ISDA® Safe, Efficient Markets

Risk Sensitive Capital Treatment for Clearing Member Exposure to Central Counterparty Default Funds

March 2013

Contact: Edwin Budding, ISDA – ebudding@isda.org

www.isda.org

ISDA gratefully acknowledges the substantial contribution of Gary Dunn[1] in connection with the preparation of this paper.

About the International Swaps and Derivatives Association, Inc. (ISDA)

Since 1985, ISDA has worked to make the global over-the-counter (“OTC”) derivatives markets safer and more efficient. Today, ISDA has over 800 member institutions from 60 countries. These members include a broad range of OTC derivatives market participants including corporations, investment managers, government and supranational entities, insurance companies, energy and commodities firms, and international and regional banks. In addition to market participants, members also include key components of the derivatives market infrastructure including exchanges, clearinghouses and repositories, as well as law firms, accounting firms and other service providers. Information about ISDA and its activities is available on the Association's web site: www.isda.org.

[1] Group Risk , Senior Manager, HSBC Bank Plc

Contents

1. Executive Summary

- ISDA has been working on a proposal that we consider can be calibrated to properly measure the risk of loss of a Clearing Member's ("CM") default fund contribution and meet regulatory requirements. The proposal builds on existing frameworks and in our view has a firm theoretical underpinning which should deliver appropriate sensitivity to the key risks to the default fund. Part of the proposal, specifically the Historic Drawdown Measure ("HDM") has been reviewed by the Joint Working Group ("JWG"). We now propose to incorporate the HDM into an Incremental Default Risk Charge ("IDRC"), which is the type of model that is currently used for trading book default risk. Our proposal is that Central Counterparties ("CCPs") would be required to provide the HDM[2] data to CMs. CMs would then run an IDRC model to estimate the 99.9th percentile loss on the basis that they might become liable for calls on the default fund over a one-year time horizon. The capital requirement covers funded and unfunded losses.

- Incorporation of HDM into an IDRC framework captures the risk of multiple CM defaults, not only on a single CCP but across all CCPs on which the CM clears. In contrast to our proposal, BCBS 227 treatments, and HDM by itself, overlook the risk of multiple CM defaults. Only the IDRC analysis provides insight into the potential contagion risk across CCPs.

- The recent risk-weighted assets ("RWA") variability exercise[3] has highlighted the variation in capital requirements generated by IDRC models and we fully understand the need to ensure a prescriptive and conservative calibration of an IDRC model used for the purpose we propose.

- The HDM data is an input into the IDRC model. This recognises that when a CM defaults it will likely default on multiple CCPs simultaneously. Thus, it must be taken into account that a CM has exposure to all of the CCPs on which it clears simultaneously and it is insufficient to capitalise exposures to each on a standalone basis[4].

- Using limited HDM data provided so far by some CCPs, we are able to estimate a conservative probability that a non-defaulting CM's default fund contribution will suffer a loss when another CM defaults, and the likely size of the loss. The approach is consistent with the IRB approach used for credit risk on the banking book and the Incremental Risk Charge (IRC)[5] applied to cover credit risk in the trading book.

[2] Stress based loss data could be provided by CCPs as an alternative
[3] http://www.bis.org/press/p130131.htm
[4] Mathematically this is analogous to combining VaR measures obtained from several CCPs rather than looking at VaR of the consolidated portfolio.
[5] IRC captures migration risk as well as default risk. IDRC was originally proposed for the trading book in the 2004 Trading Book Review.

- Our proposal can be calibrated to obtain a Loss Given Default ("LGD") for each CCP default fund based on its HDM data and other stress testing work, taking into account the default probability of each CM on a CCP. The model inputs can be tightly prescribed by regulators to control the risk of model variability. Alternatively, regulators may wish to provide CCPs and CMs with some scope for model judgement. However because of the potential for regulators to tightly prescribe model inputs we see this approach as non-IMM.

- An IDRC model could be made publicly available for all CMs to use.

Assumptions in this paper

- In this paper we have used a Gaussian Copula IDRC model[6] and used publicly available CM ratings and default probability data to illustrate the concepts and risk analysis inherent in our proposal. At this stage we consider it more important to focus on the concept of using IDRC models for the proposed purpose than to finalise the details of any such model.

- For the purposes of clarity, this paper does not take into account default scenarios for clients of a CM. It only addresses the risks of CM's defaulting. However we do see ways in which this model could potentially be applied to the issue of default fund sizing for client positions as well, and capitalisation thereof. This would involve a more innovative approach dealing with the probability of not porting and loss given failure to port a client. We could replace PD and LGD with the acronyms PNP and LGNP. However the issue of porting is a wider one and so we limit ourselves here just to house positions.

- The HDM data used in this paper is based on a historical drawdown on default funds, under a certain default scenario, specifically the simultaneous default of the two largest CMs. This is the standard specified by CPSS-IOSCO. That is, the calculation assesses appropriate capital charges for default fund contributions as a measure of historical drawdown, assuming, for each observation, that the two largest CMs default. The data used covered the last 2 years. With CCP support the HDM could be calibrated more accurately and be based on a longer history including a period of stress. The resulting figure could also be increased by 25% (1.25x stress multiplier) as per ESMA Regulatory Technical Standards.

- Our initial finding, based on the calibration assumptions and data currently available to us, is that the probability of a default causing losses to non-defaulting CMs is no more than 30%, and the expected loss would likely be less than 20% of a funded default fund contribution. We are also able to run the model over a consolidated list of CMs on a group of CCPs to which a particular CM has exposures in order to compute a consolidated IDRC charge.

[6] The Gaussian Copula has merit in that it is consistent with banking book Internal Ratings Based ("IRB") models.

2. Introduction

The BCBS has proposed two interim methods for calculating a bank's exposures to CCP default fund contributions[7].

