Risk management in clearing corporations after adoption of PFMI: A cross-country comparison

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Abstract

Given the incresaing importance of central counterparty clearinghouses (CCPs) to developments of modern financial market infrastructure governed by the CPSS-IOSCO PFMI standards, in this study we look at the the risk management practices of select large CCPs across jurisdictions as they relate to their use of risk-based margin models and collection of margins, in particular whether margins are collected by CCP from clearing members on gross versus net basis. All the CCPs considered here except Eurex use some variant of `SPAN` to evaluate the risk of a portfolio of positions and compute the applicable margins for exchange traded derivatives. The analyses to sensitivity of margins to `SPAN` parameters shows that given the design of `SPAN`, certain positions (like short butterfly) may be designed to "fall between the cracks" and escape stringent margins. At the same time, we have shown that it is not difficult to improve `SPAN` parameters and fix its observed inadequacies. In the second part of the study, we provide a quantitative comparison for evaluating the impact of collecting margins in a gross versus net system with the margin period of risk alternatively set at one and two days. We also analyze the trade-offs in gross versus net margining in (a) the scenario where a large client of a clearing member defaults idiosyncratically and (b) in the scenario where defaults arise out of 'crowded trades'. We are able to describe the conditions under which the higher MPOR does or does not offset the risks induced by net margins.

Keywords: Central counterparty clearinghouses, Financial market infrastructures, Margins, Risk management, SPAN

1 Introduction

One of the striking features of the 2008 global financial crisis (GFC) was that while banks and financial institutions of all kinds and sizes faced distress, derivatives clearing corporations, or central counterparty clearinghouses (CCPs) as they are now known, came out relatively unscathed. Whether it was a consequence of stringent collateral requirements or superior risk management practices, since then the importance of clearinghouses to reduce systemic risk has taken centerstage among the regulators (Domanski et al., 2015). Reflecting a clear shift in taxpayer preference away from bailout to resolution, the thinking behind mandating central clearing of standardized over-the-counter derivatives by both the the Dodd-Frank Wall Street Reform Act as well as the European Market Infrastructure Regulation (EMIR) runs that rigorous collateral and netting requirements would reduce interconnectedness of the financial system and stop short any contagion in its tracks (Roe, 2013).

The evidence suggests that the risk management in the OTC space has indeed improved hugely post-GFC (Acharya and Bisin, 2014), with netting and initial and variation margin becoming a standard (Faruqui et al., 2018). However, there are concerns that mutliple CCPs may indulge in race to the bottom to grab market share which may help dealers but may still be destabilizing with tail risk being an externality for all participants (BIS, 2010). The competition between the CCPs has also raised concerns about scarcity of high quality collateral (Duffie et al., 2015; Li and Marin, 2016) giving rise to wrong way risk exposures (Pirrong, 2011). From a systemic risk point of view, there are also concerns about destabilizing affects of procylicality of frequent margining (Brunnermeier and Pedersen, 2008) and having created a single point of failure in CCPs (Duffie, 2015).

Even so, given the regulatory developments, the CCPs today have become integral to all developments of modern financial market infrastructure governed by the CPSS-IOSCO[1] Principles for Financial Market Infrastructures (PFMI) adopted by the Group of Twenty countries in 2012. Given both the increasing importance of CCPs as well as the associated concerns makes the study of risk management practices of CCPs to evolving PFMI standards both relevant and timely.

We study the existing practices of clearing corporations in four different jurisdictions: the United States (Chicago Mercantile Exchange), Europe (LCH and Eurex), East Asia (Hong Kong Exchanges and Clearing) and Australia (Australian Stock Exchange) on their key risk management practices in the light of the evolving PFMI standards as they relate to risk-based margining and implications of how margins are collected by CCP from clearing members, that is whether margins are collected on a gross or net basis. As a methodological contribution, we critically evaluate the parameters underlying the widely-used `SPAN` margining model for exchange traded derivatives (ETDs) and analyze the trade-offs in gross versus net margining.

We find that while large CCPs have broadly similar practices (partly ensured by compli-

[1] Committee on Payment and Settlement Systems (CPSS) and the Technical Committee of the International Organization of Securities Commissions (IOSCO); see https://www.bis.org/cpmi/publ/d101.htm

ance with PFMI regulations), there are some critical differences between the various CCPs studied by us:

1. The European CCPs (following EMIR) used to set margins to cover a two-day price risk, that is with a margin period of risk (MPOR) of 2 days until 2015. Since 2016, European CCPs now require setting margins using one-day MPOR similar to US CCPs (following regulations of the Commodity Futures and Trading Commission). This would tend to reduce margins in European CCPs by a factor of $\sqrt{2} \approx 1.4$.

