COLLATERAL REQUIREMENTS FOR COMPREHENSIVE CENTRAL CLEARING OF OVER-THE-COUNTER DERIVATIVES

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1 Introduction

Central clearing of derivatives traded bilaterally in over-the-counter (OTC) markets is set to become more widespread. This reflects demands of G20 leaders that all standardised OTC derivatives should be cleared with central counterparties (CCPs) by the end of 2012.[2] CCPs sit between the counterparties of bilateral transactions, becoming the seller to every buyer and the buyer to every seller, and consequently taking on all counterparty credit risk. At the end of 2010, around half of all outstanding OTC interest rate swaps (IRS), less than 10% of credit default swaps (CDS) and almost no foreign-exchange or equity derivatives had been cleared with CCPs (Table 1).[3]

Some market participants have suggested that greater use of central clearing could raise significantly the collateral needs of dealers and their clients, which could boost effective trading costs and undermine the efficiency of the market.[4] CCPs often demand more collateral than under decentralised arrangements to clear equivalent positions, as they require collateral to cover both current counterparty exposures and the vast majority of potential future exposures that could arise from valuation changes. They also collect further collateral contributions from clearing system participants to help absorb any losses from counterparty defaults not covered by specific collateral posted against the defaulted exposures. In contrast, decentralised clearers often forego collateral against potential future exposures and sometimes waive collateralisation of current exposures for certain types of counterparty, including sovereigns and non-financial companies.[5] On the other hand, central clearing can reduce the overall volume of counterparty credit exposures. This occurs when bilateral positions moved onto a CCP have current or potential future values that cancel out once brought together.[6]

In this paper, we estimate the amount of collateral that prudent CCPs would require to clear IRS and CDS portfolios that are representative of those of the major derivatives dealers. IRS and CDS are two of the largest segments of the OTC derivatives market, collectively accounting for around two-thirds

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[2] See Group of Twenty (2009). Furthermore, Hull (2010) argues that non-standard OTC derivatives should also be cleared centrally, noting that some of the largest losses during the recent financial crisis arose from positions in non-standard derivatives.

[3] Time series of the shares of IRS and CDS that had been centrally cleared are available in Vause (2010(a)).

[4] See, for example, Futures and Options World (2011).

[5] See International Swaps and Derivatives Association (2010), pages 36-38.

[6] In practice, CCPs tend to specialise in clearing particular segments of the OTC derivatives market. This limits potential reductions in counterparty exposures to those that can be obtained from bringing together bilateral positions in particular classes of derivatives. Furthermore, these reductions should be traded off against declines in counterparty exposures that occur under decentralised clearing as a result of counterparties netting positions across different classes of derivatives. See Duffie and Zhu (2011).

of both the notional amount and market value of all outstanding derivatives. IRS and CDS also have different risk characteristics. In particular, the volatility of CDS values typically varies more over time than the volatility of IRS values and the probability of 'extreme' changes in the value of a CDS relative to 'normal' changes at any point in time is typically larger than for an IRS (Graph 1). We highlight the effect of these risk characteristics on collateral requirements.

Our estimates of collateral requirements depend on the structure of central clearing. We first show estimates for one CCP clearing all IRS and another CCP clearing all CDS. In this case, collateral estimates reflect the full diversification of dealers' IRS and CDS portfolios, as well as the offsetting of long and short positions in these portfolios. At present, however, central clearing of CDS is segmented along geographic lines. We therefore also show collateral estimates for three CCPs clearing respectively American, European and Asian CDS. Comparison of the total collateral requirements of these three CCPs with the lower demands of a single CCP clearing all CDS provides a first illustration of the economies of scope in central clearing. These are further illustrated by comparing collateral estimates for separate clearing of multi-name and single-name CDS with those of integrated CDS clearing. Finally, we show collateral estimates for a single CCP clearing both IRS and CDS, which are compared with requirements under one IRS CCP and one CDS CCP to provide a last illustration of the collateral savings that can result from more concentrated central clearing.

As the expansion of central clearing will raise further the importance of CCPs being extremely robust, we also investigate the effectiveness of different risk management policies.[7] In particular, we compare the robustness of CCPs that take into account current market conditions when setting collateral requirements with those that base demands only on historical frequencies of price movements. We also compare the robustness of CCPs that set collateral requirements against counterparty exposures equal to the smallest 'large' loss that these exposures might generate with those that set such requirements equal to the average 'large' loss.

The remainder of the paper is structured as follows. First, we explain the main risk management practices used by CCPs to guard against losses in the event of counterparty defaults. Next, we construct a set of hypothetical IRS and CDS portfolios for the major derivatives dealers that are representative of the way that risk is distributed within and across these institutions. We then simulate potential losses on the parts of these portfolios cleared by particular CCPs and find the collateral requirements that would protect each CCP against almost all of these potential losses. We

[7] Tucker (2011) discusses the systemic importance of CCPs.

then show how these collateral requirements vary with the structure of central clearing, before showing finally how they vary with different risk management practices and how this affects the robustness of CCPs. While the analysis in this paper is focussed on clearing the positions of major derivatives dealers, an annex provides some rough estimates of the collateral needed to clear centrally both dealer and non-dealer positions.

2 Central counterparty risk management policies

The main risk that CCPs have to manage is counterparty default risk. As CCPs sit between buyers and sellers, they have no direct vulnerability to changes in the value of cleared contracts. Any losses to buyers, for example, would be matched by offsetting gains vis-à-vis sellers. They have an indirect vulnerability, however, as losses on cleared contracts could contribute to the failure of counterparties, which could prevent a CCP from collecting the full amount of its corresponding valuation gains. At the same time, other counterparties would still require payment of the full amount of their valuation gains. To help avoid such situations, CCPs have 'participation requirements', which are minimum standards that potential counterparties must meet to be accepted as members of the central clearing system. In addition, CCPs collect collateral against current and potential future counterparty exposures through variation margin calls, initial margin requirements and default fund contributions, which are described in more detail below. Table 2 summarises how these counterparty risk management policies are implemented at present by the major CCPs in the IRS and CDS markets.[8]

Variation margins are collected to cover current counterparty exposures. These are equal to the market values of cleared portfolios. Cleared portfolios with positive market values from the point of a view of a CCP, for example, represent claims on counterparties, and collateral is collected against these claims. When portfolio market values change, collateral requirements are adjusted through variation margin calls. Specifically, CCPs demand more collateral when values change in their favour and they return collateral when values change in favour of their counterparties. Portfolios are usually re-valued at the end of each trading day, but re-valuation and requests for variation margin may occur intraday if price movements are unusually sharp. Variation margining therefore requires timely and reliable price data for all cleared derivatives. Only cash is accepted as collateral for variation margins.

[8] See also CPSS-IOSCO (2004) and CPSS-IOSCO (2011) for recommendations on counterparty risk management policies.

Initial margins are collected to cover the vast majority of potential future counterparty exposures. These can arise in the event of counterparty defaults as a defaulter's positions could lose value before a CCP could resolve them by, for example, auctioning them to remaining clearing system members. CCPs are vulnerable to losses on defaulting counterparty exposures between the times of the last variation margin payment and resolution of the defaulted portfolio. In highly liquid markets, like the markets for exchange-traded equities or futures, even large portfolios could probably be resolved in a day or two. For standardised OTC derivatives, however, a reasonable expectation might be that resolution could take at least a few days. Initial margin requirements are usually set to cover at least 99% of possible valuation changes over an appropriate resolution period. They may be paid in cash or safe and liquid securities, such as G7 government bonds.

Default funds are maintained by CCPs to cover any residual losses arising from counterparty failures after claiming the collateral posted as initial and variation margins by the defaulting counterparties. Such losses could arise from unusually large changes in the values of defaulted portfolios during resolution periods. Each member of a central clearing system is required to contribute collateral to a default fund, with contributions sometimes set equal to a fixed percentage of initial margins. Cash or safe and liquid securities are usually accepted. The contributions of defaulting counterparties are used first to absorb losses, but any residual losses are then mutualised by drawing on more of the default fund. In some cases, CCPs must commit some of their own equity capital to loss absorption ahead of mutualisation. Otherwise, equity capital is a final loss-absorbing buffer. At some stage of this loss absorption process, default funds may also be complemented by further safeguards, such as a third-party guarantees or capital calls on surviving members of the clearing system.

3 Methodology

We combine two analytical components to estimate the amount of collateral that prudent CCPs would require to clear the IRS and CDS portfolios of major derivatives dealers. The first component is a set of hypothetical IRS and CDS portfolios for the fourteen major derivatives dealers known as the 'G14 dealers' that are representative of the way that risk is distributed within and across these institutions. The second component is a joint probability distribution of changes in market values of the portfolio constituents. Our derivation of these two analytical components is described in detail below.

When combined, the two components yield a joint probability distribution of portfolio gains and losses for the G14 dealers. We assume that prudent CCPs would set variation margin calls equal to daily losses on the parts of these portfolios that they cleared and initial margin requirements equal to the 99.5th percentiles of possible five-day losses. A 99.5th percentile loss is the smallest possible 'large' loss if 'large' losses are defined as those with a chance of 1-in-200 of occurrence. Potential losses in excess of initial margins across the G14 dealers represent risks to default funds, although default funds would only be eroded if dealers defaulted when they incurred these excess losses.

This two-component approach has an important advantage over modelling directly the joint distribution of G14 dealers' profits and losses. In particular, it guarantees that changes in market values of portfolio constituents have identical effects on dealers' portfolios per unit of notional principal. This allows the extent to which dealers incur losses coincidentally and, hence, the risk to the default funds to be gauged more accurately.

3.1 Representative portfolios of derivatives dealers

As G14 dealers' portfolio holdings are proprietary, we aim to construct hypothetical portfolios for these dealers that capture the key characteristics of their actual portfolios. To this end, we require our hypothetical portfolios to comply with a number of constraints relating to the scale and distribution of risks that they may embody. First, long and short positions in individual derivatives must sum across dealers to similar values.[9] This reflects an assumption that dealers mainly intermediate risk, which implies that the dealer sector creates little net demand for derivatives. Second, each dealer's portfolio must contain a similar total volume of long and short positions. Third, long and short positions in particular derivatives must overlap on average to a significant degree in each dealer's portfolio. And fourth, some collections of long positions must hedge particular short positions. This next set of characteristics reflects the business model of derivatives dealers. This involves taking the other side of many buy and sell orders from clients, which – partly through price adjustments – would normally be roughly equal in volume, and periodically hedging the net risks that emerge from this activity. Finally, each dealer's portfolio must not contain any derivatives linked to their own financial performance or that of any affiliates.

Although we ultimately require representative portfolios of dealers' net derivatives positions, it is necessary to first form sets of long and short positions and then subtract one from the other. This is because we use an iterative proportional fitting (IPF) algorithm to derive individual dealer's positions in individual derivatives. The IPF algorithm makes some initial guesses of positions and rescales these until the sum of each dealer's positions across all derivatives is equal to a particular value (derived in

[9] Long positions are defined as those requiring fixed-rate payments for IRS and premium payments for CDS and short positions are defined as those requiring floating-rate payments for IRS and default-contingent payments for CDS.

Section 3.1.1) and the sum of all dealers' positions in each derivative is equal to another particular value (derived in Section 3.1.2). This rescaling can only be applied to positive values.

3.1.1 Total long and short positions of each dealer

The IPF algorithm used in the construction of representative dealer portfolios requires as input the total long and short positions across all IRS and CDS of each dealer. Some of these total positions are not disclosed, so it is necessary to estimate them. The information shortage is greatest for IRS. G14 dealers state in their financial reports or regulatory filings the total notional amounts of IRS that they hold or enough information to estimate these amounts using only minor assumptions. They do not report, however, the division of their total holdings between long (pay-fixed) and short (pay-floating) positions. This is also the limit of reporting of CDS positions by some G14 dealers, although several do additionally supply data on their total long (protection-bought) and short (protection-sold) positions.

Table 3 shows the values of dealers' total long and short IRS and CDS positions (as of June 2010) that we input to the IPF algorithm. The values in the white areas of the tables come from or are based closely on public financial statements, while the grey entries in the tables are estimates. The estimates of total long and short IRS positions are simply half of each dealer's total reported IRS holding. The estimates of total long and short CDS positions of dealers who do not report this data are only slightly more complicated. For these, we allocate differences between the total positions of all dealers who report to the Depository Trust & Clearing Corporation (DTCC) and the total positions of the G14 dealers who do report their total long and short positions to the remaining G14 dealers and an 'other dealers' category in proportion to their respective shares of the total volume of CDS outstanding. The IRS and CDS estimates in Table 3 are consequently as even as possible while remaining consistent with reported data in the white cells. This is consistent with derivatives dealers focussing on intermediation and, hence, aiming to have roughly equal presence on both the buy and sell sides of markets.

3.1.2 Total long and short positions in each derivative

Total long and short positions across dealers in individual IRS and CDS are also required as inputs to the IPF algorithm to construct representative portfolios. Not all of these positions are reported, so some must be estimated. The information shortage is again greatest for IRS. Data is available from TriOptima's Rates Repository on aggregate outstanding notional amounts of various categories of OTC interest rate derivatives held by the G14 dealers, but these are not allocated to long and short positions. In contrast, data from DTCC covers dealers' aggregate long and short positions in many multi-name CDS. For single-name CDS, however, only total notional amounts outstanding are available.

The data used to derive estimates of total long and short positions across G14 dealers in particular types of IRS are reported in Table 4. This shows the distribution of G14 dealers' aggregate holdings of IRS across seven maturity buckets and the distribution of their aggregate holdings of interest rate derivatives (of which the substantial majority are IRS) across seven currency buckets: six single-currency buckets and an 'other currencies' bucket.[10] We estimate G14 dealers' total long and short IRS positions for 42 maturity-currency buckets that reflect all the possible pairings of maturity ranges and individual currencies in Table 4. Specifically, we assume that for each of these maturity-currency buckets, total G14 dealer positions reflect the shares of the corresponding maturity and single-currency currency buckets in total outstanding notional amounts of IRS held by G14 dealers. So, for example, we estimate G14 dealers' total long position in 0-2 year US-dollar IRS to be 19.0% (46.8% x 42.6%) of their total long IRS positions of $201 trillion, i.e. $40 trillion. Note that this approach distributes fully IRS positions amongst the top six currencies, ensuring that the full scale of dealers' positions is captured in our analysis, while a little of their diversity is necessarily lost.

A sample of the data used to derive dealers' total protection-bought and protection-sold positions in individual CDS is reported in Table 5. Such positions, as of end-June 2010, are available directly from DTCC for 97 distinct multi-name CDS. As some of these positions represent very similar risk exposures, however, we amalgamate some of them. For example, the CDX.NA.IG series 14 CDS offers protection against default losses on a portfolio of 125 North American investment-grade corporate bonds selected in April 2010, which is a similar portfolio of credit protection to those of earlier series of the CDX.NA.IG indices. Amalgamation of similar CDS indices reduces the number of different multi-name CDS to 51. For single-name CDS, however, DTCC reports only outstanding notional amounts held by dealers, covering the top 1000 contracts. We therefore assume that total protection-bought positions held by dealers in each single-name CDS are equal to the notional amounts outstanding of each single-name CDS multiplied by the share of dealers' bought-protection positions in total outstanding notional amounts of the top 1000 single-name CDS. Similar assumptions are used for protection-sold positions in single-name CDS.

[10] Note that each contract held by a G14 dealer is counted once in the reported data, including if two different G14 dealers are counterparties to a contract. Dealers' holdings are therefore adjusted in the fourth column of the table so that all outstanding long and short positions are counted once.

A number of individual CDS are excluded from the analysis at this stage. The main reason for this is to reduce the computational intensity of deriving representative CDS portfolios. We consequently exclude single-name CDS with the 201st to 1000th largest notional amounts outstanding. In addition, we exclude some CDS from the analysis because sufficient time series of price data, defined as daily closing prices from 1/10/2004 to 30/09/2010, are not available. We also exclude CDS on the Argentine Republic and EDF Suez because of concerns about the quality of price data.[11] This reduces the number of different CDS to 196: 11 multi-name CDS and 185 single-name CDS.

To maintain the scale and certain distributional qualities of dealers' protection-bought and protection-sold positions after excluding particular CDS from our analysis, remaining positions are scaled up using data reported in Table 6. This shows the impact of exclusions on the total protection-bought and protection-sold positions of dealers by region and economic sector. For example, Table 6 shows that exclusions result in the loss of around 27% of single-name protection-bought positions referencing American financial companies. We therefore scale up remaining single-name protection-bought positions referencing this type of company by a factor of 1/0.73. In addition, since the residual 'other single-name CDS' category in Table 6 is not represented in the reduced sample, this category is dropped from the analysis and remaining single-name protection-bought and protection-sold positions are scaled up further by around 4% to maintain dealers' total single-name protection-bought and protection sold positions.

3.1.3 Long and short positions of individual dealers in individual derivatives

Given individual dealer's total IRS and CDS positions and the total positions of all dealers in particular types of IRS and CDS, the IPF algorithm may now be applied to find representative portfolios. These comprise individual dealer positions in individual derivatives. Graphically, the IPF algorithm completes the grey cells in Table 7, given the white cells.

Explanation of the IPF algorithm requires the introduction of some notation. Index derivatives by i and dealers by j, so in market $m \in \{IRS, CDS\}$, $i = 1,..., N_m$ and $j = 1,..., D_m$, where $N_{IRS} = 42$, $N_{CDS} = 196$, $D_{IRS} = 14$ and $D_{CDS} = 15$. Note that $D_{CDS} = 15$ because of the need to introduce the 'other dealers' category alongside the G14 dealers. Also, denote individual long positions in a

[11] We excluded the Argentine Republic because its CDS premium was reported to have fluctuated wildly during 2004-05, when credit news was not especially dramatic. We deleted EDF Suez because its reported CDS premium was constant through much of 2010.

particular market by L_{ij} and short position by S_{ij}. The algorithm requires that $\sum_i L_{ij} = L_j$ and $\sum_i S_{ij} = S_j$ where L_j and S_j are dealers' total long and short positions across all derivatives, as derived in Section 3.1.1. Similarly, the algorithm requires that $\sum_j L_{ij} = L_i$ and $\sum_j S_{ij} = S_i$ where L_i and S_i are the total long and short positions of all dealers in particular derivatives, as derived in Section 3.1.2.