We appreciate that BCBS 227 presents an interim framework, which the JWG is revisiting. We applaud this work as we consider that key aspects of BCBS 227 merit revision. In particular, we would emphasise the need to revise the methods employed to calculate the capital for default fund contributions to a CCP.

Interim Method 1

Method 1 calculates a theoretical or "hypothetical" regulatory capital amount that would be required to cover the CCP's exposures to its CMs. To the extent that this hypothetical capital requirement is smaller than the CCP's own financial resources in the default waterfall, CMs' own fund requirements are a function of this shortfall. The formula that determines the "own funds" requirements for all CMs collectively takes both pre-funded and unfunded contributions into account. While it does not apply risk weights to funded and unfunded default fund contribution separately, the formula that determines each individual CM's own funds requirement clearly covers both types of exposures. In fact, under method 1, the sum of CMs' regulatory capital requirements is more than the hypothetical capital that a CCP would theoretically need.

Interim Method 2

Applying a risk weight of 1250% to pre-funded default fund contributions under method 2 implies that these contributions are highly likely to be lost in their entirety on a regular basis. This risk weighting would also imply that extreme market conditions (leading to the simultaneous default of the two CMs to which the CCP has the largest exposures) must be fully backed by own funds of the CMs.

It can be presumed that a CM that selects method 2 for any CCP would only do so where the relevant CCP's hypothetical capital requirement determined under method 1 would result in risk assessments that far exceed those of both the CCP's regulatory approved margin model and the CCP's regulatory approved stress testing methodology. A CM would only employ Method 2 where the CEM does not reliably measure risk (for example, for Interest Rate Swap portfolios where there is no significant trade compression).

This paper's proposal

This paper proposes use of a default risk model based on the IDRC model used for trading book capital in conjunction with HDM and the stress testing work that CCPs undertake to arrive at a more comprehensive approach to modelling default fund risk.

We consider there to be two main causes of losses of to non-defaulting members.

I. Where the losses incurred by a defaulting CM, over and above those losses covered by its IM, its own contribution to the default fund and the CCPs own capital placed

[7]The interim framework for determining capital requirements for bank exposures to CCPs, viz. BCBS 227 of July 2012.

ahead of other non defaulting members are larger than anticipated by the CCP (based on its IM calibration and stress testing).

II. Where more CMs default than the DF calibration anticipates, leading to the need for assessments, and other additional funds ahead of service closure . This driver is not taken into account by the Methods in BCBS227.

Of these two drivers the second, multiple CM defaults, seems much the more likely to be a cause for tail loss. The assumption that only two simultaneous defaults will occur has no strong foundation. Given that CMs typically operate on multiple CCPs the contagion risk entailed by central clearing should not be understated, and the risk of multiple defaults across CCPs should not be underestimated.

A drawback of regulatory and HDM methods that are currently proposed is that they consider exposure to each CCP in isolation, and do not consider cross-CCP risk. They also do not consider that a CM has simultaneous exposure to all of the CCPs on which it clears and thus that exposures should not be capitalised to each on a standalone basis. Mathematically this is analogous to combining Value at Risk (“VaR”) measures obtained from several CCPs rather than looking at VaR of the consolidated portfolio. Hence an IDRC approach applied jointly to all CCPs on a consolidated benefit may provide some capital savings compared with a simple sum of IDRC calculations for each CCP on a standalone basis. However, against that, the capital numbers are higher than a simple standard rules basis because the risk of clearing members defaulting on multiple CCPs simultaneously, along with other systematic factors, is captured. Also IDRC is calculated to a 99.9th percentile and a one-year capital horizon whereas alternative proposals to date are broadly an expected shortfall method based on historical loss experience. This is true notwithstanding that HDM data is essentially providing an estimated LGD based on historical data because the simulation itself can generate rare multiple events. Compare this with the use of through the cycle PD and LGD estimates in IRB and IRC.

3. IRC Model

The primary mechanism for calculating capital requirements in the trading book is VaR. One of the key limitations of VaR is that it does not provide for those risks which fall beyond the VaR parameters used in the calculation, e.g., 99th percentile one-day. The IRC model has thus been developed to capitalise risks that arise out of jump-to-default and rating migration. These are rare events with the potential to have a material impact on the profit and loss of the trading book, which historical simulation VaR based on only a few years' data will likely not capture fully. The IRC model measures risk at selected percentiles, including the 99.9th percentile (which is required for regulatory capital), for a one-year capital horizon.

The IRC model captures the following risk factors:

- Default risk
- Transition risk
- Default and migration correlation risk
- Recovery risk
- Liquidity risk
- Concentration risk
- Product Basis risk
- Hedge roll-off risk

To examine CCP default fund risk we have adapted a standard Gaussian Copula version of an IRC model, which is a benchmark model for trading book capital that converges to the A-IRB capital standards when the conditions for applying A-IRB apply. Here we require only an assessment of default risk, there will be no default fund implications for a CM being downgraded[8] (other than perhaps if the downgraded CM ceases to be eligible as a CM). Default correlation is based on asset price correlation as is typically part of Merton-type default risk models. The recovery rate is set to zero in this calculation; essentially the LGD we face for a CM defaulting is some portion, or multiple, of our default fund contribution. We have made use of stress testing data from CCPs, and also some data provided by CCPs on the HDM approach, to arrive at an estimate of the probability of a non-defaulting CM losing a portion of its default fund contribution when another CM defaults, and the magnitude of that loss. Based on the available data, we estimate that the probability of a non-defaulter being affected is likely to be around 30%, and the loss on such occurrences would likely be less than 20% of the default fund. We assume a one-year liquidity horizon but it would be straightforward to introduce the alternative liquidity horizons we use in IRC. Concentration risk and product basis are not relevant for this calculation.