2. The US CCPs collect margins on a gross basis (aggregate of margins on client wise positions) while the European CCPs use net margins (margin on the net position of all clients). This would lead to higher margins in the US CCPs, but the magnitude of this effect would depend on the distribution of client positions.

3. All the CCPs except Eurex use some variant of `SPAN` to evaluate the risk of a portfolio of positions and compute the applicable margins. While `SPAN` is known to be a coherent risk measure (Artzner et al., 1999), it is also a very old system that has not been updated to reflect the massive improvements in computing power and the increasing complexity of trading strategies. Eurex on the other hand uses a different methodology (`Prisma`) which is arguably more modern.

4. On the flip side, `Prisma` is a proprietary methodology that is quite opaque compared to `SPAN`.

To provide a quantitative comparison (not found elsewhere in the literature to our knowledge), we evaluate the impact of gross versus net margins with MPOR alternatively set at 1 and 2. The impact of a higher MPOR versus margining on a net basis might partially offset each other, and it is not obvious that either the European or the US CCPs are more lax than the other. An important methodological contribution of our paper is to analyze the trade-offs in gross versus net margining in (a) the scenario where a large client of a clearing member defaults idiosyncratically and (b) in the scenario where defaults arise out of 'crowded trades' (Menkveld, 2017). We are able to find the conditions under which the higher MPOR does or does not offset the risks induced by net margins.

The last two differences also partially offset each other. It could be argued that proprietary models allow the innovator to internalize the social gains from the development of a more sophistical risk management methodology. On the other hand, proprietary models make it difficult for external observers to even determine whether the new model achieves any significant improvement in risk management. An important contribution of this paper is a detailed review of how `SPAN` parameters influence the treatment of complex positions designed to "fall between the cracks" and escape stringent margins. This leads us to conclude that it is relatively straightforward to improve `SPAN` to fix its observed inadequacies. To our knowledge, both a detailed review of `SPAN` parameters as well as describing trade-off between gross vs net margining, has not been done elsewhere in the literature.

After briefly describing risk and default management procedures at a typical clearinghouse and reviewing the literature and prevailing practices on risk-based margining, we critically review main parameters of `SPAN` and the trade-offs between gross and net margining as well the context of crowded trades. The final section concludes and points some outstanding issues for further research.

2 Risk management in CCPs: A brief overview

While requiring OTC derivatives to be cleared through CCPs is a relatively recent development, there is a long history of CCPs in the United States (Gorton, 1985). Gregory (2014) describes the process of clearing in both exchange-traded as well as OTC derivatives in a modern CCP in some detail. Even so, it is useful to lay out the main elements of clearing to establish the terminology for further discussion.

Given the focus on exchange-traded products in this study, we'll restrict our focus to the CCPs whose predominant business is providing a marketplace for clearing of standardized futures and options. In this context, following Bernanke (1990), it is useful to make a distinction between the function of a CCP as a bank and an insurance company.

By dealing only in homogeneous/standardized products, like a bank, CCP provides liquidity and reduced transaction costs while operationally also ensuring contract delivery and transfer of funds. On the other hand, by standing as a counterparty to all transactions, like an insurance company, it guarantees contract performance for both counterparties. Although it is impossible to separate CCPs banking and insurance function (ability to guarantee performance depends on availability of funds), for the purpose of this study we restrict our attention to the credit risk and information asymmetry associated with providing the insurance function.

Because a CCP is both long and short the same asset/portfolio in each trade, unless one of the counterparty defaults, it bears no market or liquidity risk. To protect itself against the credit risk and adverse selection and moral hazard (Pirrong, 2011), CCPs charge its members insurance premia in a variety of ways.

To begin with, when a contract is cleared, the CCP charges an initial margin, typically in the form of a liquid, high quality collateral (lower quality collateral are also often acceptable, but only with haircuts). Using historical data on asset returns, volatility and correlations, and depending on the position size, the quantum of initial margin is set to cover losses in all but statistically extreme loss scenarios (with a probability of less than 0.3% currently).