<u>The IPF algorithm first makes some initial guesses for the values of L_{ij} and S_{ij}</u>. These are based on draws from uniform distributions of random numbers over the unit interval, $u_{ij}^L \sim \mathrm{U}[0,1]$ and $u_{ij}^S \sim \mathrm{U}[0,1]$, and are equal to

$$L_{ij}^{(0)} = \frac{2L}{D_m N_m} u_{ij}^L \text{ , where } L = \sum_{i=1}^{N_m} L_i = \sum_{j=1}^{D_m} L_j \text{ and} \quad (1)$$

$$S_{ij}^{(0)} = \frac{2S}{D_m N_m} u_{ij}^S \text{ , where } S = \sum_{i=1}^{N_m} S_i = \sum_{j=1}^{D_m} S_j \text{ .} \quad (2)$$

The scale factors, $2L/D_m N_m$ and $2S/D_m N_m$, help to ensure that the initial guesses of individual positions sum to close to the total position volumes. This helps the algorithm to converge on final estimates of individual positions more quickly. For CDS, we overwrite a small proportion of the random initial guesses with zeros. In particular, we impose for each dealer zero protection-bought and protection-sold positions where they or an affiliate are the reference entity. This reflects legal restrictions. These positions remain equal to zero through the subsequent operation of the algorithm. Table 8 lists the zero restrictions that we impose.

<u>Next, the iterative proportional fitting routine is applied to long positions</u>. This requires positions to be normalised as

$$l_{ij}^{(0)} = \frac{L_{ij}^{(0)}}{L} \text{ , } l_i = \frac{L_i}{L} \text{ and } l_j = \frac{L_j}{L} \text{ .} \quad (3)$$

Normalised positions are then rescaled so that, when summed across derivatives, each dealer has the correct total volume of long positions. Normalised positions are then rescaled again so that, when summed across dealers, total long positions in all derivatives are correct. The second rescaling typically upsets the equality that was imposed by the first rescaling, however, so the double rescaling operation is implemented K times until this is no longer the case to a significant degree. More formally, let

$$l_{ij}^{(2k-1)} = \frac{l_j}{\sum_{a=1}^{N_m} l_{aj}^{(2k-2)}} l_{ij}^{(2k-2)} \text{ and } l_{ij}^{(2k)} = \frac{l_i}{\sum_{b=1}^{D_m} l_{ib}^{(2k-1)}} l_{ij}^{(2k-1)} \ \forall k = 1,2,...,K \, , \tag{4}$$

and stop at K such that

$$\text{Max}\left\{ \left| l_i - \sum_{j=1}^{D_m} l_{ij}^{(2K)} \right|, \left| l_j - \sum_{i=1}^{N_m} l_{ij}^{(2K)} \right| \right\} < 10^{-15} \, . \tag{5}$$

This delivers candidate long positions,

$$L_{ij}^{(2K)} = l_{ij}^{(2K)} L \, . \tag{6}$$

<u>Short positions are derived in an identical manner for IRS, but we impose additional constraints for CDS</u>.[12] These extra constraints require short positions to be such that net long positions in particular multi-name CDS are equal to net short positions in certain related single-name CDS for each dealer. For example, net long positions in multi-name CDS referencing North American companies must equal net short positions in single-name CDS referencing North American companies. This is intended to capture dealers' practice of hedging single-name positions that arise from trading with clients with multi-name contracts. Formally, we require

$$\sum_{i \in \{H_c^m\}} \left(l_{ij} - s_{ij} \right) = \sum_{i \in \{H_c^s\}} \left(s_{ij} - l_{ij} \right) \ \forall j \text{, or equivalently}$$

$$\sum_{i \in \{H_c\}} s_{ij} = \sum_{i \in \{H_c\}} l_{ij} \equiv l_j^c \quad \forall j \text{, where } H_c = \left\{ H_c^m, H_c^s \right\}.$$

H_c^m denotes the set of multi-name CDS involved in a particular hedging strategy, c, and H_c^s denotes the set of single-name CDS involved in the same strategy. Given data limitations, we only impose two broad hedging strategies, which are based on the CDS listed in Table 9.[13]

[12] So, for IRS, just substitute S for L and s for l in equations (3) – (6).

[13] In practice, however, dealers employ a larger number of finer hedging strategies, such as using single indices to hedge positions in numerous index constituents. In consequence, the full extent to which offsetting long and short positions reduce

To impose additional constraints, the iterative proportional fitting routine is modified when applied to short CDS positions. In particular, the steps documented in equations (3) – (6) are replaced by

$$s_{ij}^{(0)} = \frac{S_{ij}^{(0)}}{L}, \; s_i = \frac{S_i}{S} \text{ and } s_j = \frac{S_j}{S}, \tag{7}$$

$$s_{ij}^{(4k-3)} = \frac{s_j}{\sum_{a=1}^{N_m} s_{aj}^{(4k-4)}} s_{ij}^{(4k-4)}, \; s_{ij}^{(4k-2)} = \frac{s_i}{\sum_{b=1}^{D_m} s_{ib}^{(4k-3)}} s_{ij}^{(4k-3)}, \tag{8}$$

$$\left.\begin{array}{ll} s_{ij}^{(4k-2+c)} = \dfrac{l_j^c}{\sum_{a \in \{H_c\}} s_{aj}^{(4k-3+c)}} s_{ij}^{(4k-3+c)} & \forall j, i \in \{H_c\} \\ s_{ij}^{(4k-2+c)} = s_{ij}^{(4k-3+c)} & \forall j, i \notin \{H_c\} \end{array}\right\} \; \forall c \in \{1, 2\}, \tag{9}$$

with K reached when

$$\text{Max}\left(\left| s_i - \sum_{j=1}^{D_m} s_{ij}^{(4K)} \right|, \left| s_j - \sum_{i=1}^{N_m} s_{ij}^{(4K)} \right|\right) < 10^{-15} \text{ and } \text{Max}\left| l_j^c - \sum_{i \in \{H_c\}} s_{ij}^{(4K)} \right| < 10^{-15} \; \forall c, j. \tag{10}$$

Candidate short positions are then

$$S_{ij}^{(4K)} = s_{ij}^{(4K)} S. \tag{11}$$

Finally, candidate long and short positions emerging from the iterative proportional fitting routines are required to have a particular degree of overlap. If this is not the case, we reject the candidate positions and construct new candidates from a new set of random numbers in equations (1) and (2). The degree of overlap between each dealer's long and short positions is evaluated on the basis of the similarity metric,

$$\kappa_j = \frac{\sum_i \min(L_{ij}, S_{ij})}{\frac{1}{2}\sum_i (L_{ij} + S_{ij})} \; \forall i \in \{1, \ldots, N_m\}. \tag{12}$$

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risk in dealer portfolios may not be captured in our hypothetical CDS portfolios. If this is case, our estimates of possible CDS portfolio losses and collateral requirements for comprehensive central clearing of CDS may be regarded as upper-bound estimates.

Conversations with market participants suggested that the value of this similarity metric typically lies between 0.95 and 0.99 for a G14 dealer's IRS portfolio. Furthermore, a discussion with the International Swaps and Derivatives Association (ISDA), based on some preliminary results, suggested that a relatively high value within this range is often appropriate. We therefore reject candidate pay-fixed and pay-floating positions unless $0.95 < \kappa_j < 0.99$ for each G14 dealer's portfolio and the mean value of κ_j across these portfolios is within 0.001 of 0.98.[14] Our overlap requirements for long and short CDS positions are based on Goldman Sachs' second quarter of 2010 regulatory filing to the US Securities and Exchange Commission. This reported that Goldman Sachs had sold $2,148 billion of CDS, bought $2,289 billion and that $1,975 billion of the bought positions offset sold positions. These positions generate a similarity metric of 0.89.[15] Unfortunately, other G14 dealers do not report equivalent information.[16] We therefore accept candidate protection-bought and protection-sold positions if they generate a mean similarity metric across dealers within 0.001 of 0.89. One set of positions that meets this criterion, which we take forward, has κ_j ranging from 0.80 to 0.94 across the G14 dealers.

Long and short positions generated by the IPF algorithm that comply with the overlap requirements are considered to be representative portfolios. The results in this paper are based on one such set of portfolios for IRS and one for CDS, samples of which are shown in Tables 10 and 11 respectively.[17]

3.1.4 Validation of representative portfolios

As the degree of overlap between long and short IRS positions was calibrated using qualitative information, we seek to corroborate the representativeness of our hypothetical IRS portfolios. To this end, we compare the total variation margins that a CCP would collect against these portfolios if it set variation margins equal to the net market value of positions wherever this was positive from its point of view with those collected in actuality by SwapClear, which sets variation margins in the same way.

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[14] The discussion with ISDA happened after publication of Heller and Vause (2011). In that paper, we required the mean value of the similarity metric across dealers to be within 0.001 of 0.97, rather than 0.98. This is the main reason why estimates of collateral requirements for IRS clearing are higher in that publication.

[15] The numerator of equation (12) is equal to the position overlap of $1,975 billion and the denominator is equal to the average of the total bought-protection and sold-protection positions, which is $2,219 billion.

[16] A few other G14 dealers report the volume of protection bought on reference entities for which they have also sold some protection, but this is not the same as our similarity metric. For example, if a dealer had sold $100 of protection on a particular reference entity and bought $120 of protection on the same entity, the dealer would report the $120 amount, whereas our similarity metric requires the $100 amount.

[17] We also generated results using other sets of representative portfolios. Estimates of collateral requirements typically varied by 10-20% across different sets of results, while the outcomes of qualitative comparisons – for example between collateral requirements for IRS and CDS or different clearing structures – were not affected.

The market values of our hypothetical IRS portfolios, and hence the variation margins required to clear them, depend on the extent to which the prices of their constituent contracts have changed since they were signed. We therefore need to know the origination dates of all of the contracts in each hypothetical IRS portfolio. This is inferred by constructing a distribution of contracts by original maturity that is consistent with the distribution of contracts by residual maturity in the hypothetical portfolios, and then subtracting residual maturities from original maturities. For simplicity, we assume that all outstanding contracts have original maturities of 2, 5, 10, 15, 20, 30 or 40 years. These maturities correspond to the edges of the residual-maturity buckets shown in Table 4, with the 40-year maturity acting as an upper edge for the 30+ year bucket. We also assume that all contracts mature at regular intervals, when they are replaced by new contracts of the same original maturity. This results in stable distributions of contracts by original and residual maturities, which are mutually consistent. The relationship between these two distributions is shown in Table 12. This is used to infer the distribution of contracts by original maturity for positions in each residual-maturity bucket. Origination dates are then obtained by subtracting residual maturities from original maturities, using the mid-points of residual-maturity buckets in order to derive precise answers. Results are shown in Table 13.

Given estimates of the ages of contracts in our hypothetical IRS portfolios, an IRS valuation equation may now be employed to compute the market values of these contracts. The market value of an IRS is equal to the difference between the present value of the floating-rate coupons promised by one of the counterparties and the present value of the fixed-rate coupons promised by the other counterparty. The market value of IRS with a notional principal amount of one dollar, from the point of view of the fixed-rate payer, may therefore be written as

$$V_{i,t+h}\left(x_{it}\left(M_i\right)\right)=\underbrace{\frac{1}{f}\sum_{m=1}^{f\left(M_i-h\right)} w_{t+h}\left(\tfrac{m}{f}\right)e^{-z_{t+h}\left(\frac{m}{f}\right)\frac{m}{f}}}_{\text{Receive floating}}\underbrace{-\frac{x_{it}\left(M_i\right)}{f}\sum_{m=1}^{f\left(M_i-h\right)} e^{-z_{t+h}\left(\frac{m}{f}\right)\frac{m}{f}}}_{\text{Pay fixed}}. \tag{13}$$

Equation (13) shows the value of an IRS that was signed on date t, when it had an original maturity of M_i.[18] Coupons are paid f times a year (although we assume $f=4$ for all of the IRS in our hypothetical portfolios). So, at date $t+h$, where we chose for simplicity h to be a coupon payment date, there are $f\left(M_i-h\right)$ coupons still to be paid. These are indexed by m. Fixed-rate coupons are

[18] See Hull (2011), page X, for a fuller description of the valuation of interest rate swaps.

paid at rate $x_{it}(M_i)$ and discounted to present values using 'zero rates', $z_{t+h}\left(\frac{m}{f}\right)$ for maturity $\frac{m}{f}$. These are interest rates on zero-coupon investments that are considered to have essentially no default risk. The uncertain future floating-rate coupons may be exchanged for known future amounts at prevailing forward rates, $w_{t+h}\left(\frac{m}{f}\right)$, where $\frac{m}{f}$ denotes the forward rate applicable to the period $t+\frac{m-1}{f}$ to $t+\frac{m}{f}$. The present values of floating-rate coupons may then be computed by discounting the equivalent certain coupons at zero rates of corresponding maturities.

The IRS valuation equation may be re-written, so it is easier for us to use. As swap rates are chosen so that IRS have zero value at inception, the following inference can be made:

$$V_{i,t+h}\left(x_{it}(M_i-h)\right)=0 \Rightarrow \frac{1}{f}\sum_{m=1}^{f(M_i-h)} w_{t+h}\left(\tfrac{m}{f}\right) e^{-z_{t+h}\left(\frac{m}{f}\right)\frac{m}{f}} = \frac{x_{it}(M_i-h)}{f}\sum_{m=1}^{f(M_i-h)} e^{-z_{t+h}\left(\frac{m}{f}\right)\frac{m}{f}}.$$

This allows equation (13) to be re-written, without referring to floating-rate coupons, as

$$V_{i,t+h}\left(x_{it}(M_i)\right)=\frac{x_{it}(M_i-h)-x_{it}(M_i)}{f}\sum_{m=1}^{f(M_i-h)} e^{-z_{t+h}\left(\frac{m}{f}\right)\frac{m}{f}}.$$

And because IRS have zero value at inception, the change in value is also

$$\Delta V_{hit}=V_{i,t+h}\left(x_{it}(M_i)\right)-V_{i,t}\left(x_{it}(M_i)\right)=\frac{x_t(M-h)-x_t(M)}{f}\sum_{m=1}^{f(M-h)} e^{-z_{t+h}\left(\frac{m}{f}\right)\frac{m}{f}}. \tag{14}$$

The key data input required by the IRS valuation equation is the difference between the swap rate of the residual maturity of the IRS on the valuation date and the swap rate of the original maturity of the IRS when it was issued. Historical data on swap rates, however, rarely extends back for much more than a decade. Where this was the case, missing swap rates were approximated by government bond yields plus the average difference between the swap rate and the government bond yield for the period for which both were available. It was also necessary to estimate some swap rates by interpolation (e.g. some 13-year swap rates were estimated by linear interpolation of 12-year and 15-year rates) or extrapolation (e.g. some 40-year swap rates were set equal to 30-year rates). Table 14 shows a sample of the data on swap rates that we used in our calculations, with grey shading illustrating where approximations had to be made. In addition, the IRS valuation equation requires risk-free discount rates out to the residual maturity of the contract. The yield curve of US dollar zero rates as of 30 June 2010 was used for this purpose.

Graph 2 shows the variation margins that a CCP would collect against our hypothetical IRS portfolios if it set margin requirements equal to the net market value of each dealer's positions wherever these were positive from its point of view. On this basis, 9 of our 14 hypothetical portfolios would require variation margins to be posted, ranging from $1.5 billion to $29.3 billion and totalling $97.5 billion. This is somewhat more than double the variation margins of $36 billion posted by G14 dealers to SwapClear at the end 2010.[19] At this time, however, G14 dealers only cleared centrally around half of their IRS positions, whereas our calculations apply to all positions. Our variation margins therefore appear to be in the right ballpark, which gives us more confidence that our hypothetical portfolios are reasonably representative of the actual G14 dealer portfolios.

3.2 Potential changes in market values of portfolio constituents

The second analytical component that we need to estimate the collateral that prudent CCPs would require to clear G14 dealers' IRS and CDS portfolios is a joint probability distribution of potential changes in the market values of representative portfolio constituents.

We estimate joint probability distributions of potential changes in market values of IRS and CDS by a four-step process. This is based largely on Frey and McNeil (2000). The first step aims to capture key time-series characteristics of the drivers of market values, such as volatility clustering, by fitting Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models to historical data. The drivers of market values are swap rates, CDS premiums and discount rates. The second step fits continuous probability distribution functions to the residuals of the GARCH models. Each of these functions has three segments. Two segments are Generalised Pareto Distributions (GPDs), which are fitted optimally to the upper and lower tails of the GARCH residuals through the choice of two parameter values. The third segment, which covers the middle of each distribution where there is much more historical data, is fitted non-parametrically. The third step combines the continuous probability distribution functions for each residual into a joint probability distribution over all the residuals using a copula function. Parameters of the copula determine the shape of the joint distribution and are chosen so that this fits optimally the pattern of residuals across derivatives observed on different days. The final step samples from the fitted joint distribution and maps these samples of GARCH residuals to the drivers of market values and hence to changes in market values.

[19] See International Swaps and Derivatives Association (2011), page 11.

This four-step approach has a number of benefits. First, the GARCH modelling typically leaves the residuals free of volatility clustering. This means that continuous probability distribution functions can be fitted to the residuals with greater precision than could be achieved for the drivers of market values. Second, because the GARCH models capture the dynamics of the drivers of market values, potential changes in market values over any number of days can be computed. This is useful for setting initial margins, which should cover almost all possible losses over a several-day horizon. Third, use of GARCH models allows potential changes in market values, and hence initial margins, to be conditioned on prevailing levels of volatility in the drivers of market values. Conditional collateral requirements can then also be compared with those of an unconditional approach. Fourth, fitting GPDs to the tails of the residual distributions is a robust way to estimate the likelihood of changes in market values that are rarely observed in practice. This follows from a theoretical proof that the tails of distributions always have this particular functional form, regardless of the shape of the rest of the distribution (except in some special cases that do not apply here). Finally, sampling from the fitted joint distribution generates many more pseudo observations than actual historical observations. This allows frequencies of changes in market values to be estimated more accurately, including coincident extreme changes in the market values of different portfolio constituents. As a result, this approach sheds valuable light on risk beyond the percentiles at which initial margins are typically set, allowing assessments to be made about the adequacy of default funds.