An average asset price correlation of 79% has been assumed across CMs. This may be conservative compared with industry standards. Default correlation is considerably less than this, and is a function of default probabilities as well as asset price correlation, but between, for example, two single A rated CMs the default correlation would be, using our PDs, around 5%.

---

[8] Of course in the event of a CM being downgraded the CCP may call for more IM (which would affect the DF liability) and may even ask the CM to step down. These actions would affect potential loss and could be taken into account in a model. This could be a subject for further research but there will always be an issue reconciling behavioural assumptions with what a CCP actually does in such circumstances. In any case, what we mean in the text is that a downgrade of a CM does not directly lead to a loss for the CCP, which may result in a call on the default fund. Only defaults lead to direct losses. This is in contrast to the use of IRC for Trading Book exposures where a downgrade leads to a fall in MTM of debt issued by that obligor and held on the trading book.

The annual default probabilities we used for this calculation are averages based on transition matrices available from Moody's, S+P and Fitch covering around 20 years. The default probability by rating is:

AAA	0.00%
AA	0.03%
A	0.08%
BBB	0.25%
BB	1.48%
B	3.92%
CCC	23.98%

To emphasise again, these probability and correlation assumptions are for illustrative purposes. We believe them to be conservative assumptions but actual calibration would be something we would expect regulators to provide guidance on if this approach were to be adopted.

4. Application to CMs

IRC is typically based on a single pool of obligors, whereas for this exercise we wish to look across CCPs, and are also interested in exposure by CCP. Thus, we have modified the usual model so that it simulates scenarios across several sets of obligors simultaneously, each set of obligors being a list of CMs for a particular product segment within a CCP. At present we have covered a list of 8 CCPs and product segments. In order to avoid potential false conclusions about the relative security of CCPs we have preserved their anonymity in this paper, referring to them simply as A-H.

We first combine these sets to form a consolidated list of CMs covering all CCPs, with each CM shown only once. We then run the Monte Carlo engine performing 100,000 simulations[9] to calculate the occurrences of default by entity. Where an entity defaults according to this simulation, we recognise the default across each CCP. We are then able to calculate risk both by CCP and on a consolidated basis.

4.1. Standalone CCP Risk

We typically capitalise the trading book for default risk at a 99.9th percentile one-year loss. Based on these inputs the 99.9th percentile number of defaults for each CCP considered is as follows:

	A	B	C	D	E	F	G	H	Sum	Consolidated
99.9th	1	7	8	2	2	3	7	7	39	28

Table 1 – 99.9th percentile default events

This means that there is a one in 1000 year chance of observing 8 defaults in a year at C, 7 at B, 7 at G and H and so on. The sum of defaults across CCPs at the 99.9th percentile is 39 but of course we would not expect all trigger events to occur simultaneously. On the other hand a number of CMs clear on several CCPs so that a default by one of them would appear as a default event on each CCP of which it is a member. When a CM defaults on multiple CCPs, we potentially incur a loss on each CCP on which the defaulter clears. On a consolidated basis the total count of default events at the 99.9th percentile is 28 in this simulation.

4.2. Application to Contagion Risk

Before turning to a capital charge, we note that IDRC can be used to analyse CCP risk in other ways that might be useful to clearing members and regulators. For example a necessary

[9] IRC Model methodologies are well documented in academic literature and by firms using such models for capital.

step in the capital calculation provides the probability of one, two, three and more CMs defaulting simultaneously not only on a single CCP but also across multiple CCPs that a particular CM may be exposed to.

Table 2: Probability of n CM defaults at each CCP

	Probability of n defaults										
n	0	1	2	3	4	5	6	7	8	9	10
A	98.02%	1.21%	0.32%	0.15%	0.10%	0.04%	0.04%	0.02%	0.02%	0.01%	0.01%
B	99.55%	0.35%	0.07%	0.02%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
C	97.67%	1.37%	0.40%	0.18%	0.12%	0.07%	0.04%	0.03%	0.01%	0.02%	0.01%
D	99.16%	0.62%	0.13%	0.03%	0.03%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%
E	98.09%	1.16%	0.31%	0.16%	0.07%	0.05%	0.04%	0.02%	0.02%	0.01%	0.01%
F	99.08%	0.66%	0.14%	0.05%	0.02%	0.02%	0.01%	0.01%	0.00%	0.00%	0.00%
G	99.31%	0.52%	0.10%	0.03%	0.02%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%
H	97.14%	1.79%	0.46%	0.22%	0.12%	0.07%	0.05%	0.04%	0.02%	0.01%	0.01%
All	**95.47%**	**1.89%**	**0.89%**	**0.43%**	**0.27%**	**0.18%**	**0.14%**	**0.10%**	**0.09%**	**0.06%**	**0.05%**

The important result in Table 2 is the final 'ALL' row, which shows the default experiences across all CCPs on a consolidated basis. In this simulation if a CM defaults we count the defaults on each of the CCPs of which it is a CM. The probability of incurring at least one default across all CCPs (= 1-probability of incurring no defaults) is greatly increased at 4.53% across all CCPs compared to 2.86% for H, the highest risk CCP by this measure. The probability of incurring exactly one default across all CCPs is only marginally higher than 1 default for CCP H, because when one default occurs the CM cannot have been clearing using more than one CCP, nor can simultaneous defaults have occurred across CCPs. However for higher numbers of defaults the probability is materially increased compared to any single CCP, for example the probability of incurring two defaults across all CCPs is 0.89%, compared with only 0.46% for H. The probability of incurring higher numbers of defaults is increased compared to a single CCP mainly because of the presence of many CMs on several CCPs so that a default impacts several CCPs.

