profile for Netting set #15
8.	Arcelormittal Brasil SA	Internally modelled profile for netting set #15
9.	All-in portfolio (all counterparties) (=1)+2)+3)+4)+5)+6)+7)+8))	Internally modelled profiles
10.	Sub all-in portfolio (counterparties with traded CDS) (=1)+2)+3)+4)+6))	Internally modelled profiles

[26] Netting set #15: unmargined IR + FX all-in netting set; netting set # 24:_margined IR + FX all-in netting set.