It is both necessary and advantageous in the four-step approach to model the drivers of market values, rather than work directly with changes in market values. It is necessary because data on changes in market values of IRS and CDS are not available directly. It is advantageous because the domains of GPDs, which extend to infinity, do not match those of potential changes in market values. Potential losses for a fixed-rate payer in an IRS, for example, are capped by the inability of floating rates to fall below zero. Similarly, the potential loss of a CDS protection seller cannot exceed the notional amount that has been insured against default losses. Fitting GDPs directly to changes in the market value of IRS or CDS would therefore suggest non-zero probabilities of losses greater than those that are actually possible. In contrast, the drivers of IRS and CDS market values are such that changes in the natural logarithms of their levels could potentially extend to positive or negative infinity. GPDs may therefore be fitted to the upper and lower tails of these variables without the possibility of fitted values amounting to impossible predictions. As a result, these fitted values can always be mapped to changes in market values.

3.2.1 Discount rates

In addition to swap rates and CDS premiums, the market values of IRS and CDS depend on a number of discount rates. Since the derivatives in dealers' representative portfolios are assumed to generate quarterly cash flows, some of which will continue for a further 35 years, the market values of these derivatives depend on up to 140 discount rates.

Rather than model a large number of discount rates alongside the other drivers of CDS and IRS market values, we approximate each of these discount rates with a function of three 'principal components'. This has little effect on the results, as discount factors tend to be less important drivers of IRS and CDS market values than swap rates and CDS premiums and because the discount rates based on principal components approximate closely actual discount rates. In fact, they explain over 99% of the historical variation in actual discount rates.

In general, principal components analysis represents n different data series as a linear combination of n unobserved components that are orthogonal to each other. The first component explains as much of the variance of the n original series as possible. The second component then explains as much of the remaining variance of the n original series as possible. And so on.

We obtain three principal components of discount rates by applying principal components analysis to historical data on zero rates. In particular, the analysis is applied to end-of-day US dollar zero rates with different maturities, denoted $z_t(\tau)$, where $z_t(\tau) = 0.25, 0.5, \ldots, 35$ years, from 1 October 2004 to 30 September 2010. These rates are normalised as

$$s_t(\tau) = \frac{z_t(\tau) - \mu_z(\tau)}{\sigma_z(\tau)},$$

where $\mu_z(\tau)$ and $\sigma_z(\tau)$ are respectively the time-series mean and standard deviation of $z_t(\tau)$. Principal components analysis delivers the three factors, f_{1t}, f_{2t} and f_{3t} that explain hierarchically as much as possible of the variance of $s_t(\tau)$, as well as the loadings of zero rates on each of these factors, $\varphi_1(\tau)$, $\varphi_2(\tau)$ and $\varphi_3(\tau)$. Approximate discount rates are consequently given by

$$\hat{z}_t(\tau) = [\varphi_1(\tau) f_{1t} + \varphi_2(\tau) f_{2t} + \varphi_3(\tau) f_{3t}]\sigma_z(\tau) + \mu_z(\tau).$$

Results of the principal components analysis are shown in Graph 3. As in many previous studies, the pattern of factor loadings (left-hand panel) suggests that f_{1t} mainly drives the level of the zero curve, f_{2t} drives its slope and f_{3t} drives its curvature.[20] The middle panel shows the evolution of these factors over time. Finally, the right-hand panel illustrates how the factors combine, using the appropriate loadings, to fit discount rates very effectively.

3.2.2 GARCH models of drivers of market values

We aim to capture key time-series characteristics of swap rates, CDS premiums and discount rates via a set of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. More specifically, we fit the natural logarithm of each swap rate, $\ln(x_{it})$, the natural logarithm of each CDS premium, $\ln(p_{it})$, and each principal component of the natural logarithm of discount rates, f_{it}, to a target-variance GARCH model. This may be represented as

$$r(i)_t = \gamma(i) + \delta(i) r(i)_{t-1} + \sigma(i)_t u(i)_t \text{, where } u(i)_t = {}^{\varepsilon(i)_t}\!\big/_{\sigma(i)_t} \sim \text{iid } N(0,1), \tag{15}$$

$$\sigma(i)_t^2 = \omega(i)\sigma(i)^2 + \alpha(i)\varepsilon(i)_{t-1}^2 + \beta(i)\sigma(i)_{t-1}^2, \tag{16}$$

$$\omega(i) = 1 - \alpha(i) - \beta(i) \text{, for} \tag{17}$$

$$r(i)_t \in \{\Delta \ln(x_{it}), \Delta \ln(p_{it}), \Delta f_{1t}, \Delta f_{2t}, \Delta f_{3t}\}. \tag{18}$$

The parameters γ and δ in equation (15) respectively capture any drift or first-order autocorrelation in each driver of market values. These are often small and difficult to distinguish statistically from zero. For some of the drivers of market values, however, these terms are important and their inclusion helps to support the assumption that the standardised residuals, u_t, are independently distributed and have zero means. In addition, it is assumed that these residuals have standard normal distributions.

Despite the assumption that each standardised residual is distributed normally, the GARCH models can still capture non-normal unconditional distributions of drivers of market values. This follows from equation (16), given that α was estimated to be strictly positive for each driver of market values.

[20] See, for example, Litterman and Scheinkman (1991).

This implies that large deviations of r_{t-1} from expectations are signs of increased risk as they lead to higher conditional volatilities, σ_t, which increases the chance of subsequently observing a large deviation of r_t from expectations. Furthermore, initial increases in conditional volatilities persist as a result of β, which was also always estimated to be strictly positive. Since it was always found that $\alpha + \beta < 1$, however, changes in conditional volatilities do eventually dissipate as they return them to their unconditional levels, σ. But as $\alpha + \beta$ was close to one for a number of CDS premiums, the return to unconditional volatility levels is a very gradual one for these particular drivers of market values. Clustering of volatility at high and low levels results in unconditional distributions of r_t being more leptokurtic than a normal distribution, having fatter tails as well as relatively more mass near the means.

Samples of results of fitting target-variance GARCH models to daily data from 01/10/2004 to 30/09/2010 are shown in Table 15 and Graph 4. Table 15 summarizes the estimated values of parameters. Note that even if the assumed normal distribution of standardised residuals is not a close approximation of reality, the maximum likelihood fitting procedure that was used delivers consistent estimates of parameters, so these are unlikely to have significant biases given the number of data observations.[21] Graph 4 shows autocorrelation functions of r_t^2 and u_t^2 for the four-year euro swap rate and JP Morgan's five-year senior-debt CDS premium. It suggests that the GARCH modelling of these variables has been successful in capturing the volatility clustering in these variables, as significant correlations, which are present between r_t^2 and r_{t-j}^2 for several values of j, are not observed in the standardised residuals.

3.2.3 Continuous distributions of GARCH model residuals

Next, we fit a continuous probability distribution function comprised of three segments to each of the GARCH model residuals. Fitting the upper and lower tails of these distributions draws on the theoretical results of Balkema and de Haan (1974) and Pickands (1975). They showed that the distribution of threshold exceedances of data from a wide range of distribution functions tends to that of a GPD as the threshold increases, and that GPDs are often good approximations of distributions of exceedances over less extreme thresholds. Fitting exceedance distributions to the tails our GARCH model residuals generates much better estimates of the probabilities of extreme

[21] See Gourieroux (1977), chapter 4.

changes in market values than can be obtained from the historical frequencies of such rarely observed events. The middle sections of the residual distributions are fitted non-parametrically, such that they cover the probability mass not accounted for by the upper and lower tails.

<u>The upper and lower segments of the fitted distribution functions cover the top and bottom deciles of each residual distribution</u>. To fit the upper tail, the extent to which observations exceed the 90th percentile are first recorded, while to fit the lower tail, the extent to which observations fall short of the 10th percentile are recorded. GPDs are then fitted to the distributions of these exceedances, from which fitted values of the upper and lower segments of each residual's probability distribution are inferred. More formally, for a given threshold $\overline{u}(i)$, the relationship between the cumulative probability distribution function of exceedances, $\widetilde{F}_i[u(i)-\overline{u}(i)]$, the cumulative probability distribution function of residuals, $F_i[u(i)]$, and the GPD approximation of the distribution of exceedances, $G_i[u(i)-\overline{u}(i)]$, is

$$\widetilde{F}_i[u(i)-\overline{u}(i)] = \frac{F_i[u(i)]-F_i[\overline{u}(i)]}{1-F_i[\overline{u}(i)]} \approx G_i[u(i)-\overline{u}(i);\xi_i,\upsilon_i]$$, where …

$$G_i[u(i)-\overline{u}(i);\xi_i,\upsilon_i] = \begin{cases} 1-\left(1+\frac{\xi_i}{\upsilon_i}[u(i)-\overline{u}(i)]^{-\frac{1}{\xi_i}}\right) & \text{if} \quad \xi_i \neq 0 \\ 1-\exp\left(-\frac{1}{\xi_i}[u(i)-\overline{u}(i)]\right) & \text{if} \quad \xi_i = 0 \end{cases}.$$

The cumulative probability distribution function of residuals is therefore approximated by

$$F_i[u(i)] = 1-(1-F_i[\overline{u}(i)])(1-\widetilde{F}_i[u(i)-\overline{u}(i)]) \approx 1-\tfrac{1}{10}\left(1+\tfrac{\hat{\xi}_i}{\hat{\upsilon}_i}[u(i)-\overline{u}(i)]^{-\frac{1}{\hat{\xi}_i}}\right),$$

where $\hat{\xi}_i$ and $\hat{\upsilon}_i$ are parameter estimates obtained by maximum likelihood fitting of $G_i[u(i)-\overline{u}(i);\xi_i,\upsilon_i]$ to the 10% of residuals that exceed $\overline{u}_i$. This procedure requires the residuals to be identically and independently distributed, which the GARCH modelling of Section 3.2.2 helps to ensure.

<u>Samples of the continuous distribution functions fitted to GARCH model residuals are shown in Graphs 5 and 6</u>. The left-hand and centre panels of these graphs focus on the upper and lower tails, showing that these fit well the available historical data for euro swap rate residuals and JP Morgan CDS premium residuals. The right-hand panels shows the complete three-segment distribution functions fitted to these two sets of residuals.

3.2.4 Joint distribution of all GARCH model residuals

The next step is to amalgamate the continuous probability distribution functions of each driver of market values into a joint distribution function. This joint function measures the probability of any combination of IRS, CDS and discount factor residuals. Combinations of IRS and discount factor residuals are used to establish potential valuations of IRS portfolios, while combinations of CDS and discount factor residuals are used to establish potential valuations of CDS portfolios.

The joint probability distribution function is constructed using a copula function. A copula function, $C(.)$, joins marginal probability distributions, such as those for each driver of market value, $F_i[u(i)]$, into a joint distribution function:

$$F[u(1),...,u(N_{IRS}+N_{CDS}+3)]=C(F_1[u(i)],...,F_{N_{IRS}+N_{CDS}+3}[u(N_{IRS}+N_{CDS}+3)]).$$

We assume that an appropriately-calibrated t-copula, $C(.)=t(\rho,\theta)$, will fit well the relative historical frequencies of different combinations of IRS, CDS and discount factor residuals. We then chose the values of parameters, ρ and θ, to maximize the likelihood that this copula, in combination with the marginal probability distribution functions, could have generated the historical data. These parameters are respectively a matrix of pair-wise correlations between the residuals of the GARCH models and a single 'degrees of freedom' parameter. The degrees-of-freedom parameter controls the average degree to which co-dependence between residuals is greater for extreme values and smaller for non-extreme values than that captured in the correlation matrix of residuals.

Results of the copula-fitting exercise are shown in Table 16. The high estimated value of the degrees of freedom parameter shown in the first row of the table implies little tendency for the GARCH residuals to have joint extremes more often and joint non-extremes less often than the pair-wise correlations across all (extreme and non-extreme) values would suggest. These pair-wise correlations, reported in the remaining rows of the table, imply a strong tendency for swap rates to move together, a fairly strong tendency for CDS premiums to move together and a moderate tendency for swap rates and CDS premiums to move in opposite directions. The latter might be expected as positive economic news tends to drive swap rates up and CDS premiums down and *vice versa*.

3.2.5 Potential changes in market values from samples of joint distribution

The final step in building the joint distribution of changes in market values of representative portfolio constituents takes samples from the joint distribution of GARCH residuals and maps each sample to a change in market value of a representative portfolio constituent.

Samples are taken from the joint distribution of GARCH model residuals by simulating $N_{IRS} + N_{CDS} + 3$ dependent uniform random variables, $v(i) \sim U[0,1]$, where $i \in \{1,\ldots, N_{IRS} + N_{CDS} + 3\}$. The dependence among these variables is that of a t-copula with pair-wise correlations and degrees of freedom as estimated in Section 3.2.4. Each of these random samples corresponds to the value of a particular GARCH residual according to $u(i) = F_i^{-1}[v(i)]$.

Samples of GARCH residuals are then mapped to the drivers of market values. This involves inputting the samples of GARCH residuals to the GARCH models described in equations (15) – (18) as $u(i)_{t+1}$, given the prevailing level of volatility, $\sigma(i)_t$, and previous values of $u(i)_t$ and $r(i)_t$, to obtain $r(i)_{t+1},\ldots, r(i)_{t+h}$, where h is the forecast horizon. These forecasts are related to the drivers of market values according to

$$x(i)_{t+h} = \exp\left(\ln[x(i)_t] + r(i)_{t+1} + r(i)_{t+2} + \ldots + r(i)_{t+h}\right) \quad \forall i \in \{IRS\},$$

$$p(i)_{t+h} = \exp\left(\ln[p(i)_t] + r(i)_{t+1} + r(i)_{t+2} + \ldots + r(i)_{t+h}\right) \quad \forall i \in \{CDS\}, \text{ and}$$

$$\hat{z}_{t+h} = \exp\left(\begin{array}{c} \varphi_1\left[f_{1t} + r(N+1)_{t+1} + \ldots + r(N+1)_{t+h}\right] + \varphi_2\left[f_{2t} + r(N+2)_{t+1} + \ldots + r(N+2)_{t+h}\right] + \ldots \\ \varphi_3\left[f_{3t} + r(N+3)_{t+1} + \ldots + r(N+3)_{t+h}\right] \end{array}\right).$$

Next, we use equation (14) to map samples of valuation drivers to changes in the market values of all 42 categories of IRS in our representative portfolios. The assumed residual maturities of these IRS are as reported in Table 12. Where not available directly, we estimated swap rates of these maturities by interpolating swap rates of neighbouring maturities or extrapolating swap rates of nearby maturities. In addition, the discount rates estimated in Section 3.2.1, $\hat{z}_{t+h}$, are used in place of z_{t+h}.

A similar procedure is followed to map samples of valuation drivers to changes in market values of CDS. This uses a valuation equation based on Duffie and Singleton (2005).[22] This equation holds for any CDS that promised when signed at date t to pay an annual premium of p_{it} per unit of notional

[22] See, in particular, Section 8.4.1 on pages 186-188.

principal f times a year until maturity M_i years later as long as no credit events, such as default, occurred, in exchange for a one-off payment equal to the magnitude of losses should a credit event happen. The value of the CDS on date h years after being signed therefore depends on the prevailing default intensity, $\lambda_{i,t+h}$.[23] From the point of view of a protection buyer this value is

$$V_{i,t+h}\left(\lambda_{i,t+h}, \bar{z}_{t+h}(m), p_{it}\right) = \underbrace{\left[b_{i,1}\left(\lambda_{i,t+h}, z_{t+h}\left(\tfrac{1}{f}\right)\right) + \ldots + b_{i,f(M-h)}\left(\lambda_{i,t+h}, z_{t+h}\left(M_i - h\right)\right)\right]\left(1-R\right)}_{\text{Contingent leg}}$$

$$-\underbrace{\left[a_{i,1}\left(\lambda_{i,t+h}, z_{t+h}\left(\tfrac{1}{f}\right)\right) + \ldots + a_{i,f(M-h)}\left(\lambda_{i,t+h}, z_{t+h}\left(M_i - h\right)\right)\right]\frac{p_{it}}{4}}_{\text{Premium leg}}, \qquad (19)$$

where $a_{i,m}\left(\lambda_{i,t+h}, z_{t+h}\left(\tfrac{m}{f}\right)\right) = e^{-\left(\lambda_{i,t+h} + z_{t+h}\left(\frac{m}{f}\right)\right)\frac{m}{f}}$ and $b_{i,m}\left(\lambda_{i,t+h}, z_{t+h}\left(\tfrac{m}{f}\right)\right) = e^{-z_{t+h}\left(\frac{m}{f}\right)\frac{m}{f}}\left[e^{-\lambda_{i,t+h}\frac{m-1}{f}} - e^{-\lambda_{i,t+h}\frac{m}{f}}\right]$

and R is the recovery rate in the event of default. The market value is the difference between the present value of the default-contingent payment and that of the future stream of premiums. We again establish present values using the discount rates estimated in Section 3.2.1.

An expression for changes in market values of CDS can be obtained by recognizing that premiums are initially set such that CDS have zero market value. We consequently, input premiums and discount rates on date t into equation (19) to infer $\lambda_{i,t}$. Similarly, we input simulated premiums and discount rates for date $t+h$ into equation (19) to infer a $\lambda_{i,t+h}$ for each simulation. Changes in market value per unit of notional amount are then given by

$$\Delta V_{hit} = V_{i,t+h}\left(\lambda_{i,t+h}, \bar{z}_{t+h}\left(\tfrac{m}{f}\right), p_{it}\right) - V_{it}\left(\lambda_{i,t+h}, \bar{z}_{t+h}\left(\tfrac{m}{f}\right), p_{it}\right) = V_{i,t+h}\left(\lambda_{i,t+h}, \bar{z}_{t+h}\left(\tfrac{m}{f}\right), p_{it}\right) \quad \forall i \in \{CDS\}.$$

We apply this equation to each of the 196 CDS in our representative portfolios to establish changes in market values. In doing so, we use a residual maturity of 3.5 years in all cases. This is based on distributions of notional amounts outstanding across maturity buckets reported by some of the G14

[23] This default intensity is the average rate over time at which reference entities are expected to default conditional on not having previously defaulted. More specifically, it is the default intensity reflected in the prices of traded CDS. As such it is a risk-neutral intensity. Risk-neutral default intensities are explained in more detail in Duffie and Singleton (2005).

dealers.[24] In addition, we use a fixed recovery rate of 40%, reflecting standard practice in the valuation of many CDS contracts.