Although we have noted above that the default correlation between two CMs within a CCP is low – around 5% – we can use our simulation results to explore the likelihood of a default occurring at two CCPs simultaneously. The correlation matrix across CCPs is as follows:

	A	B	C	D	E	F	G	H
A	1.000	0.670	0.638	0.695	0.499	0.575	0.627	0.575
B	0.670	1.000	0.915	0.831	0.770	0.825	0.876	0.820
C	0.638	0.915	1.000	0.780	0.718	0.781	0.873	0.830
D	0.695	0.831	0.780	1.000	0.665	0.713	0.726	0.677
E	0.499	0.770	0.718	0.665	1.000	0.904	0.701	0.676
F	0.575	0.825	0.781	0.713	0.904	1.000	0.759	0.726
G	0.627	0.876	0.873	0.726	0.701	0.759	1.000	0.820
H	0.575	0.820	0.830	0.677	0.676	0.726	0.820	1.000

Correlations above 0.8 are highlighted. The table shows that the default correlation across individual CMs is quite low, but the joint correlation across CCPs, which is the tendency for defaults to occur simultaneously across CCPs (within 1 year), is still very high. This is driven by the systemic factors in the Gaussian Copula model and the fact that many CMs clear on multiple CCPs.

4.3. Sizing potential default fund exposures – the capital charge

The main factor determining the number of defaults across CCPs is the number of CMs. A default is a binomial event akin to tossing a coin biased towards heads, in other words the higher the number of tosses the more tails you are likely to observe. Intuitively one might have expected larger CCPs with more CMs to be safer however there are arguments both ways about the benefits of a CCP with more CMs. Losses are spread more widely when there are more CMs, but there are more CMs to default. So it would seem that with more CMs the default fund should be sized to capture more simultaneous defaults. An assumption of two simultaneous defaults seems to be reasonable based on our analysis where there are just a couple of dozen CMs, but where the number moves into triple digits then more simultaneous defaults are a realistic possibility. If default funds were arranged in this way, the default fund contributions of each CM would be reduced less materially as the number of CMs increases. Whatever default fund size an individual CCP chooses, our proposed model takes the default fund contributions as already given by the CCP so that the mutualisation of losses is already accounted for.

Counting defaults across CCPs is less meaningful than it is for a single CCP. It is the quantum of loss that matters and this will vary across CCPs. As noted, the default fund is typically calibrated to absorb the losses of the <u>two</u> largest defaulting CMs in excess of their IM contributions and the remaining CMs stand liable for their contribution to the default fund. Of course, the CM with the largest exposure is not necessarily the one that will default, and all but one default on a CCP must be smaller than the largest, which means that if the CCP has calibrated the default fund correctly we would expect to lose somewhat less than half the default fund, on average. Moreover, losses from unwinding the defaulting CM's positions may be covered by that CM's IM, its own default fund contributions, and capital placed by the CCP ahead of the non-defaulting CMs' contributions. So there is a reasonable chance that no loss is incurred by non-defaulting CMs. We have used two sources of data available to us from CCPs to estimate the expected loss to a non-defaulting CM when a CM defaults – CCP stress testing data, which is used to size the default fund, and data constructed to explore the HDM proposed by ISDA.

4.3.1. Making use of CCP Stress data

We used data provided by CCPs on the distribution of losses under stressed scenarios to assess what proportion of the default fund might be expected to be used when a default occurs. In each case we were given anonymised default losses for only the seven largest defaulters. These data were provided for seven separate stress test dates covering September 2012 to January 2013. We fitted a Gaussian function to the stressed losses and extrapolated these to cover the top 20 CMs' losses in excess of their own IM. The resulting fits are shown in the charts in Appendix 2. From this extrapolation we arrive at a reasonable estimate of the average loss generated by a defaulting CM in excess of its IM contribution. It should be noted that were this method adopted the extrapolation would not be necessary since CCPs could provide the worst stressed losses for all their CMs, or alternatively the average stressed loss.

On the basis that the default fund is calibrated to cover the stressed losses of the two largest defaulting CMs, we found that for CCP1 a reasonable assumption was that the average loss to the default fund would be around 20%. For CCP2 we found a lower expected loss of only around 10%. The results are summarised below:

CCP 1 ($mns)

	Sep-12	Oct-12	Nov-12	Dec-12	Jan-13
DF	1,670	1,442	1,646	1,598	1,353
Av Hit	313	299	289	275	232
%	19%	21%	18%	17%	17%

CCP 2 ($mns)

	Sep-12	Oct-12	Nov-12	Dec-12	Jan-13
DF	719	570	591	736	977
Av Hit	65	51	69	105	106
%	9%	9%	12%	14%	11%

4.3.2. Making use of HDM Data

An alternative source of data available to us for calibrating losses to the default fund from a CM defaulting is that obtained from a CCP to explore the HDM method proposed by ISDA. HDM is similar to back testing at a CCP and analyses each day at the shortfall that would have been occurred had each CM defaulted that day, based on the stressed losses. That is, it examines stressed loss in excess of IM and Variation Margin ("VM") paid. In addition this data takes into account the defaulting CMs' own contribution to the default fund and the capital contributed by the CCP before the non-defaulting CMs' contributions are employed. Data was provided to ISDA for the sum of the two largest shortfalls each day over a period of two years[10]. The data is summarised in the following table.

Table 3 – HDM data

Trading Data	Sum of 2 largest VM/IM shortfalls	Sum of 2 GF contributions	GF shortfall including CCP contribution
29 Jun 2012	-10.37%	1.24%	-1.44%
21 Jun 2012	-4.26%	0.31%	0.00%
03 Feb 2012	-0.31%	0.15%	0.00%
16 Dec 2012	-1.44%	0.36%	0.00%
21 Nov 2011	-0.62%	0.31%	0.00%
12 Sep 2011	-0.49%	0.31%	0.00%
23 Jun 2011	-17.14%	1.93%	-7.52%
05 May 2011	-19.51%	8.52%	-3.30%
07 Dec 2010	-0.54%	0.31%	0.00%
07 Sep 2010	-1.90%	0.31%	0.00%

[10] This data was provided to ISDA on a summary basis for illustrative purposes. Accordingly, the HDM data in this submission is insufficient for any formal conclusion. For actual calibration, we would expect regulators to provide guidance on, for example, data collection procedures.