3.3 Joint distribution of losses on representative portfolios

The final methodological step brings together the representative portfolios constructed in Section 3.1 and the joint probability distribution of changes portfolio constituent values estimated in Section 3.2 to form joint distributions of possible changes in representative portfolio market values. These are expressed in terms of portfolio losses, π_{jt}, where

$$\pi_{jt} = -\sum_{i} \Delta V_{hit} \left(L_{ij} - S_{ij} \right) \quad \forall j \in \{1,\ldots,14\}. \tag{20}$$

The variation margins, initial margins and contributions to default funds that prudent CCPs would require under comprehensive central clearing are all driven by these potential portfolio losses. As variation margins are paid by dealers when they incur losses, we assume that a prudent CCP would equate these to π_{jt} with h set at one day. Similarly, as initial margins are intended to cover most possible losses that counterparties could incur over several days, we assume that a prudent CCP would equate these to the 99.5th percentile of π_{jt} with h set at five days. Losses beyond this percentile represent risk to the default fund and other residual buffers of the CCP. If these losses contributed to the default of one or more counterparties then the default fund and other buffers would be called upon to absorb the excess losses. We assume that a prudent CCP would evaluate the extent to which initial margins could plausibly fall short of portfolio losses for multiple dealers at the same time, threatening the solvency of these dealers, and set default fund contributions such that they could absorb this shortfall.

We construct joint distributions of G14 dealer losses for eight overlapping segments of the derivatives market, reflecting different possible structures of central clearing. First, a joint distribution of G14 dealer losses is constructed for all IRS and another is constructed for all CDS by using respectively $i \in \{\mathrm{IRS}\}$ and $i \in \{\mathrm{CDS}\}$ in equation (20). From these we estimate the collateral requirements of a single CCP clearing IRS and a single CCP clearing CDS. Next, we use

[24] For each dealer reporting such information, the weighted average residual maturity was calculated. These ranged from 3.4 to 3.7 years and averaged 3.5 years. This masks a range of residual maturities held by each dealer. It would have been possible to have included CDS holdings of different maturities in representative portfolios and to have estimated changes in market values for contracts with these various maturities. Since the relationship between changes in the natural logarithm of CDS premiums and changes in CDS market values is almost linear in residual maturity, however, this would make little difference to the values of representative portfolios.

$i \in \{\text{American CDS}\}$, $i \in \{\text{European CDS}\}$ and $i \in \{\text{Asian CDS}\}$ in equation (20) to obtain joint distributions of G14 dealer losses on representative American, European and Asian CDS positions. From these we estimate the collateral requirements of geographically-focussed CDS CCPs. Similarly, using $i \in \{\text{multi - name CDS}\}$ and $i \in \{\text{single - name CDS}\}$ in equation (20) delivers joint distributions of G14 dealer losses on representative multi-name and single-name CDS positions. From these we estimate the collateral requirements of product-focussed CDS CCPs. Finally, using $i \in \{\text{IRS}, \text{CDS}\}$ in equation (20) delivers a joint distribution of G14 dealer losses on their combined IRS and CDS positions. From these we estimate the collateral requirements of a single CCP clearing these integrated portfolios. In each case, the joint distribution of G14 dealer losses is based on 100,000 samples of the same pseudo-random numbers.

4. Results on collateral requirements

<u>In this section, we report our estimates of the collateral that prudent CCPs would demand as variation margins, initial margins and default fund contributions to clear G14 dealers' IRS and CDS portfolios under different clearing structures</u>. First, we show results for one CCP clearing IRS and a second CCP clearing CDS (Section 4.1). This highlights some differences in collateral requirements that stem from the contrasting risk characteristics of IRS and CDS. In addition, the IRS results are pertinent to the current structure of clearing, which has one dominant CCP for IRS in SwapClear. In contrast, CDS clearing is presently fragmented on a regional basis, with ICE Clear Credit clearing North American CDS, ICE Clear Europe clearing European CDS and the Japan Securities Clearing Corporation clearing (a limited range of) Asian CDS.[25] A second set of results therefore shows the collateral requirements of three regionally-focussed CCPs clearing CDS (Section 4.2). We compare these requirements with those of a single CDS CCP to quantify the economies of scope that would be foregone if CDS clearing were to remain geographically fragmented in this way. We also estimate the economies of scope available to CCPs and their clearing members from the expansion of CDS clearing from multi-name contracts to also cover comprehensively single-name contracts (Section 4.3). This reflects the present situation in which central clearing of multi-name CDS is much more widespread than for single-name CDS. Finally, the collateral requirements of a single CCP clearing both IRS and CDS are reported in Section 4.4. We compare these results with those of Section 4.1 to estimate the economies of scope to cross-segment clearing of OTC derivatives.

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[25] In fact, the Japan Securities Clearing Corporation has only cleared different series of the iTraxx Japan index since it began clearing CDS in July 2011.

Under each clearing structure, we show how collateral requirements should vary with prevailing levels of volatility of the drivers of IRS and CDS market values. In particular, we report results for 'low', 'medium' and 'high' levels of volatility. Low volatility levels are defined as those of 30 June 2006, which was before the recent financial crisis. Medium volatility levels are defined as those of 14 March 2008, which was just before Bear Stearns was supported by JP Morgan and the US Federal Reserve, during the financial crisis. High volatility levels are defined as those of 10 October 2008, which was amidst the negative market reaction to the Troubled Asset Relief Program at the peak of the crisis. Graph 7 shows time series of conditional volatilities of selected drivers of IRS and CDS market values, as estimated by the GARCH models described in Section 3.2.2, with the volatility levels of 30/06/2006, 14/03/2008 and 10/10/2008 highlighted.

4.1 One CCP clearing each class of derivatives

The left-hand panels of Graphs 8 and 9 show respectively potential variation margin requirements of a prudent CCP clearing either IRS or CDS, conditional on different levels of market volatility. In particular, they show the 99.5th percentiles of possible daily variation margin requirements. So, the left-hand panel of Graph 8 shows that Dealer 7, for example, could expect daily variation margin calls of (at least) $0.5 billion with 0.5% probability in an environment of low market volatility. If market volatility increased to medium, this potential margin call would rise to $1.2 billion, while if market volatility increased to high, it would rise to $1.7 billion. Potential variation margin calls also increase quite steadily with market volatility for the representative IRS portfolios of the other G14 dealers. In contrast, potential daily variation margin calls on our representative CDS portfolios generally jump up with increases in volatility from low (pre-crisis) levels (Graph 9). For Dealer 7, for example, the potential margin call rises from $0.4 billion to $1.9 billion (medium volatility) or $4.2 billion (high volatility).

The right-hand panels of Graphs 8 and 9 show respectively potential cumulative variation margin calls on our hypothetical IRS and CDS portfolios. In particular, they show the 99.5th percentiles of possible variation margins calls summed over up to one month of trading days for each G14 dealer relative to its cash holdings as of mid-2010. Furthermore, the figures relate to an environment of high market volatility, so they may be considered 'worst case' estimates. In these conditions, one G14 dealer could expect IRS variation margin calls to drain (at least) 14% of its cash over one month with 0.5% probability. Similarly, one G14 dealer could expect CDS variation margin calls to drain 52%

of its cash over one month with 0.5% probability.[26] Note, however, that only around half of all IRS and 5% of all CDS had been centrally cleared as of mid-2010 and that dealers may chose to raise the share of their assets held as cash under more comprehensive central clearing.

The left-hand panels of Graphs 10 and 11 show respectively initial margin requirements of a prudent CCP clearing either IRS or CDS, conditional on different levels of market volatility. As for variation margins, initial margin requirements on IRS portfolios tend to increase quite steadily as market volatility increases, whereas it generally jumps up on CDS portfolios as market volatility rises from a low (pre-crisis) level. Across the G14 dealers, initial margin requirements on IRS portfolios total $15 billion in an environment of low market volatility, rising to $29 billion if market volatility increased to medium and $43 billion if it increased to high. For CDS, total initial margin requirements jump from $10 billion in an environment of low market volatility to $51 billion and $107 billion as volatility rises to medium and high.

The centre panels of Graphs 10 and 11 show how initial margin requirements compare with unencumbered assets. They also show how initial margins compare with total assets, as not all G14 dealers report data on unencumbered assets. For both IRS and CDS portfolios, initial margins would only encumber a small proportion of G14 dealer's assets, even when these margin requirements are set amidst high levels of market volatility. Although many of these assets may not be acceptable as collateral to CCPs in the first instance, dealers could swap these assets for eligible securities, either through outright sales and subsequent purchases or via asset swaps.

The right-hand panels of Graphs 10 and 11 show respectively the likelihoods of initial margin shortfalls across all or some of the G14 dealers for either IRS or CDS. The blue lines show probability distributions of losses in excess of initial margins for the single G14 dealer that can potentially generate the largest excess losses. If this dealer defaulted whenever it incurred an excess loss, the blue lines would represent the distribution of *losses* for default funds to absorb. As it is not clear, however, whether this dealer would always default in such circumstances, the blue lines only show the *risk* of default fund losses from the single most important dealers. The purple lines then show the risk to default funds from the two most important dealers, taking into account the possibility that

[26] Although we think our portfolios are quite representative of the distribution of risk (potential portfolio losses) across the G14 dealers, we do not know how the portfolios in the distribution should be assigned to particular dealers with their particular cash holdings. The 14% and 52% figures arise from relatively high risk portfolios being assigned to dealers with relatively low cash holdings. One may therefore prefer to focus on the middle, rather than the top, of the distribution of blue lines in the right-hand panels of Graphs 8 and 9. Even so, the potential cash calls are significant.

they may both have margin shortfalls at the same time. Finally, the orange lines show the risk to default funds from all of the G14 dealers.

Policymakers are presently refining guidance about the size of default funds. In particular, the Committee on Payment and Settlement Systems (CPSS) and the International Organization of Securities Commissions (IOSCO) have recently published a consultative report that seeks feedback on whether default funds should be intended to protect CCPs against the failure of one or two clearing members.[27] If the final guidance, due in early 2012, recommends protection again two clearing members rather than one, then default funds may need to be around 50% larger. Such a figure may be obtained, for example, by comparing the total margin shortfalls that could be expected with 0.1% probability from the single most important dealer with that of the two most important dealers.[28]

4.2 Three regionally-focussed CDS CCPs

In this section, we show how collateral requirements for central clearing of CDS would differ if the eventual clearing structure of this segment of the derivatives market had three regionally-focussed CCPs, rather than a single CCP clearing all contracts. We assume that one of these CCPs would clear all American CDS, a second would clear all European CDS and the third would clear all Asian CDS.[29] Dealers with geographically diversified CDS portfolios would then have to split their portfolios for clearing purposes. The risks perceived by each clearer would therefore not reflect the geographic diversification of the portfolio and dealers would be required to post more collateral in total to the three CCPs than if there were only one.

The left-hand panel of Graph 12 shows, for example, that G14 dealers would be required to post 16-34% less initial margin under a single CCP than under three regionally-focussed CCPs. Across the G14 dealers the total saving would be 25%. Alternatively, should a regionally-focussed clearing structure emerge, the estimates of initial margin requirements in Section 4.1 should be rescaled so that these savings are not included. Undoing a 25% saving from the $51 billion of initial margins collected by a single CCP in an environment of medium market volatility, for example, would result in an estimate of $68 billion of initial margins collected in total by three regionally-focussed CCPs.

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[27] See Principal 4 of CPSS-IOSCO (2011) see 3.4.10 on page 35.

[28] Note that this assumes the relative size of total shortfalls that occur at a particular probability level is similar to the relative size of total default fund losses that occur at a probability level. Recall that margin shortfalls only generate losses for default funds if counterparties contributing to the total margin shortfall default coincidentally.

[29] One contract in our hypothetical CDS portfolios does not fit neatly into this three-way regional decomposition. This is the CDX.EM index of emerging market sovereign CDS. We include this in the Asian CDS category.

While the left-hand panel of Graph 12 shows how five-day 99.5th percentile losses at three-regionally focussed CCPs compare with those at a single CCP, the right-hand panel of Graph 12 shows how losses at different percentiles summed across all the G14 dealers compare. Assuming initial margins are set at the 99.5th percentile, ratios of losses above the 99.5th percentile show how netting benefits reduce the risk to default funds. The ratio moves down from about 75% to 72% beyond the initial margin percentile, which implies that merging CCPs along geographical lines could reduce risk to default funds by a little more than 25%, even though total initial margins would already have been reduced by 25%. At percentiles below the initial margin threshold, savings are fairly steady at about 25%. This shows, for example, that over a five-day horizon, large variation margin payments that could be expected with particular quite low levels of probability would fall by around 25%.

4.3 Two product-focussed CDS CCPs

Central clearing of CDS has so far been more prevalent for multi-name contracts than for single-name contracts. Table 1 shows that as of the end of 2010, 14% of all multi-name CDS traded over the counter were subsequently cleared by a CCP, while the equivalent figure for single-name CDS was only 4%. This may reflect the often superior liquidity of multi-name CDS, which ensures prices are regularly available at which CCPs could trade, giving them the confidence to offer clearing of those contracts. Although the liquidity of single-name CDS may not always be as high, leading to a risk that CCPs may occasionally have to trade at prices somewhat different from last recorded quotes or prices, the benefits of clearing multi-name and single-name CDS together can be substantial.[30]

Graph 13 shows similar information to Graph 12, comparing total initial margins (left-hand panel) and total losses (right-hand panel) when one CCP clears all multi-name CDS and another clears all single-name CDS with those of a single CCP clearing all CDS. Total initial margins that would cover 99.5% of all possible losses under one CCP would be 48% of the amount under two product-focussed CCPs. The initial margins required to clear both multi-name and single-name CDS ($51 billion) are actually less than the initial margins required to clear multi-name CDS on a standalone basis ($60 billion). This reflects the use by dealers of multi-name CDS to hedge positions in single-name CDS. Across individual dealers, the ratio of initial margin requirements ranges from 36% to 77%. Ratios of losses at different percentiles increase with the magnitude of the percentile. This means that default funds do not gain from quite as large netting benefits as initial margins set at the 99.5th percentile,

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[30] Vause (2010b) describes a number of measures that have helped to standardise single-name CDS and improve liquidity in this segment of the market.

although the savings are still large. This may reflect multi-name positions not hedging single-name positions as effectively as usual when there are extreme movements in the values of portfolios. This could reflect the occasional crystallisation of basis risk, whereby the premium on a CDS index moves in the opposite direction to those of its constituents. This suggests that CCPs should not impose theoretical relationships, such CDS index premiums being equal to index-weighted averages of their constituents' premiums, when modelled potential losses on counterparties' portfolios.

4.4 One CCP clearing all classes of derivatives

In this section, we briefly illustrate additional economies of scope that could be attained if a single IRS CCP merged with a single CDS CCP. The results are illustrated in Graph 14 in the way as previous results were presented in Graphs 12 and 13. Initial margins requirements would range across G14 dealers from 62% to 83% of those required by separate IRS and CDS CCPs. In aggregate, initial margin requirements would be 74% of those demanded by separate IRS and CDS CCPs. Beyond the 99.5th percentile, the ratio of total integrated portfolio losses to total segregated portfolio losses rises slightly, implying that risk to default funds would not be reduced by quite as much as initial margins, if these were still set at the 99.5th percentile.

5 Effect on results of different initial margin setting practices

As more widespread central clearing raises further the importance of CCPs being extremely robust, this section investigates two policies that could potentially help to reduce the failure probabilities of CCPs. These ideas follow from some of the results above that reflect the different risk characteristics of IRS and CDS. First, appropriate variation margins, initial margins and contributions to default funds varied more with market volatility for CDS than for IRS. It may therefore be particularly important that CDS CCPs allow for such time variation in volatility. Indeed, Table 2 shows that ICE Clear Credit and ICE Clear Europe already use a model to set initial margins, which captures the dynamics of CDS values.[31] In contrast, SwapClear sets initial margins equal to the biggest historical loss over the past five years, which only changes very occasionally.[32] Below, we investigate the implications of setting fixed and time-varying initial margins for both IRS and CDS. Second, the risk to default funds was a higher multiple of initial margins for CDS than IRS, which reflects the greater tail risk of CDS than IRS.

[31] See IntercontinentalExchange (2009).

[32] See LCH.Clearnet (2011).

Hence, we experiment by setting initial margins equal to a certain percentile *plus* the expected shortfall associated with that percentile, rather than just a particular percentile.

5.1 Time-varying and fixed initial margins

The left-hand panel of Graph 15 shows how time-varying and fixed initial margins compare with actual five-day losses on one of our representative portfolios of interest rate swaps. For illustrative purposes, the fixed initial margin is set so that 5% of the observations in the sample from October 2004 to September 2010 exceed actual losses. Similarly, the time-varying initial margin is set equal to the 95th percentile of 10,000 pseudo losses constructed by sampling from GARCH residuals and mapping these to market values, in a similar way to that described in Section 3.2.4. The only difference is that for each data point plotted in Graph 15, the samples are conditioned on the level of volatility at that time, rather than on a fixed date such as 30 June 2006.

The benefits of time-varying initial margins can be seen through the final quarter of 2008. Although, they had not increased early enough to protect against a loss in mid-September, this large loss boosted volatility, which was subsequently captured by the GARCH models, leading to higher margin requirements. These higher margin requirements meant that several large losses through the final quarter of 2008 led to smaller exceedances than would otherwise have been the case. Fixed initial margins can not benefit from a similar response. The consequence of this difference can be seen in the right-hand panel of Graph 15, which shows the distribution of excess losses over initial margins. Both margin-setting techniques have excess losses around 5% of the time, but they are generally smaller under the time-varying technique. For excess losses that could be expected with 1% probability, for example, these are about half as large under the time-varying technique as under the fixed initial margins. Graph 16 shows equivalent information for one of our representative CDS portfolios, which is essentially the same as for IRS.

There is a possible externality, however, which could weigh against the private benefits of time-varying margins to CCPs and their clearing members. In particular, demanding that clearing members post additional collateral when markets become more volatile could amplify price movements. For example, if volatility increased as credit spreads widened, dealers would be requested to post more collateral against their CDS positions. To do this, however, they may need to sell some credit assets in order to buy securities such as G7 government bonds that are acceptable to their CCP. But this would put further upward pressure on credit spreads and volatility. The circle may then repeat.

5.2 Percentile-based and shortfall-based initial margins

For several of the dealers, there are greater risks in their CDS portfolios beyond the 99.5th percentile of possible losses than for their IRS portfolios. Graph 17, for example, shows in the left-hand panel the distribution of possible losses one of our representative IRS portfolios. The middle panel shows the same information for one of our representative CDS portfolios. The CDS portfolio has a longer tail, implying that the expected loss conditional on the initial margin threshold being breached is a greater proportion of that initial margin than for IRS. This is reflected in the greater proportionate distance between the orange and purple vertical lines for CDS than for IRS. As the right-hand panel of Graph 17 shows, the same is true for many, but not all, of the G14 dealer portfolios.

The tail risk measure known as 'expected shortfall' takes into account potential losses beyond particular high percentiles. In this section, we consequently experiment by setting initial margins for each of the dealers in two ways. First, as previously, we set them equal to the 99.5th percentile (Method 1). Second, we set them equal to a different, slightly lower, percentile *plus* the expected shortfall associated with that percentile (Method 2). Furthermore, for the Method 2 we pick the new percentile so that initial margin requirements for each IRS portfolio are unchanged. We then use these percentiles plus the associated expected shortfalls to set new initial margins for the CDS portfolios.

The results, in Graph 18, show that factoring the greater tail risk of CDS portfolios into initial margins brings the risk to the default fund closer to that of IRS, but not significantly. Even setting initial margins using Method 2 barely captures the differential impact of tail risk on default funds. This suggests there are no straightforward risk management techniques that CCPs could apply both to IRS and CDS and expect equal success. It would not be wise, for example, to use a rule that set default fund contributions equal to a certain proportion of initial margins (even if these were set using Method 2) and to use the same proportion for IRS and CDS. Instead, it would be better to simulate the effects of any given initial margin setting technique on default fund risk and then set default fund contributions to reduce that risk to the desired remote probability level.

6 Conclusions

Our key conclusions are:

- Variation margin calls of CCPs that cleared all of the IRS or CDS positions of the G14 dealers could over a few weeks cumulate to a substantial proportion of the current cash holdings of some of these dealers, especially in environments of high market volatility. At least some of the G14 dealers should therefore consider increasing their cash balances ahead of more comprehensive central clearing of OTC derivatives. (Right-hand panel of Graphs 8 and 9).

- Initial margin requirements of CCPs that cleared all of the IRS or CDS positions of the G14 dealers would only amount to a small proportion of the unencumbered assets of these dealers. This would remain the case even if CCPs varied initial margin requirements with the volatility of IRS and CDS valuations and prevailing levels of volatility were high. (Centre panels of Graphs 10 and 11).

- The total extent to which initial margins could occasionally fall short of losses on G14 dealer portfolios of IRS and CDS being comprehensive cleared by CCPs is significantly greater for the CDS portfolios than for the IRS portfolios. Total initial margin shortfalls that could be expected with very low levels of probability would be at least twice as large a proportion of total initial margins for the CDS portfolios than the IRS portfolios, assuming initial margins were set equal to high percentiles of potential portfolio losses. Note that these shortfalls represent risks to default funds that would only crystallise if dealers contributing to the shortfalls also defaulted. (Right-hand panels of Graphs 10 and 11).

- Policymakers are presently considering whether guidance for CCPs should recommend that default funds ought to cover the vast majority of possible losses not already covered by initial margins that could stem from the failure of the single or two most important counterparties. Based on relative magnitudes of potential initial margin shortfalls, we suggest that default funds would need to be about 50% larger to cover the potential losses of CCPs clearing all of G14 dealer's IRS or CDS positions from the default of the two most important dealers rather than the single most important dealer. Again, this assumes that the CCPs set initial margins equal to high percentiles of each dealer's potential portfolio losses. (Right-hand panels of Graphs 10 and 11).

- Total collateral requirements for centralised clearing of all G14 dealer's IRS and CDS positions depends on the structure under which comprehensive clearing would be conducted. For example, if a single CCP cleared all CDS, this would require roughly 25% less collateral for variation margins, initial margins and default fund contributions than three regionally-focussed CDS CCPs. If a single CCP comprehensively cleared multi-name and single-name CDS together, this would cut collateral requirements by just over 50% compared with two CCPs specialising in each product. And if one CCP comprehensively cleared dealer's IRS and CDS portfolios this would reduce collateral requirements by around 25% compared with a single CCP in each segment. (Graphs 12, 13 and 14).

- If CCPs that cleared all G14 dealers' positions in IRS or CDS varied initial margin requirements over time with the volatility of IRS and CDS market values, rather than keeping them fixed, risk to default funds would be reduced substantially. For example, total shortfalls of initial margins that could be expected with low probabilities could be reduced by 50% for both IRS and CDS. (Right-hand panels of Graphs 15 and 16).

- Risk to default funds would be much greater relative to initial margins for comprehensive clearing of CDS than for IRS. This would remain the case even if initial margins were set equal to a high percentile of possible losses plus the 'expected shortfall' associated with that percentile. Applying a simple rule like setting default fund contributions equal to a fixed percentage of initial margins would not work consistently well across derivatives classes. Instead, a CCP clearing different types of derivatives would be better advised to simulate risk to the default fund having chosen a methodology for setting initial margins and then determine default fund contributions based on these simulations. (Graph 17).

Annex: Collateral requirements for central clearing of non-dealer positions

In this paper, we have estimated the amount of collateral that major derivatives dealers would be required to post if all outstanding IRS and CDS were cleared centrally. For almost all of these contracts, a derivatives dealer is at least one of the original counterparties, and often another dealer is the other counterparty, but not always. Trades between dealers and non-dealers would require the non-dealer as well as the dealer to post collateral if they were to be cleared centrally. While the burden of such collateral requirements for dealers has been captured in the analysis above, which estimated the collateral needed to clear centrally major derivatives dealer's whole portfolios of IRS and CDS, obligations for non-dealers have not yet been quantified.[33]

In this annex, we estimate roughly the collateral that non-dealers would need to post to have all of their IRS and CDS positions cleared centrally by multiplying estimates of their total IRS and CDS positions by average margin rates that might be applied to these positions. We are not able to construct representative portfolios for non-dealers and calculate collateral requirements for these portfolios, as we did for the major derivatives dealers, due to data limitations. Below, we illustrate this alternative methodology for initial margin requirements and explain how it could also be applied to variation margin requirements.

We estimate the total IRS and CDS positions of groups of non-dealers using data on the distribution of dealers' counterparties and the representative portfolios of IRS and CDS for the G14 dealers constructed above. Information on the distribution of dealers' IRS counterparties is limited. This is collected in the left-hand panel of Table 16, which shows that non-financial institutions were counterparties to 7.5% of dealers' positions as of mid-2010 and financial institutions (other than dealers and CCPs) were counterparties to a further 5.6% of these positions.[34] More detailed information is available on the distribution of dealers' CDS counterparties. This is reported in the right-hand panel of Table 16.

We estimate average margin rates for non-dealers portfolios by considering the similarity of these portfolios to those of dealers. In particular, we consider the approximate degree of hedging in these

[33] Although central clearing for non-dealers is quite new, it seems unlikely that such firms will have direct access to CCPs – and hence post collateral directly to CCPs – even as central clearing becomes more widespread. Rather, it seems likely that non-dealers will access CCPs via dealers by holding their derivatives in a segregated account with a dealer. This would keep the non-dealer's positions apart from those of the dealer. The dealer would then clear the segregated account with a CCP, which would demand collateral and the dealer would pass on those demands to the non-dealer.

[34] We assume that none of the outstanding positions between dealers and CCPs were positions between dealers and non-dealers before being assigned to a CCP. Central clearing of non-dealer positions is quite new and only small volumes have been cleared to date.

portfolios from offsetting long and short positions relative to dealers' portfolios. In addition, for the remaining long and short positions that are not offsetting, we consider the approximate degree of diversification amongst these positions relative to that of dealers' portfolios. Our judgmental assessments of these similarity measures are reported in Table 17.

<u>If we had considered a particular group of non-dealers to hold portfolios of IRS or CDS that were as well hedged and diverse as those of the major derivatives dealers, we would have applied the same average margin rates to their positions as were applied to the G14 dealers' representative portfolios above</u>. These are equal to the total initial margins demanded on the representative portfolios divided by the notional amount of all the long and short positions in these portfolios. With a CCP setting initial margins equal to the 99.5th percentile of possible five-day losses in an environment of medium market volatility, for example, this would generate an average margin rate of 0.1% for CDS positions. Average margin rates for other volatility levels and for IRS are reported in Table 17.

<u>In contrast, if we had considered a particular group of non-dealers to hold portfolios of IRS and CDS that benefitted from no risk reduction via hedging or diversification, we would have set average margin rates for this group as if each member was the counterparty to a single dealer position</u>. The initial margin that our CCP would demand on any single position is equal to the 99.5th percentile of its possible valuation losses over five days. The average margin rate for this group would then have been set equal to a weighted average of the single-position margin rates, with weights reflecting the prevalence of these positions in dealers' representative portfolios (to which the non-dealers are counterparts).

<u>If we had considered a particular group of dealers to hold portfolios of IRS and CDS that contained no offsetting positions, but a highly diversified collection of long-only or short-only positions, we would have set average margin rates for this group at intermediate values</u>. These values would be equal to the 99.5th percentiles of five-day losses on only the long (or only the short) positions in dealers' representative portfolios, divided by the total notional amount of long (or short) positions in these portfolios, averaged over the dealers.

<u>For groups of non-dealers whose portfolios we considered to be somewhere between 0% and 100% similar to dealers in terms of diversification or hedging of positions, we interpolated</u>. To explain precisely how the interpolation was conducted, denote the average margin rate for highly-diversified portfolios of long and short positions as μ_{D2}, the rate for highly-diversified long only or short only portfolios as μ_{D1} and the rate for single-derivative portfolios as μ_{N1}. Also denote the similarity of portfolios of a particular group of non-dealers, i, to those of dealers in terms of diversification as d_i

and in terms of hedging as h_i. Then, the average margin rate applied to the positions of this group of non-dealers was

$$\mu_i = \mu_{N1}\left(\frac{\mu_{D1}}{\mu_{N1}} d_i + (1 - d_i)\right)\left(\frac{\mu_{D2}}{\mu_{D1}} h_i + (1 - h_i)\right).$$

Our rough estimates of initial margin requirements for central clearing of non-dealers' IRS and CDS positions are shown in Table 17. Although non-dealers collectively have smaller portfolios than the major derivatives dealers, the average margin rates applied to their positions are often significantly higher. This reflects principally a much smaller degree of hedging of positions in non-dealers portfolios, which is natural for end users and contrasts with intermediaries. These rough estimates of initial margin requirements for non-dealers are added to our estimates for dealers derived above in Table 18, to derive estimates of the total initial margins that would be required for comprehensive central clearing of IRS and CDS.

Rough estimates of variation margins that might be demanded of non-dealers under comprehensive central clearing may be derived by applying to variation margins the same scale factors that link non-dealer and dealer initial margins. Table 18 shows, for example, that our estimates of total non-dealer initial margins are about three times higher than our estimates for dealers. The non-dealer initial margin estimates were derived by estimating non-dealer portfolios as a scale factor of the aggregate portfolio of dealers and the average margin rates applied to non-dealers portfolios were multiples of the average margin rates for dealers' portfolios. These scale factors and multiples reflect characteristics of non-dealer portfolios relative to dealers' portfolios, which are as applicable to estimation of variation margins as to estimation of initial margins.

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Graphs and tables

Central clearing in the OTC derivatives market

As of end-2010

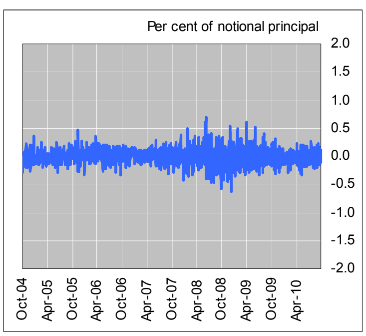
Market segment	Notional amount outstanding[1] (Trillions of dollars)	Share cleared centrally[2] (Per cent)
Interest rate derivatives	465	31[3]
- Interest rate swaps	365	48[4]
Credit default swaps (CDS)	30	8
- Single-name CDS	18	4
- Multi-name CDS	12	14
Foreign exchange derivatives	58	0[5]
Equity derivatives	6	0[5]
Commodity derivatives	3	20-30[5]
…	…	…
Total market	601	n.a.

[1] According to Bank for International Settlements statistics. [2] When an OTC derivatives position between *A* and *B* is assigned to a central counterparty (CCP), it is replaced by two equivalent positions: one between *A* and the CCP and another between the CCP and *B*. Shares of outstanding OTC derivatives that had been cleared centrally were therefore computed as $0.5z$ / (y-$0.5z$), where z is the volume of outstanding positions with a CCP and y is the total volume of outstanding positions. [3] Share of derivatives in TriOptima's Rates Repository that had been cleared centrally. [4] Share of non-exotic single-currency interest rate swaps, including overnight indexed swaps, in TriOptima's Rates Repository that had been cleared centrally. [5] Estimates, as of September 2010, taken from Financial Stability Board (2010).

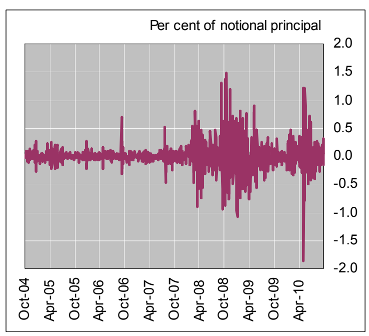
Sources: Bank for International Settlements, Financial Stability Board (2010), TriOptima and authors' calculations. Table 1

Risk characteristics of interest rate swaps (IRS) and credit default swaps (CDS)[1]

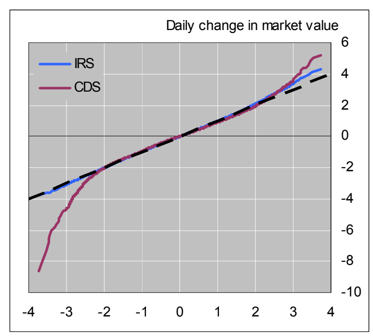
Time-varying volatility: IRS[2]



Time-varying volatility: CDS[2]



Tail risk: IRS and CDS[3]



[1] The IRS and CDS shown in the charts are the four-year euro fixed-for-floating IRS and JP Morgan's five-year senior CDS. [2] The charts show daily changes in market values, measured as percentages of notional principal amounts. [3] This is a 'quantile-quantile' plot. Each point plots a particular quantile of the distribution of daily changes in market value of either the IRS or the CDS (on the y-axis) against the same quantile of the Gaussian distribution (on the x-axis). All quantiles have been normalised by dividing by the standard deviations of the respective distributions. Departures from the dotted 45-degree line at the far left and far right of the chart indicate that the distributions of market value changes have 'fatter tails' than the Gaussian distribution.

Sources: Thomson Datastream and authors' calculations. Graph 1

Risk management practices of selected central counterparties

Central counterparty	SwapClear	ICE Trust US	ICE Clear Europe
Owner	LCH.Clearnet	IntercontinentalExchange Inc.	
Market segment	Interest rate swaps	North American credit default swaps	European credit default swaps
Participation requirements	Credit rating of A or equivalent and equity of $5 billion[1]	Credit rating of A or equivalent and equity of $5 billion[1]	
Basis of variation margins	Daily changes in portfolio market values[2]	Daily changes in portfolio market values[2]	
Basis of initial margins	Largest five-day decline in portfolio market value over past 1,250 trading days.	Large five-day decline in portfolio market value derived from a combination of stress tests and a proprietary model that captures the "dynamics of the asymmetric distribution of credit spreads and co-movement amongst CDS products"[3]	
Basis of default fund	Potential losses from default of single largest clearing member or simultaneous defaults of second and third largest clearing members, based on historical and theoretical stress tests[4]	Potential losses from "default of multiple large counterparties", as derived from a combination of stress tests and a proprietary model (as above)	
Size of default fund	$0.9 billion as of February 2011	$3.2 billion as of December 2010	$2.0 billion as of December 2010
Equity	$0.4 billion as of December 2010	$2.8 billion as of December 2010	

[1] Plus other requirements such as particular risk management and operational capabilities. [2] Intraday margin calls may be made in special circumstances. [3] The model takes into account possible default, changes in CDS premiums and interest rates and additional costs that may arise when liquidating large portfolios. [4] Plus any losses from affiliates of these clearing members and the five lowest-rated members of LCH.Clearnet, which are assumed to also default in these circumstances. [5] This fund is shared by all central clearing operations of LCH.Clearnet. The contribution from SwapClear was $0.2 billion.

Sources: IntercontinentalExchange Inc. and LCH.Clearnet. Table 2

G14 dealer's total interest rate swap and credit default swap positions[1]

Notional amounts in billions of dollars, as of end-June 2010

Interest rate swaps (IRS)[2]

	Pay fixed	Pay floating	Total
Bank of America	21,800	21,800	43,600
Barclays	20,643	20,643	41,287
BNP Paribas[4]	20,335	20,335	40,670
Citigroup	12,645	12,645	25,290
Credit Suisse	13,109	13,109	26,217
Deutsche Bank[4]	22,627	22,627	45,255
Goldman Sachs	13,892	13,892	27,783
HSBC	6,411	6,411	12,821
J.P. Morgan	21,724	21,724	43,448
Morgan Stanley	15,791	15,791	31,581
RBS	10,323	10,323	20,646
Société Générale	5,429	5,429	10,858
UBS[4]	14,443	14,443	28,886
Wells Fargo	1,380	1,380	2,761
G14 dealers' total	200,552	200,552	401,103

Credit default swaps (CDS)[3]

	Protection bought	Protection sold	Total
Bank of America	2,423	2,421	4,844
Barclays	1,398	1,527	2,925
BNP Paribas[4]	1,074	1,173	2,246
Citigroup	1,289	1,180	2,469
Credit Suisse	1,185	1,130	2,315
Deutsche Bank[4]	2,314	2,526	4,840
Goldman Sachs	2,240	2,103	4,343
HSBC	559	564	1,122
J.P. Morgan	2,631	2,621	5,251
Morgan Stanley	2,270	2,230	4,500
RBS	918	1,003	1,921
Société Générale	923	1,008	1,932
UBS[4]	1,240	1,143	2,383
Wells Fargo	60	58	119
Other dealers	820	895	1,715
Dealers' total	21,345	21,581	42,926

[1] White cells show total positions where available, else trading positions. Note that trading positions account for almost all of total positions where both are reported. Positions were converted into dollar values where necessary using closing exchange rates on 30 June 2010. Positions in grey cells were estimated. See Section 3.1.1 for details. [2] Where IRS were not distinguished from other interest rate derivatives, IRS positions were estimated by scaling total interest rate derivatives positions by the ratio of outstanding IRS to total interest rate derivatives in the market, i.e. by about 77%. [3] Where CDS were not distinguished from other credit derivatives, CDS positions were estimated by scaling total credit derivatives positions by the ratio of outstanding CDS to total credit derivatives in the market, i.e. by about 98%. [4] Data for end-2009 used in the absence of data for end-June 2010.

Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, US Securities and Exchange Commission and authors' calculations. Table 3

Outstanding interest rate derivatives of G14 dealers

Notional amounts in billions of dollars, as of end-June 2010

	Counterparty			Share of total (%)[2]
	Other G14 dealers	All (single counting)[1]	All (double counting)[1]	
Interest rate swaps (by maturity)				
0-2 years	17,196	154,640	171,836	46.8
2-5 years	7,199	78,501	85,700	23.3
5-10 years	6,677	66,883	73,560	20.0
10-15 years	1,139	10,656	11,795	3.2
15-20 years	826	7,070	7,896	2.2
20-30 years	1,449	13,104	14,553	4.0
30+ years	507	1,384	1,891	0.5
Total	34,993	332,238	367,231	100.0
Interest rate derivatives (by currency)				
USD	46,171	173,308	219,479	42.6
EUR	22,624	151,825	174,449	33.8
JPY	7,093	55,871	62,964	12.2
GBP	7,348	38,497	45,845	8.9
AUD	1,118	5,665	6,783	1.3
CHF	929	5,022	5,951	1.2
Other	5,058	19,014	24,072	n.a.
Total (exc. other)	90,341	449,202	539,543	100.0

[1] 'Single counting' means that the same contracts reported by any two G14 dealers are counted once. 'Double counting' means that such positions are counted twice, once for the dealer paying fixed and once for the dealer paying floating. [2] Excluding any 'other' categories from totals.

Sources: TriOptima and authors' calculations. Table 4

Aggregate dealer positions in credit default swaps (CDS)[1]

Notional amounts in billions of dollars, as of end-June 2010

Multi-name CDS	Series	Protection bought by dealers	Protection sold by dealers	Total protection outstanding[2]
CDX.NA.IG	CDX.NA.IG series 14 Off-the-run CDX.NA.IG Dow Jones CDX.NA.IG	3,333	3,349	4,063
…	…	…	…	…
Total multi-name		8,597	8,666	10,350
Single-name CDS	Sector	Protection bought (by dealers)	Protection sold (by dealers)	Total protection outstanding[2]
Republic of Italy	Government	203	206	226
JP Morgan Chase	Financials	73	74	81
Telecom Italia	Technology & telecoms	54	55	60
Daimler	Consumer goods	51	52	57
…	…	…	…	…
Top 1000 single names		12,748	12,915	14,200
Total		21,345	21,581	24,549

[1] Entries shaded grey were estimated by scaling the total protection outstanding of each single-name CDS by the ratio of total protection bought (or sold) by dealers to total protection outstanding over the top-1000 single-name CDS. [2] Counts inter-dealer trades once, rather than counting separately the positions of the two dealers involved in each of these trades.

Sources: Depository Trust & Clearing Corporation and authors' calculations. Table 5

Impact of sample reduction on dealers' total credit default swap positions[1]

Protection bought	Full sample (in billions of dollars)					Retained sample (as percent of full sample)				
	Americas	Europe	Asia	No region[2]	Total	Americas	Europe	Asia	No region[2]	Total
MN: corporate	3,932	3,666	268	98	7,964	97.2	99.9	27.5	100.0	96.1
MN: government	0	182	9	0	190	n.a.	73.8	0.0	n.a.	70.5
MN: other	431	5	0	6	442	0.0	0.0	n.a.	0.0	0.0
SN: basic materials	312	403	75	0	790	36.3	39.2	0.0	n.a.	34.3
SN: consumer goods	706	563	66	0	1,335	37.3	52.8	0.0	n.a.	42.0
SN: consumer services	1,000	724	121	0	1,845	37.2	49.3	58.4	n.a.	43.4
SN: financials	1,430	1,185	253	0	2,868	73.3	63.1	0.0	n.a.	62.6
SN: government	410	1,235	268	0	1,914	75.7	69.1	86.7	n.a.	73.0
SN: health care	205	75	0	0	279	0.0	56.2	n.a.	n.a.	15.0
SN: industrials	489	461	72	0	1,022	24.5	30.8	0.0	n.a.	25.6
SN: oil & gas	332	121	13	0	467	14.5	66.7	0.0	n.a.	27.7
SN: technology & telecoms	410	591	88	0	1,089	40.6	71.3	30.2	n.a.	56.4
SN: utilities	231	400	17	0	648	0.0	46.1	0.0	n.a.	28.5
SN: other	0	0	0	490	490	n.a.	n.a.	n.a.	0.0	0.0
Total	9,888	9,611	1,251	594	21,345	63.3	73.7	32.3	16.5	64.9
Protection sold	Full sample (in billions of dollars)					Retained sample (as percent of full sample)				
	Americas	Europe	Asia	No region[2]	Total	Americas	Europe	Asia	No region[2]	Total
MN: corporate	3,951	3,703	271	97	8,022	97.1	99.9	27.3	100.0	96.1
MN: government	0	190	9	0	199	n.a.	74.1	0.0	n.a.	70.7
MN: other	435	5	0	6	446	0.0	0.0	n.a.	0.0	0.0
SN: basic materials	316	408	76	0	800	36.3	39.2	0.0	n.a.	34.3
SN: consumer goods	715	570	67	0	1,353	37.3	52.8	0.0	n.a.	42.0
SN: consumer services	1,013	734	122	0	1,869	37.2	49.3	58.4	n.a.	43.4
SN: financials	1,449	1,201	256	0	2,906	73.3	63.1	0.0	n.a.	62.6
SN: government	416	1,251	272	0	1,939	75.7	69.1	86.7	n.a.	73.0
SN: health care	208	76	0	0	283	0.0	56.2	n.a.	n.a.	15.0
SN: industrials	495	467	73	0	1,035	24.5	30.8	0.0	n.a.	25.6
SN: oil & gas	337	123	13	0	473	14.5	66.7	0.0	n.a.	27.7
SN: technology & telecoms	415	599	90	0	1,104	40.6	71.3	30.2	n.a.	56.4
SN: utilities	234	406	17	0	657	0.0	46.1	0.0	n.a.	28.5
SN: other	0	0	0	497	497	n.a.	n.a.	n.a.	0.0	0.0
Total	9,983	9,732	1,267	600	21,581	63.2	73.6	32.2	16.2	64.8

[1] 'MN' denotes 'multi-name' and 'SN' denotes 'single-name'. [2] No specific region. For example, CDX.EM CDS contracts offer protection against emerging market corporate defaults around the world.

Sources: Depository Trust & Clearing Corporation and authors' calculations. Table 6

Example inputs to algorithm for estimating representative portfolios

Notional amounts in billions of dollars, as of end-June 2010

Pay-fixed interest rate swaps (IRS)

Dealer	0-2 year USD	2-5 year USD	…	0-2 year EUR	…	Total IRS
Bank of America						21,800
Barclays						20,643
BNP Paribas						20,335
Citigroup						12,645
…						…
G14 dealers' total	39,957	19,928	…	31,759	…	200,552

Bought-protection credit default swaps (CDS)

Dealer	CDX.NA.IG	…	Republic of Italy	JP Morgan	…	Total CDS
Bank of America						2,423
Barclays						1,398
…						…
JP Morgan				0		2,631
…						…
Total	3,333	…	203	73	…	21,345

Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Table 7

Zero positions imposed on representative credit default swap portfolios

Dealer	Reference entities for which zero positions enforced		
Bank of America	Bank of America Corp.	Merrill Lynch & Co. Inc.	
Barclays	Barclays Bank Plc.		
BNP Paribas	BNP Paribas		
Citigroup	Citigroup Inc.		
Credit Suisse	Credit Suisse (USA) Inc.	Credit Suisse Group Ltd.	
Deutsche Bank	Deutsche Bank AG		
Goldman Sachs	THE Goldman Sachs Group Inc.		
HSBC	HSBC Bank Plc.	HSBC Finance Corporation	
J.P. Morgan	JPMorgan Chase & Co.		
Morgan Stanley	Morgan Stanley		
RBS	Bank of Scotland Plc.	The Royal Bank of Scotland N.V.	The Royal Bank of Scotland Plc.
Société Générale	Société Générale		
UBS	UBS AG		
Wells Fargo	Wells Fargo & Co.		

Sources: Depository Trust & Clearing Corporation and authors' calculations. Table 8

Hedging constraints imposed on representative credit default swap (CDS) portfolios

Constraint	Net multi-name protection bought	=	Net single-name protection sold[1]
1	CDX.NA.IG		Region = Americas[2]
	CDX.NA.HY		Sector ≠ Government
2	iTraxx Europe		Region = Europe
	iTraxx Europe XO		Sector ≠ Government
	iTraxx Europe HiVol		
	iTraxx Europe Industrials		
	iTraxx Europe Senior Financials		
	iTraxx Europe Sub Financials		

[1] Definitions of regions and sectors as used by Depository Trust & Clearing Corporation. [2] Manual inspection revealed only names from North America in the sample of retained CDS, consistent with constituents of the CDX.NA.IG and CDX.NA.HY indices.

Sources: Depository Trust & Clearing Corporation and authors' calculations. Table 9

Sample of representative interest rate swap portfolios

Notional amounts in billions of dollars, as of end-June 2010

G14 dealer	USD swaps (0-2 year maturities)[1]			USD swaps (2-5 year maturities)[1]				Total interest rate swaps		
	Pay fixed	Pay floating	Net	Pay fixed	Pay floating	Net		Pay fixed	Pay floating	Net
Dealer 1	3,761	3,728	33	3,919	3,809	111		21,800	21,800	0
Dealer 2	542	1,079	-537	224	585	-362		20,643	20,643	0
Dealer 3	2,774	2,749	25	1,975	1,997	-22		20,335	20,335	0
Dealer 4	4,274	4,166	108	596	627	-31		12,645	12,645	0
Dealer 5	2,241	2,240	1	1,590	1,483	107		13,109	13,109	0
Dealer 6	11,371	11,159	212	868	882	-14		22,627	22,627	0
Dealer 7	1,134	1,227	-93	4,312	4,128	184	…	13,892	13,892	0
Dealer 8	282	320	-38	519	528	-8		6,411	6,411	0
Dealer 9	2,319	2,243	76	2,558	2,426	133		21,724	21,724	0
Dealer 10	508	552	-45	977	1,053	-76		15,791	15,791	0
Dealer 11	3,698	3,565	133	468	456	12		10,323	10,323	0
Dealer 12	2,051	2,005	46	990	969	22		5,429	5,429	0
Dealer 13	4,514	4,445	68	755	810	-56		14,443	14,443	0
Dealer 14	489	478	11	176	174	1		1,380	1,380	0
Total	39,957	39,957	0	19,928	19,928	0		200,552	200,552	0

[1] Residual maturities.

Sources: Bank for International Settlements, company financial reports, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Table 10

Sample of representative credit default swap portfolios

Notional amounts in billions of dollars, as of end-June 2010

Dealer	CDX.NA.IG			JP Morgan Chase & Co				Total credit default swaps		
	Protection bought	Protection sold	Net	Protection bought	Protection sold	Net		Protection bought	Protection sold	Net
Dealer 1	237	124	113	11	14	-3		2,423	2,421	2
Dealer 2	556	522	34	5	5	0		1,398	1,527	-129
Dealer 3	216	133	83	0	1	-1		1,074	1,173	-99
Dealer 4	183	36	147	13	17	-4		1,289	1,180	109
Dealer 5	407	404	3	9	10	0		1,185	1,130	55
Dealer 6	276	123	153	23	27	-5		2,314	2,526	-213
Dealer 7	190	330	-140	13	11	2	…	2,240	2,103	138
Dealer 8	145	175	-31	1	0	1		559	564	-5
Dealer 9	300	420	-120	0	0	0		2,631	2,621	10
Dealer 10	617	709	-92	10	7	3		2,270	2,230	40
Dealer 11	367	357	10	1	1	0		918	1,003	-84
Dealer 12	65	99	-34	6	5	1		923	1,008	-85
Dealer 13	22	130	-108	15	11	4		1,240	1,143	97
Dealer 14	19	22	-3	0	0	0		60	58	2
Non-G14 dealers	158	195	-37	2	2	1		820	895	-75
Total	3,759	3,780	-21	109	111	-1		21,345	21,581	-237

Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, US Securities and Exchange Commission and authors' calculations. Table 11

Interest rate swaps in representative portfolios by residual and original maturities

Residual maturities		Original maturities		Assumed relationship between residual-maturity and original-maturity positions[1]
Bucket (years)	Positions[2]	Assumed (years)	Positions[2]	
0-2	$L_{k+1,j}$	2	$Y_{k+1,j}$	$L_{k+1,j} = Y_{k+1,j} + (2/5)Y_{k+2,j} + (2/10)Y_{k+3,j} + (2/15)Y_{k+4,j} + (2/20)Y_{k+5,j} + (2/30)Y_{k+6,j} + (2/40)Y_{k+7,j}$
2-5	$L_{k+2,j}$	5	$Y_{k+2,j}$	$L_{k+2,j} = (3/5)Y_{k+2,j} + (3/10)Y_{k+3,j} + (3/15)Y_{k+4,j} + (3/20)Y_{k+5,j} + (3/30)Y_{k+6,j} + (3/40)Y_{k+7,j}$
5-10	$L_{k+3,j}$	10	$Y_{k+3,j}$	$L_{k+3,j} = (5/10)Y_{k+3,j} + (5/15)Y_{k+4,j} + (5/20)Y_{k+5,j} + (5/30)Y_{k+6,j} + (5/40)Y_{k+7,j}$
10-15	$L_{k+4,j}$	15	$Y_{k+4,j}$	$L_{k+4,j} = (5/15)Y_{k+4,j} + (5/20)Y_{k+5,j} + (5/30)Y_{k+6,j} + (5/40)Y_{k+7,j}$
15-20	$L_{k+5,j}$	20	$Y_{k+5,j}$	$L_{k+5,j} = (5/20)Y_{k+5,j} + (5/30)Y_{k+6,j} + (5/40)Y_{k+7,j}$
20-30	$L_{k+6,j}$	30	$Y_{k+6,j}$	$L_{k+6,j} = (10/30)Y_{k+6,j} + (10/40)Y_{k+7,j}$
30+	$L_{k+7,j}$	40	$Y_{k+7,j}$	$L_{k+7,j} = (10/40)Y_{k+7,j}$

[1] Shown for long (pay-fixed) positions, but also applied to short (pay-floating) positions by substituting S for L. [2] $k = 7(h-1)$, where h = 1, …, $N_m/7$, (N_m denotes the number of different types of interest rate swaps in representative portfolios).

Sources: TriOptima and authors' calculations. Table 12

Interest rate swaps in representative portfolios by age of positions

Residual maturity (years)		Positions							Age (years)						
		Original maturity (years)							Original maturity (years)						
Bucket	Assumed	2	5	10	15	20	30	40	2	5	10	15	20	30	40
0-2	1	$Y_{k+1,j}$	$(2/5)Y_{k+2,j}$	$(2/10)Y_{k+3,j}$	$(2/15)Y_{k+4,j}$	$(2/20)Y_{k+5,j}$	$(2/30)Y_{k+6,j}$	$(2/40)Y_{k+7,j}$	1	4	9	14	19	29	39
2-5	3½		$(3/5)Y_{k+2,j}$	$(3/10)Y_{k+3,j}$	$(3/15)Y_{k+4,j}$	$(3/20)Y_{k+5,j}$	$(3/30)Y_{k+6,j}$	$(3/40)Y_{k+7,j}$		1½	6½	11½	16½	26½	36½
5-10	7½			$(5/10)Y_{k+3,j}$	$(5/15)Y_{k+4,j}$	$(5/20)Y_{k+5,j}$	$(5/30)Y_{k+6,j}$	$(5/40)Y_{k+7,j}$			2½	7½	12½	22½	32½
10-15	12½				$(5/15)Y_{k+4,j}$	$(5/20)Y_{k+5,j}$	$(5/30)Y_{k+6,j}$	$(5/40)Y_{k+7,j}$				2½	7½	17½	27½
15-20	17½					$(5/20)Y_{k+5,j}$	$(5/30)Y_{k+6,j}$	$(5/40)Y_{k+7,j}$					2½	12½	22½
20-30	25						$(10/30)Y_{k+6,j}$	$(10/40)Y_{k+7,j}$						5	15
30+	35							$(10/40)Y_{k+7,j}$							5

[1] Notation as in Table 11.

Sources: TriOptima and authors' calculations. Table 13

Example swap rates used to estimate variation margins paid to date[1]

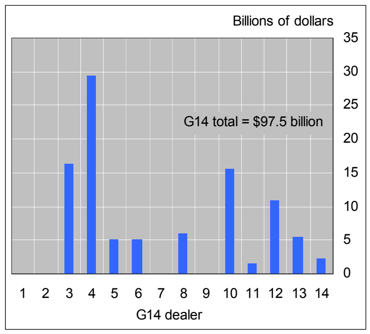
In per cent

Residual maturity (years)	Rates on contract origination dates (shown by original maturity of IRS in years)[2]							Rates on 30 June 2010[2]
	2	5	10	15	20	30	40	
1	1.52	5.68	6.32	7.44	8.98	13.72	6.81	0.72
3		4.26	3.84	6.10	6.88	11.42	7.49	1.35
8			4.67	4.42	6.14	9.29	8.93	2.72
13				4.83	4.69	7.11	11.42	3.27
18					4.91	6.11	9.29	3.50
25						4.67	7.05	3.66
35							4.67	3.68

[1] In particular, US dollar rates. [2] Due to lack of data, grey-shaded cells were estimated either by interpolating swap rates of neighbouring maturities, extrapolating swap rates of nearby maturities or equating swap rates to the yields of equivalent-maturity government bond plus the average historical difference between these government bond yields and swap rates.