The last column of the table shows that over two years there were only 10 occasions on which any CMs' stressed losses would have exceeded the sum of their margin contributions and of these, on only three occasions would the losses have also exceeded that CM's default fund contributions. On this basis we might reasonably assume that the probability of a default leading to a charge on non-defaulting CMs' contributions is around 30%. The HDM data also supports the notion that losses to non-defaulting CMs would be less than 10% of their contribution.

Table 5 sets out a stylised distribution of default fund contributions that a CM might have at the set of CCPs discussed. The numbers have been chosen to be realistic but also to allow us to distinguish the effects of default fund contribution from number of defaults. For completeness, we have included a zero contribution for H.

Table 4: Assumed DF Contributions ($mn)

$mn	**Funded DF**
A	20
B	240
C	120
D	250
E	50
F	60
G	5
H	0

The IDRC model for CCPs was enhanced so that at each occurrence of default a uniformly distributed random variable (between 0 and 1) was generated. If this number fell below some threshold –0.3 based on our HDM results - then a loss of 20% of the default fund contribution at that CCP was assumed. In practice the model could be calibrated to HDM and stress testing data provided by CCPs (this would have to be done on a regular basis –much like hypothetical capital). The thresholds have been set so that alternative assumptions can be used. The following table shows the losses incurred if 50% of the default fund is lost on a default, a 20% loss occurs only with a probability of 30% and a 2% loss occurs with a 30% probability.

Table 5: 99.9th percentile losses across CCPs as of 29th November 2012 ($mn)

99.9th percentile ($mn)	A	B	C	D	E	F	G	H	Sum	**Consolidated**
Def Count	*-1*	*-8*	*-9*	*-2*	*-2*	*-3*	*-7*	*-7*	*-39*	*-28*
50% LGD	-11	-896	-531	-253	-50	-90	-18	0	-1848	-538
20%LGD & 30% P(L)	-4	-143	-71	-51	-10	-12	-3	0	-294	-78
2%LGD & 30% P(L)	0	-14	-7	-5	-1	-1	0	0	-29	-13

The default count row of the table shows the average number of defaults simulated. If we assumed that 50% of our default fund contributions were lost every time a default occurred then the losses would typically be the number of defaults multiplied by 50% of our default fund. On this basis we see more material netting benefits across CCPs when we consider default fund size than when we simply count defaults. This is because the losses are dominated by those CCPs where a CM has large default fund contributions, so that a CM defaulting on two CCPs simultaneously does not have twice the impact for a non-defaulter if its exposures are small on one of the CCPs. Hence the sum of losses at the 99.9th percentile across the 8 CCPs considered is $1.8bn but the 99.9th percentile loss across them on a consolidated basis is only $538m.

However when we introduce only a 30% probability of a default generating a loss for non-defaulting CMs, and the loss averaging 20% of the default fund, then the loss we expect to occur at the 99.9th percentile level is considerably reduced, dropping from $538mn to $78mn across all CCPs. Moving to the more aggressive losses of 2% of default fund, suggested from the HDM data, reduces losses to become immaterial.

5. Conclusion

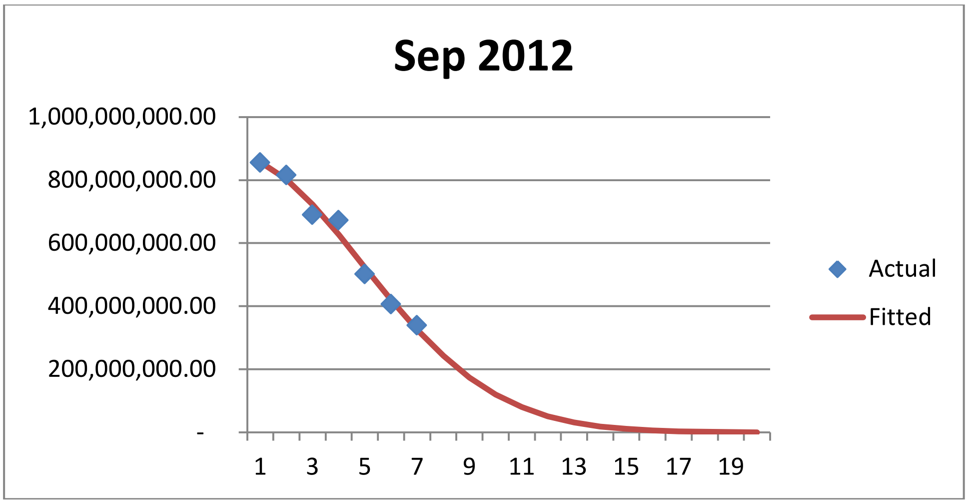
Capitalisation of CMs' exposure to CCPs should be done on a consolidated basis across all CCPs, not at the CCP level which is the current regulatory requirement. Capitalising by CCP on a standalone basis is the same as summing VaR across risk factors rather than taking into account diversification benefits.