Sources: TriOptima and authors' calculations. Table 14

Variation margins to clear representative interest rate swap (IRS) portfolios[1]

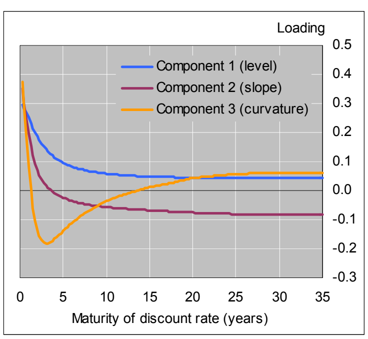


[1] Estimates of outstanding variation margins collected by a central counterparty clearing the hypothetical IRS portfolios in Table 9.

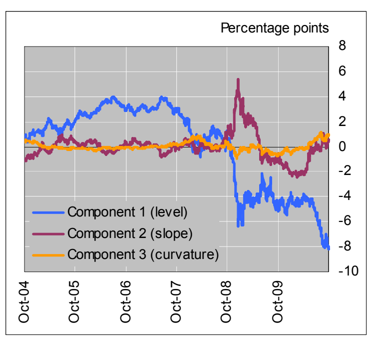
Sources: Bank for International Settlements, company financial reports, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Graph 2

Principal components of discount rates[1]

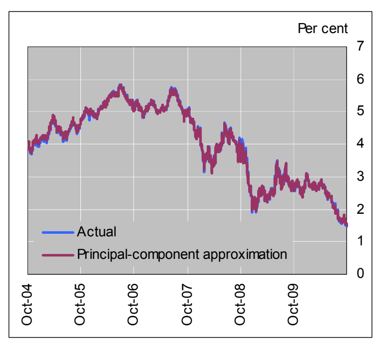
Loadings on components



Time series of components



Fitting of discount rates[2]



[1] In particular, US-dollar ‘zero rates’ with maturities from 0.25 to 35 years. See Section 3.2.1 for a description of principal components methodology and outputs. [2] Illustrated for 5-year US-dollar rate.

Sources: Thomson Datastream and authors’ calculations. Graph 3

Parameter estimates for GARCH models of drivers of IRS and CDS market values[1]

Parameter	Swap rates			Credit default swap premiums			Discount rates		
	Min	Median	Max	Min	Median	Max	Min	Median	Max
γ	-0.0005	0.0000	0.0006	-0.0033	-0.0005	0.0043	-0.0002	0.0006	0.0010
δ	-0.0909	0.0140	0.1584	-0.2436	0.0670	0.2602	-0.0014	0.0115	0.0260
α	0.0024	0.0473	0.1447	-0.0009	0.1425	0.3832	0.0457	0.0610	0.1162
β	0.8144	0.9490	0.9954	0.0497	0.8046	0.9979	0.8717	0.9354	0.9530
$\alpha+\beta$	0.9254	0.9956	0.9994	0.0918	0.9498	0.9999	0.9879	0.9964	0.9986

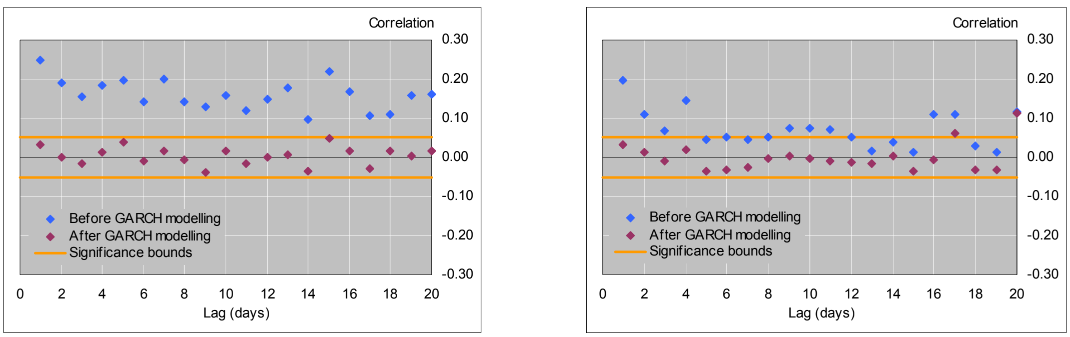
[1] The GARCH model, described in Section 3.2.2, is applied separately to 42 swap rates, 196 CDS premiums and 3 discount factors, resulting in 241 sets of parameter estimates.

Sources: Thomson Datastream and authors' calculations. Table 15

Illustrative autocorrelations of swap rates and credit default swap premiums[1]

Four-year euro swap rates

Five-year JP Morgan credit default swap premiums



[1] The charts show autocorrelations between $r(t)^2$ and $r(t\text{-}j)^2$ ("before GARCH modelling") and $u(t)^2$ and $u(t\text{-}j)^2$ ("after GARCH modelling) for lags (j) of 1 to 20 days, where *r(t)* is the daily change in the natural logarithm of the swap rate or CDS premium and *u(t)* is the residual of a GARCH model of these variables. The model is described in Section 3.2.2.

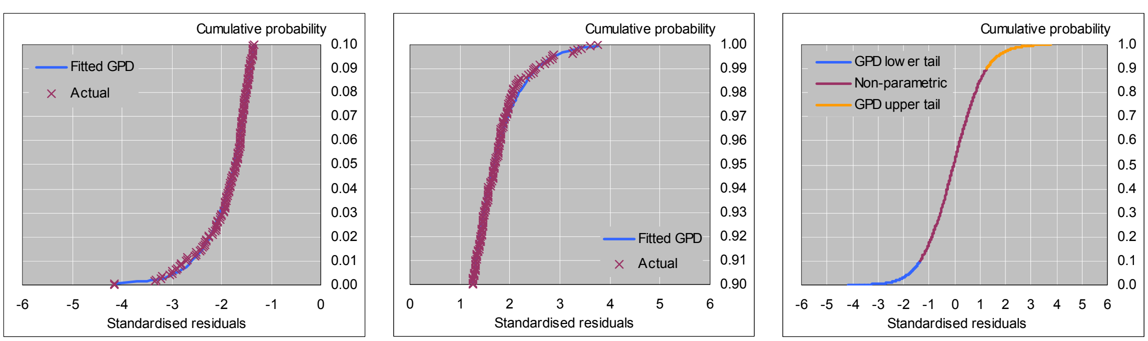
Sources: Thomson Datastream and authors' calculations. Graph 4

Distribution of GARCH model residuals for a swap rate[1]

Lower tail

Upper tail

Whole distribution

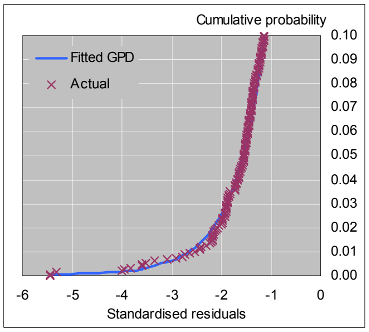


[1] In particular, the four-year fixed-for-floating euro swap rate. The GARCH model is described in Section 3.2.2.

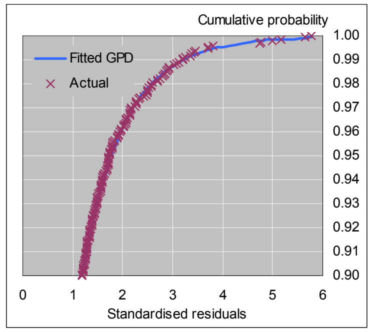
Sources: Thomson Datastream and authors' calculations. Graph 5

Distribution of GARCH model residuals for a credit default swap premium[1]

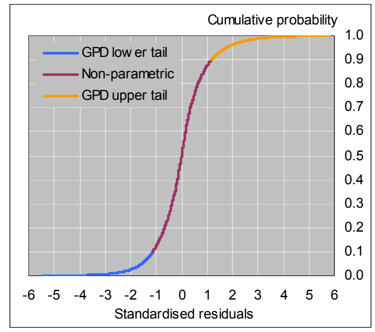
Lower tail



Upper tail



Whole distribution



[1] In particular, JP Morgan's five-year senior-debt credit default swap premium. The GARCH model is described in Section 3.2.2.

Sources: Thomson Datastream and authors' calculations. Graph 6

Parameter estimates for copula function[1]

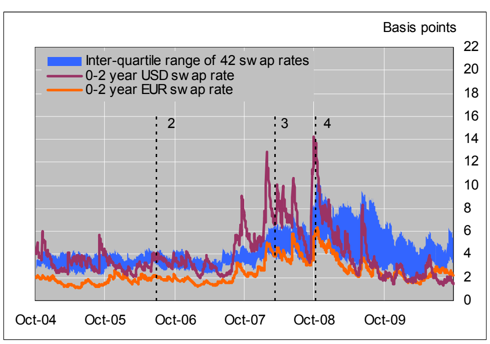
Parameters	Percentile (where applicable)		
	25th	50th	75th
Pairwise correlations between different IRS residuals	0.33	0.46	0.60
Pairwise correlations between different CDS residuals	0.31	0.37	0.44
Pairwise correlations between IRS and CDS residuals	-0.21	-0.18	-0.15
Degrees of freedom		32	

[1] A copula function is used to join the distribution functions of individual drivers of IRS and CDS market values into a joint probability distribution function. This function is described in more detail in Section 3.2.4.

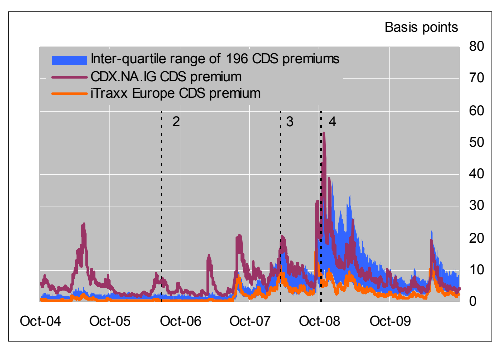
Sources: Thomson Datastream and authors' calculations. Table 16

Conditional volatilities[1]

Swap rates



Credit default swap (CDS) premiums

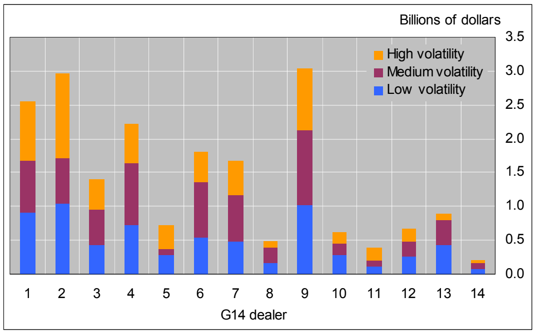


[1] The charts show standard deviations of possible changes in swap rates or CDS premiums at different points in time. The volatilities of individual swap rates and CDS premiums, shown in purple and orange, relate to some of the largest holdings in our representative G14 dealer derivatives portfolios. [2] Low volatility (30/06/2006: Before the recent financial crisis). [3] Medium volatility (14/03/2008: Just before the resolution of Bear Stearns). [4] High volatility (10/10/2008: Amidst the negative market reaction to the Troubled Assets Relief Program at the peak of the crisis).

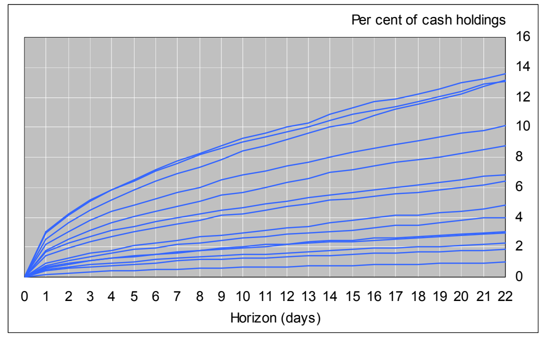
Sources: Thomson Datastream and authors' calculations. Graph 7

Potential variation margin requirements for interest rate swap (IRS) portfolios[1]

Across G14 dealers[2]



Over time[3]

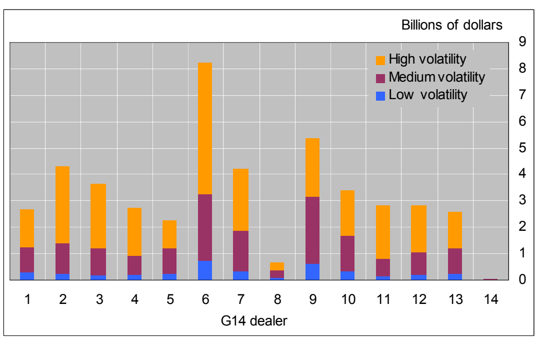


[1] The charts show the 99.5th percentiles of potential variation margin requirements for our representative IRS portfolios. [2] Potential variation margin requirements within one day, conditional on the prevailing level of market volatility being either low (as of 30/06/2006), medium (as of 14/03/2008) or high (as of 10/10/2008). [3] Potential cumulative variation margin requirements over 1-22 trading days, conditional on the prevailing level of market volatility being high (as of 10/10/2008).

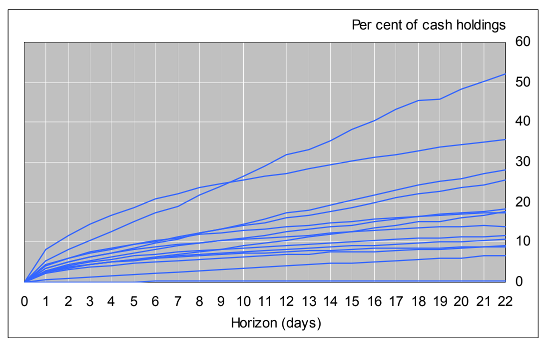
Sources: Bank for International Settlements, company financial reports, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Graph 8

Potential variation margin requirements for credit default swap (CDS) portfolios[1]

Across G14 dealers[2]



Over time[3]

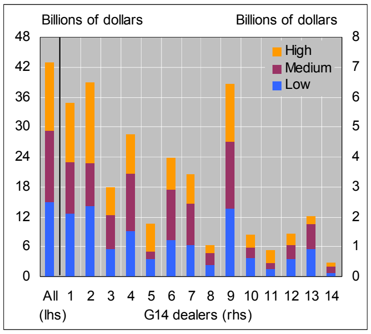


[1] The charts show the 99.5th percentiles of potential variation margin requirements for our representative IRS portfolios. [2] Potential variation margin requirements within one day, conditional on the prevailing level of market volatility being either low (as of 30/06/2006), medium (as of 14/03/2008) or high (as of 10/10/2008). [3] Potential cumulative variation margin requirements over 1-22 trading days, conditional on the prevailing level of market volatility being high (as of 10/10/2008).

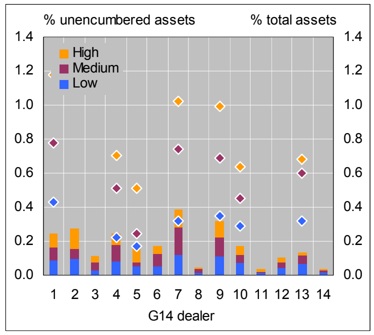
Sources: Bank for International Settlements, company financial reports, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Graph 9

Initial margin requirements and potential shortfalls for IRS portfolios

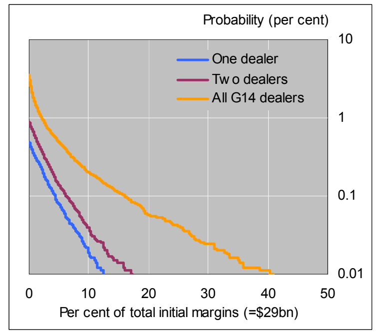
Initial margins[1]



Initial margins relative to assets[1,2]



Initial margin shortfalls[3]

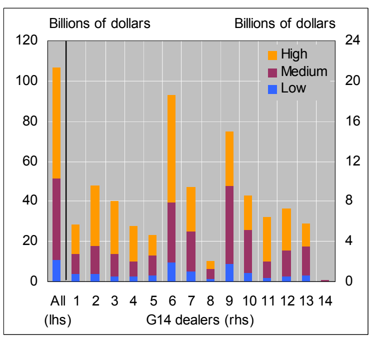


[1] Initial margins set equal to the five-day 99.5th percentile losses of our representative IRS portfolios, conditional on the prevailing level of market volatility being either low (as of 30/06/2006), medium (as of 14/03/2008) or high (as of 10/10/2008). [2] Bars show initial margins as a percentage of total assets, while diamonds show initial margins as a percentage of unencumbered assets (where reported). [3] The chart shows total losses in excess of initial margins that could be incurred simultaneous by one, two or any of the G14 dealers, conditional on the prevailing level of market volatility being medium (as of 14/03.2008), where the particular one and two dealers were chosen to be those with the largest potential margin shortfalls. The y-axis records the probability of initial margin shortfalls greater than those shown on the x-axis.

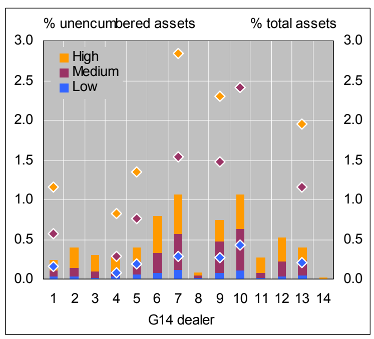
Sources: Bank for International Settlements, company financial reports, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Graph 10

Initial margin requirements and potential shortfalls for CDS portfolios

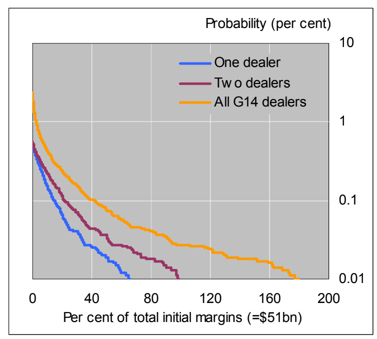
Initial margins[1]



Initial margins relative to assets[1,2]



Initial margin shortfalls[3]

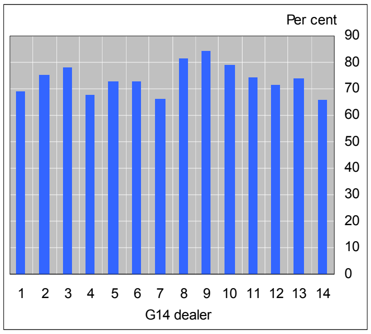


[1] Initial margins set equal to the five-day 99.5th percentile losses of our representative IRS portfolios, conditional on the prevailing level of market volatility being either low (as of 30/06/2006), medium (as of 14/03/2008) or high (as of 10/10/2008). [2] Bars show initial margins as a percentage of total assets, while diamonds show initial margins as a percentage of unencumbered assets (where reported). [3] The chart shows total losses in excess of initial margins that could be incurred simultaneous by one, two or any of the G14 dealers, conditional on the prevailing level of market volatility being medium (as of 14/03.2008), where the particular one and two dealers were chosen to be those with the largest potential margin shortfalls. The y-axis records the probability of initial margin shortfalls greater than those shown on the x-axis.

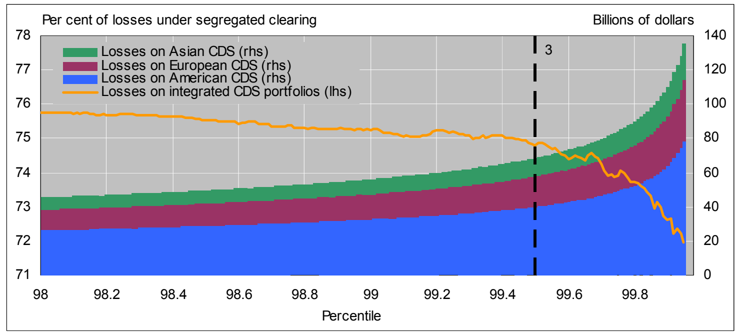
Sources: Bank for International Settlements, company financial reports, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Graph 11

Benefits of geographically integrated central clearing of credit default swaps (CDS)

Initial margin savings[1]



Comparison of G14 dealer losses at different percentiles[2]

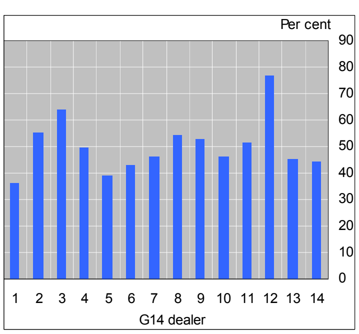


[1] The chart shows the initial margin requirements of a CCP clearing all CDS as proportions of the sums of margin requirements of three CCPs separately clearing American, European and Asian CDS. Each of these hypothetical CCPs sets initial margin requirements equal to the 99.5th percentile of possible five-day losses, conditioned on a medium level of market volatility. [2] Sum of each dealer's five-day loss at indicated percentiles, conditioned on a medium level of market volatility. [3] 99.5th percentile, at which our hypothetical CCPs set initial margins.

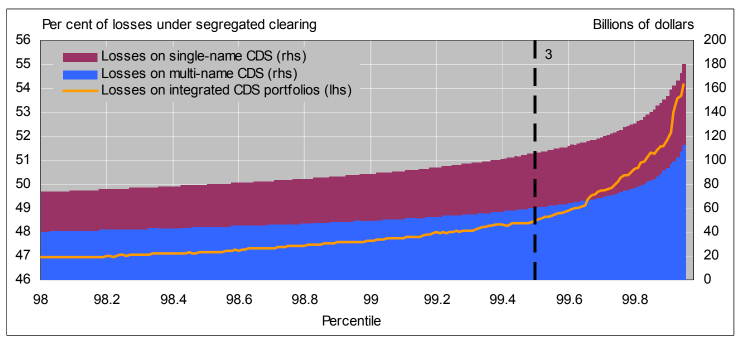
Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, US Securities and Exchange Commission and authors' calculations. Graph 12

Benefits of integrated central clearing of multi-name and single-name CDS

Initial margin savings[1]



Comparison of G14 dealer losses at different percentiles[2]

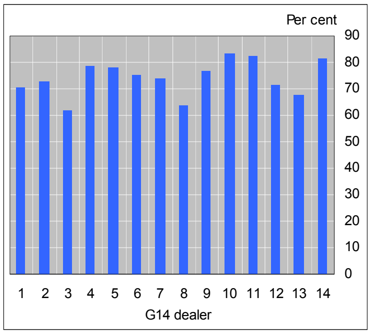


[1] The chart shows the initial margin requirements of a CCP clearing all CDS as proportions of the sums of margin requirements of two CCPs separately clearing multi-name and single-name CDS. Each of these hypothetical CCPs sets initial margin requirements equal to the 99.5th percentile of possible five-day losses, conditioned on a medium level of market volatility. [2] Sum of each dealer's five-day loss at indicated percentiles, conditioned on a medium level of market volatility. [3] 99.5th percentile, at which our hypothetical CCPs set initial margins.

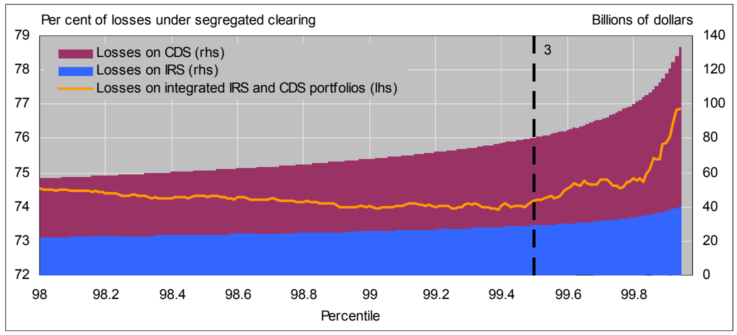
Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, US Securities and Exchange Commission and authors' calculations. Graph 13

Benefits of integrated central clearing of IRS and CDS

Initial margin savings[1]



Comparison of G14 dealer losses at different percentiles[2]

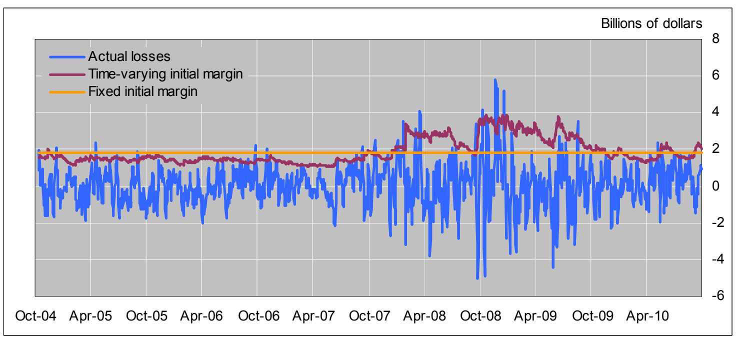


[1] The chart shows the initial margin requirements of a CCP clearing both American and European CDS as proportions of the sums of margin requirements of two CCPs separately clearing American CDS and European CDS. Each of these hypothetical CCPs sets initial margin requirements equal to the 99.5th percentile of possible five-day losses, conditioned on a medium level of market volatility. [2] Sum of each dealer's five-day loss at indicated percentiles, conditioned on a medium level of market volatility. [3] 99.5th percentile, at which our hypothetical CCPs set initial margins.

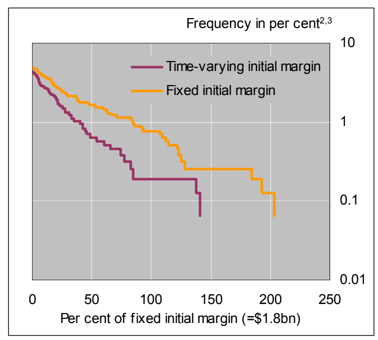
Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Graph 14

Historical interest rate swap (IRS) losses vs. time-varying and fixed initial margins[1]

Time profile of margin shortfalls



Distribution of margin shortfalls

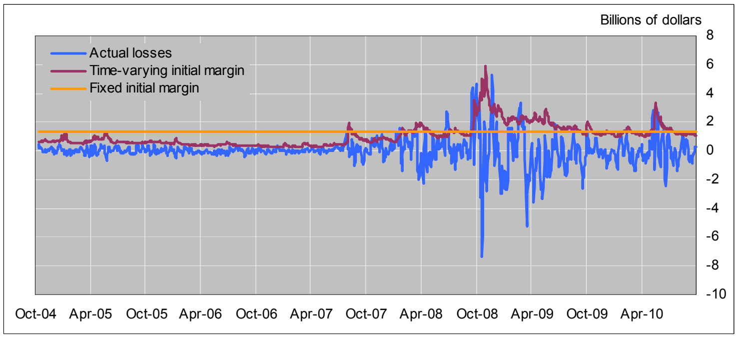


[1] For one randomly-chosen G14 dealer's representative portfolio. Time-varying and fixed initial margins respectively set equal to the 95th percentiles of this portfolio's conditional and unconditional five-day loss distributions. Time-varying margins, which are set at date *t* to protect against possible losses between *t* and *t+5*, are plotted as of *t+5* in the chart. This facilitates visual comparison with actual losses between *t* and *t+5*, which are also plotted at date *t+5*. [2] Historical frequencies of initial margin shortfalls greater than those shown on the x-axis. [3] Logarithmic scale.

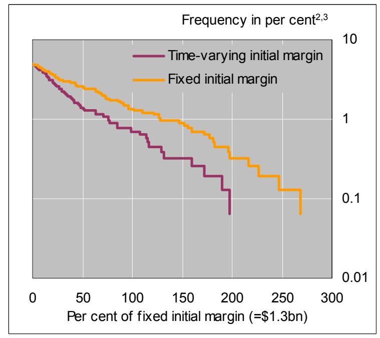
Sources: Bank for International Settlements, company financial reports, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Graph 15

Historical credit default swap (CDS) losses vs. time-varying and fixed initial margins[1]

Time profile of margin shortfalls



Distribution of margin shortfalls

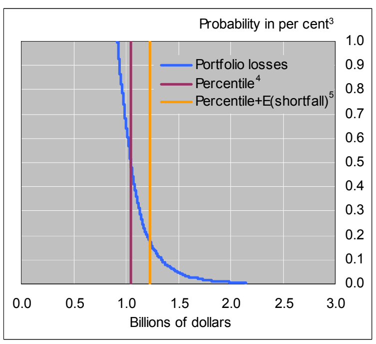


[1] For one randomly-chosen G14 dealer's representative portfolio. Time-varying and fixed initial margins respectively set equal to the 95th percentiles of this portfolio's conditional and unconditional five-day loss distributions. Time-varying margins, which are set at date *t* to protect against possible losses between *t* and *t+5*, are plotted as of *t+5* in the chart. This facilitates visual comparison with actual losses between *t* and *t+5*, which are also plotted at date *t+5*. [2] Historical frequencies of initial margin shortfalls greater than those shown on the x-axis. [3] Logarithmic scale.

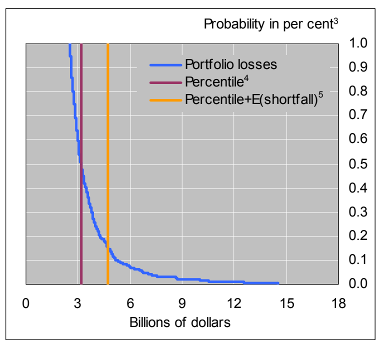
Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, US Securities and Exchange Commission and authors' calculations. Graph 16

Tail risk in interest rate swap (IRS) and credit default swap (CDS) portfolios

IRS losses and initial margins[1]



CDS losses and initial margins[1]



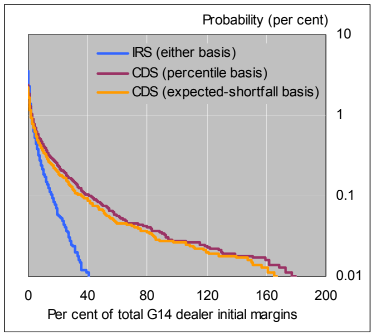
Expected shortfalls[2]

	IRS	CDS
Dealer 1	17.5	17.4
Dealer 2	16.2	27.2
Dealer 3	19.3	23.3
Dealer 4	18.9	16.3
Dealer 5	16.2	16.9
Dealer 6	20.2	21.0
Dealer 7	19.0	53.5
Dealer 8	18.9	57.0
Dealer 9	17.8	56.9
Dealer 10	15.3	58.2
Dealer 11	18.0	25.5
Dealer 12	17.7	48.3
Dealer 13	19.8	56.8
Dealer 14	19.9	55.0

[1] For the representative portfolio of one of the G14 dealers. [2] Of five-day losses relative to the 99.5th percentile loss, as a percentage of this percentile loss. Expected shortfalls are the mean values of losses in excess of a given percentile, conditional on that percentile being exceeded. [3] The y-axis records the probability of a five-day loss greater than the values shown on the x-axis. [4] The 99.5th percentile of five-day losses. [5] The 99.5th percentile of five-day losses plus the associated expected shortfall.

Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Graph 17

Initial-margin shortfalls under alternative margin-setting practices[1]



[1] The chart shows the total potential exposures in excess of initial margins of a central counterparty clearing either interest rate swaps or credit default swaps to all G14 dealers. In one case, the excess exposures were calculated based on initial margins set equal to the 99.5th percentiles of possible losses on the representative portfolio for each dealer. In the other case, they were set equal to slightly lower percentiles plus the expected shortfalls corresponding to these percentiles. These lower percentiles were chosen carefully so that initial margins for each representative portfolio of interest rate swaps were identical under the two approaches. The y-axis show the probability of occurrence of total initial-margin shortfalls no greater than the values shown on the x-axis.

Sources: Bank for International Settlements, company financial reports, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations.

Graph 18

Dealers' derivatives positions by counterparty type

As of end-June 2010

Interest rate swaps[1]

Counterparty type	Notional amount outstanding[2]	Dealer long (paying fixed)		Dealer short (paying floating)	
	$ billions	$ billions	% of total	$ billions	% of total
Other dealers	79717	79717	37.3	79717	37.3
Non-dealer financials	235721	117861	55.2	117861	55.2
CCPs	211696	105848	49.6	105848	49.6
Non-CCPs	24025	12013	5.6	12013	5.6
Non-financial institutions	32070	16035	7.5	16035	7.5

Credit default swaps

Counterparty type	Dealer long (bought protection)		Dealer short (sold protection)	
	$ billions	% of total	$ billions	% of total
Other dealers	15776	67.9	15773	69.2
CCPs	1589	6.8	1589	7.0
Banks and securities firms	3937	16.9	3827	16.8
Insurance firms	205	0.9	68	0.3
Special purpose vehicles	321	1.4	201	0.9
Hedge funds	261	1.1	400	1.8
Other financial institutions	704	3.0	541	2.4
Non-financial institutions	454	2.0	390	1.7

[1] Positions in the grey-shaded cells were inferred or assumed. [2] The notional amounts of contracts with two dealers as counterparties that are reported by both dealers are counted only once.

Sources: Bank for International Settlements, TriOptima and authors' calculations.

Table 16

Initial margins required to clear centrally all non-dealer IRS and CDS positions

Possible portfolio structures	Average margin rates (as a percentage of notional amounts)											
	Long IRS (paying fixed)			Short IRS (paying floating)			Long CDS (bought protection)			Short CDS (sold protection)		
	Low vol	Med vol	High vol	Low vol	Med vol	High vol	Low vol	Med vol	High vol	Low vol	Med vol	High vol
Single-contract portfolios	0.826	1.485	2.190	0.800	1.495	2.283	0.393	2.451	4.928	0.633	4.448	8.405
Diversified one-way portfolios	0.625	1.164	1.699	0.600	1.155	1.729	0.268	1.554	2.997	0.394	2.741	4.979
Diversified two-way portfolios	0.004	0.008	0.011	0.004	0.008	0.011	0.024	0.119	0.254	0.024	0.119	0.254

Type of non-dealer	Estimated aggregate positions (in billions of dollars)				Similarity to dealers (0-100%)[1]			
	Long IRS (Paying fixed)	Short IRS Paying floating	Long CDS (Bought protection)	Short CDS (Sold protection)	IRS portfolios		CDS portfolios	
					Diversification	Hedging	Diversification	Hedging
Non-financial institutions	15,055	15,055	369	417	75	25	25	0
Non-dealer non-CCP financials	11,278	11,278			75	25		
Banks and securities firms			3,624	3,615			75	50
Insurance firms			64	188			75	0
Special purpose vehicles			190	295			50	0
Hedge funds			379	240			75	75
Other financial institutions			512	646			75	50

Type of non-dealer	Initial margin requirements (in billions of dollars)											
	Long IRS (paying fixed)			Short IRS (paying floating)			Long CDS (bought protection)			Short CDS (sold protection)		
	Low vol	Med vol	High vol	Low vol	Med vol	High vol	Low vol	Med vol	High vol	Low vol	Med vol	High vol
Non-financial institutions	76.3	140.8	206.1	73.6	140.3	211.2	1.3	8.2	16.4	2.4	16.8	31.5
Non-dealer non-CCP financials	57.2	105.5	154.4	55.1	105.1	158.3						
Banks and securities firms							5.9	34.7	68.4	8.7	59.7	110.9
Insurance firms							0.2	1.1	2.2	0.9	6.0	11.0
Special purpose vehicles							0.6	3.8	7.5	1.5	10.6	19.7
Hedge funds							0.4	2.1	4.1	0.3	2.1	4.0
Other financial institutions							0.8	4.9	9.7	1.6	10.7	19.8
All non-dealers	133.5	246.2	360.6	128.7	245.5	369.5	9.3	54.8	108.4	15.3	105.9	196.9

[1] Judgemental assessment of degree to which non-dealer portfolios come close to those of the major derivatives dealers in terms of diversification (attained by holding many different positions in the same direction, i.e. all long or all short) and hedging (attained by holding long and short positions that offset each other's risks).

Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Table 17

Initial margin requirements for comprehensive central clearing of OTC derivatives[1]

In billions of dollars

Interest rate swaps (IRS)

	Volatility of market values		
	Low	Medium	High
Dealers[2]	15	29	43
Non-dealers	262	492	730
Total	277	521	773

Credit default swaps (CDS)

	Volatility of market values		
	Low	Medium	High
Dealers[2]	10	51	107
Non-dealers	25	161	305
Total	35	212	412

[1] Estimates for one CCP clearing IRS and one CCP clearing CDS, with both CCPs setting initial margin requirements equal to the 99.5th percentiles of possible losses on counterparties' portfolios, where possible losses are conditioned on prevailing levels of volatility of IRS and CDS market values. [2] The estimates are for the group of fourteen major derivatives dealers, although these dealers account for an overwhelming majority of all derivatives dealers' positions.

Sources: Bank for International Settlements, company financial reports, Depository Trust & Clearing Corporation, Thomson Datastream, TriOptima, US Securities and Exchange Commission and authors' calculations. Table 18