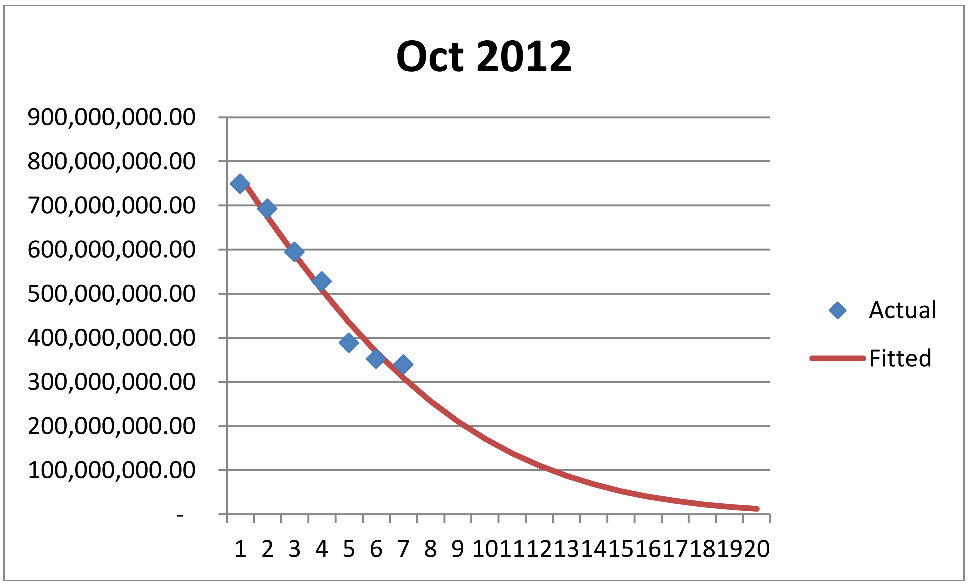
On a consolidated basis – and by CCP – the IRC approach delivers a capital requirement for total default fund liabilities, funded and unfunded. Our binomial analysis suggests that capital should be proportional to the square root of the number of CMs.

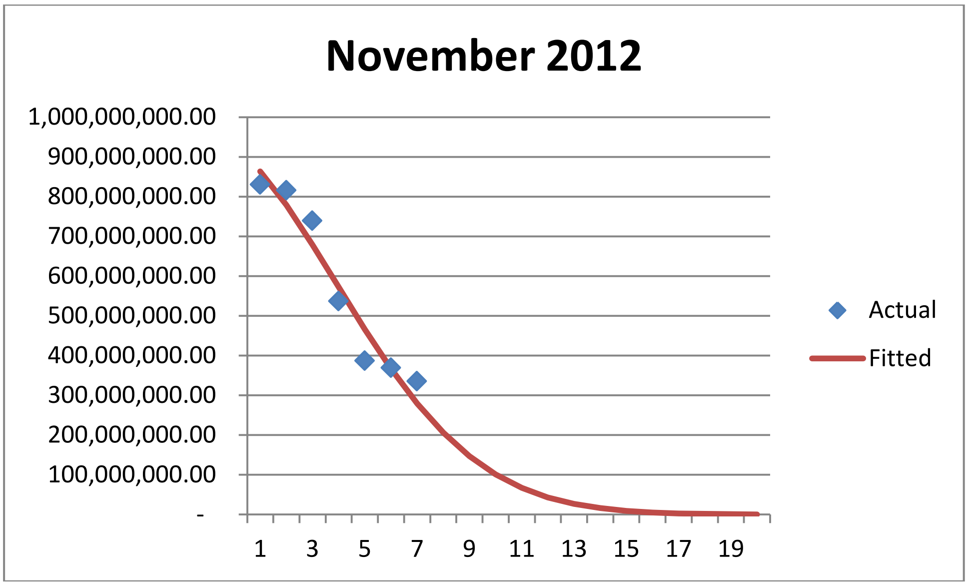
6. Appendix 1 – Fit of distribution of losses to stress based results

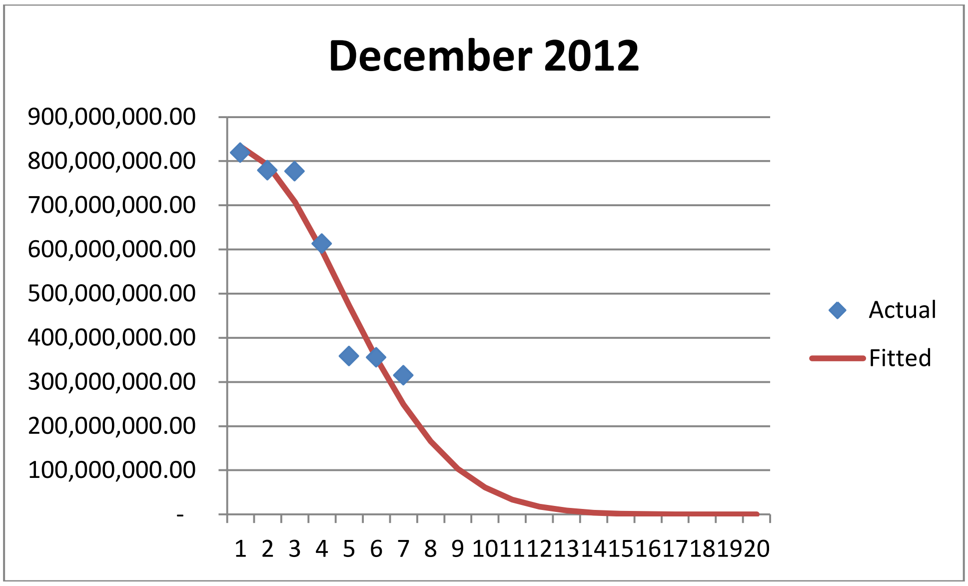
CDS:

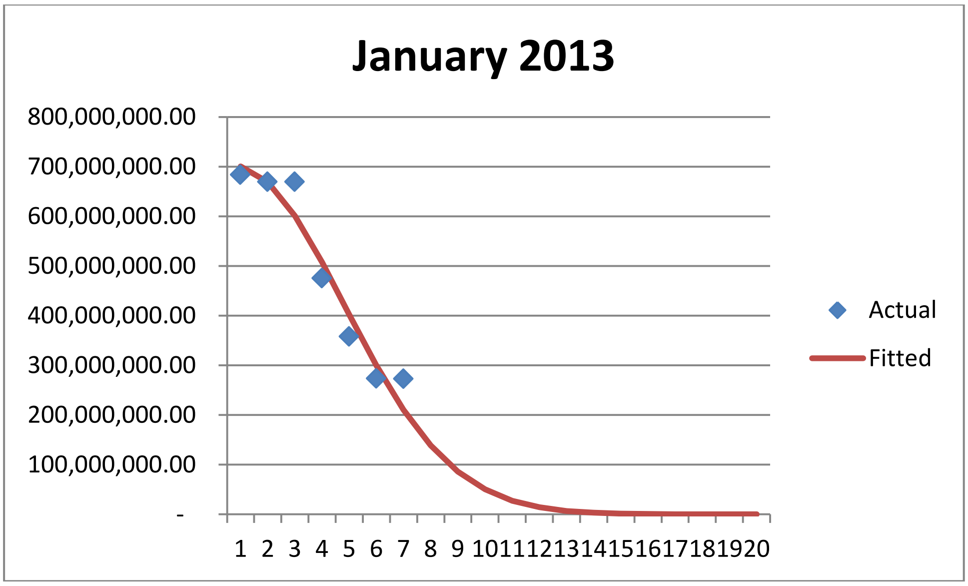
We fitted the function $L_i = a * e^{-\left(\frac{i-b}{c}\right)^2}$ for CDS and obtained the following charts:







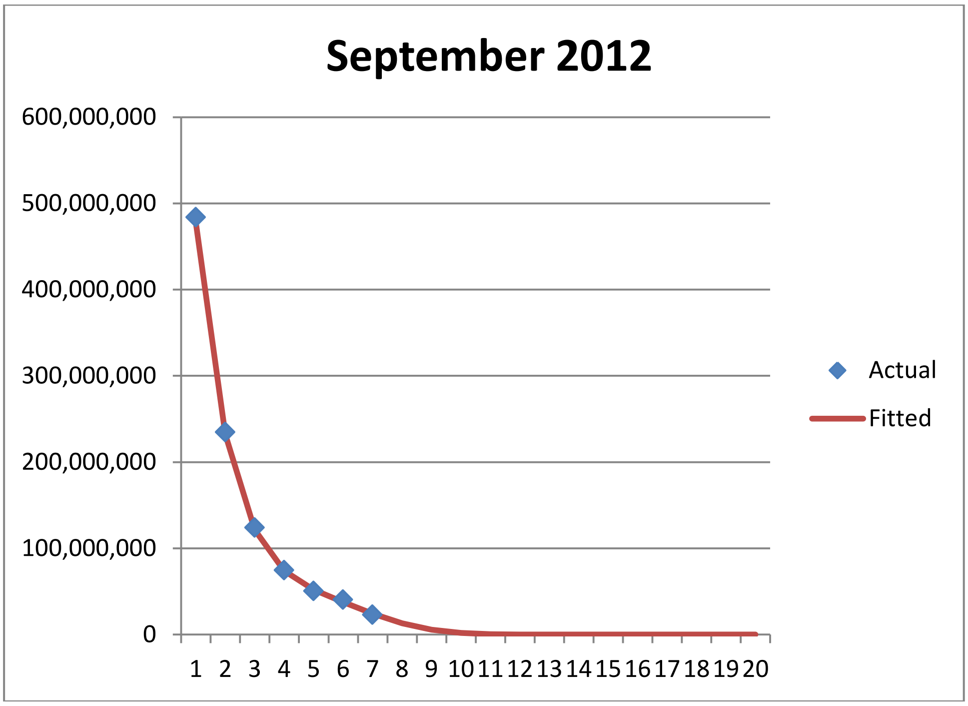


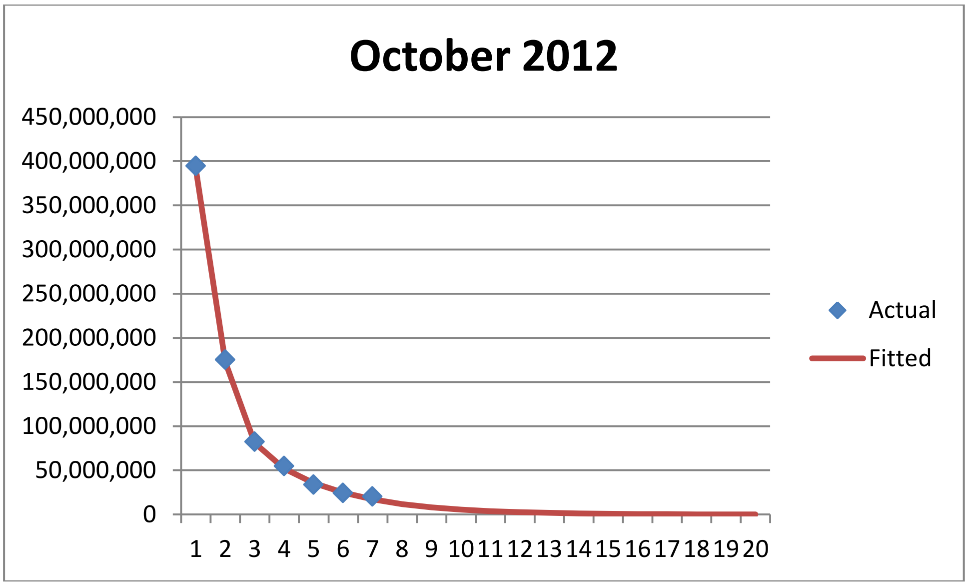


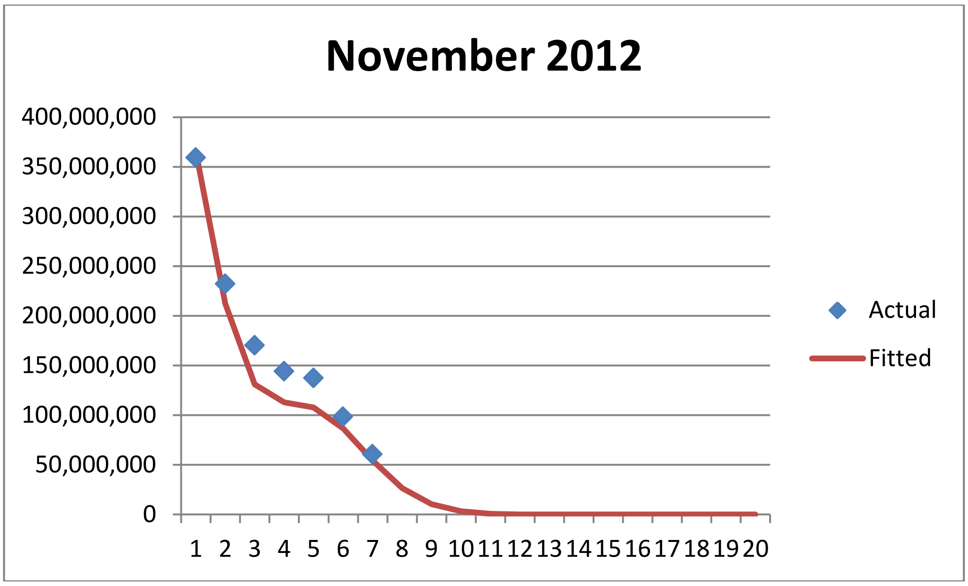
For energy we needed a more complicated extrapolation formula – a double Gaussian:

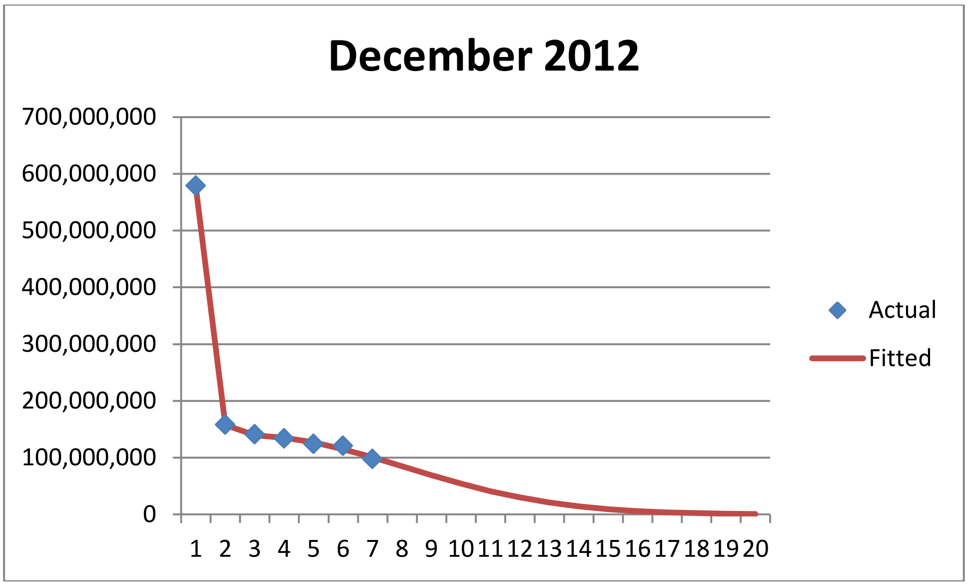
$$L_i = a_1 * e^{-\left(\frac{i-b_1}{c_1}\right)^2} + a_2 * e^{-\left(\frac{i-b_2}{c_2}\right)^2}$$

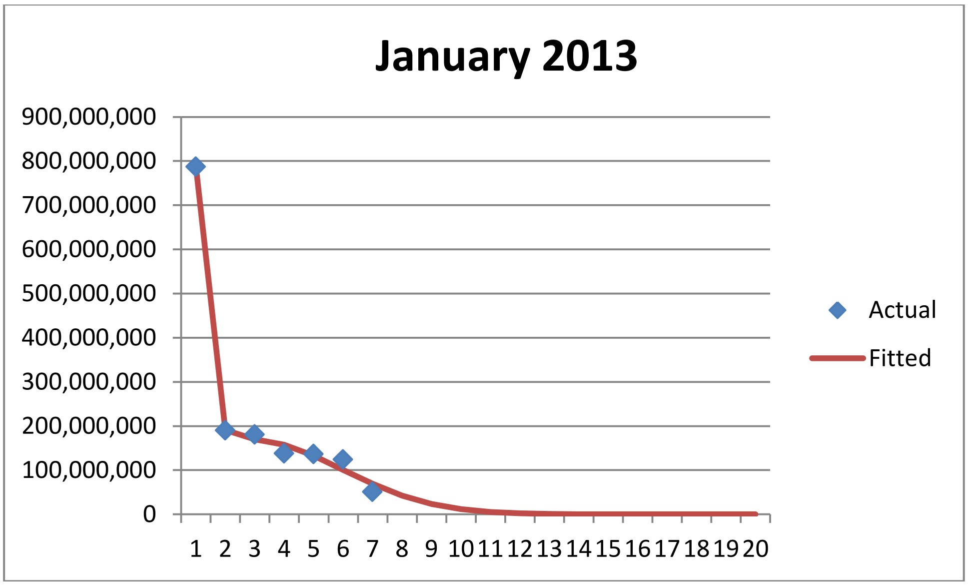
We obtained the following charts:






November 2012
400,000,000
350,000,000
300,000,000
250,000,000
200,000,000
150,000,000
100,000,000
50,000,000
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Actual
Fitted


December 2012
700,000,000
600,000,000
500,000,000
400,000,000
300,000,000
200,000,000
100,000,000
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Actual
Fitted


January 2013
900,000,000
800,000,000
700,000,000
600,000,000
500,000,000
400,000,000
300,000,000
200,000,000
100,000,000
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Actual
Fitted