While the initial margin is designed to cover potential future losses, CCPs also regularly (usually daily, but sometimes more frequently) collect variation margin capturing daily mark-to-market losses/gains which it transfers between the counterparties. This is as much a book-keeping function as a risk management function. During extreme market moves and in the event of any default, initial margin may not be enough. In those circumstances, a CCP is no more protected from market and liquidity risks. It is then the responsibility of the CCP to unwind both the defaulting member's positions as well as the associated collateral. For such circumstances, CCPs mutualize losses down to its clearing members by what is called a default waterfall process (Gregory, 2014; Pirrong, 2011).

Given the focus of our study, it is useful to understand risk management function at a typical CCP as divided between defaulter and non-defaulter pays model:

1. *Margins (Defaulter Pays Model)*: The idea of collecting upfront margins in the form of collateral from all parties is to ensure that the defaulter pays for its losses. This works adequately when the price changes are not extreme. As long as the collateral is adequate to cover the loss, there is no need for anybody else to bear losses. For example, when Lehman Brothers failed, the major CCPs (CME in the US and LCH in Europe) suffered no losses because the margins provided by Lehman were adequate to cover all losses on the Lehman positions even in a situation of extreme market stress. For this reason, margins are characterized as a defaulter pays or polluter pays model.

2. *Default Waterfall (Non Defaulters Pay Model)*: As Bernanke (1990) points out, even if price changes are not extreme, the defaulter pays model alone may be insufficient. A CCP also needs to monitor the trades of its members to reduce adverse selection (CCPs can only monitor trade of its members, and not necessarily the clients of the members). If monitoring were perfect, in theory loss-sharing rules could be set to ensure that defaulters bear most of the cost (Baer et al., 1995). The real costs of monitoring imply that loss-sharing rules must be set more broadly, and this leads most CCPs to mutualize losses. Each clearing member is required to contribute to what is called a guaranty fund which can be tapped into by a CCP if required. So if losses exceed the collateral, some of the losses have to be borne by non-defaulters from their contribution to the guaranty fund. The Default Waterfall defines the loss allocation to: the clearing member who was clearing the trades of the defaulting client, other non defaulting clearing members (default fund contributions), the CCP itself (skin in the game; see Saguato (2017)), non defaulting clients of non defaulting members (variation or initial margin haircutting).

The CCP literature tends to favour using the defaulter pays model to the maximum extent possible (Roe, 2013; Peirce, 2016), and restricting loss allocation to extreme scenarios where the margin framework proves to be inadequate. However, Pirrong (2011) has argued that the margin system actually reallocates losses from the CCP to other creditors of the defaulter, and that any financial system that allows leverage is necessarily a non-defaulter pays model.

2.1 PFMI: Margin models and netting

The PFMI document contains 24 principles that apply to all areas of clearing, ranging from legal and governance issues to margins and credit risk management. Given the focus of this study, however, we restrict our attention to their risk management practices as they relate to their use of risk-based margin models and collection of margins, in particular whether margins are collected by CCP from clearing members on gross versus net basis. It is in that context that prevailing practices of different CCPs are reviewed and compared below.

3 Margining

3.1 Risk models for margining: SPAN and other approaches

Other than Eurex, all other CCPs covered in this study compute initial margins for ETDs based on the Standard Portfolio Analysis of Risk (SPAN) approach developed by the CME in 1989. Its popularity with practitioners and regulators lies in its simplicity and ease of implementation (CME provides a free PC SPAN software). It is also theoretically attractive as it is also a coherent risk measure (Artzner et al., 1999).

SPAN approach calculates margins on portfolio basis, requiring combing futures and options with the same underlying referred to as the 'combined commodity'. In words of Artzner et al. (1999, pg. 212),

> The calculation can be viewed as producing the maximum of the expected loss under each of sixteen probability measures. For the first fourteen scenarios the probability measures are point masses at each of the fourteen points in the space of securities prices. The cases of extreme moves correspond to taking the convex combination (0.35, 0.65) of the losses at the "extreme move" point under study and at the "no move at all" point (i.., prices remain the same). We shall call these probability measures "generalized scenarios."

The collection of scenarios across all market conditions constitutes what are called 'Risk Arrays'. The specification of the scenarios depend on the SPAN parameters which each exchange/CCP must decide on depending on the extent of risk coverage they seek. The main SPAN parameters constitute the following:

1. The number and specification of scenarios underlying the risk arrays, referred to as the scanning grid
2. The extent of price movements possible in each scenario, referred to as the Price Scan Range (PSR)
3. The change in volatility (applied as a factor/shift applied to prevailing implied volatility) in each scenario, referred to as the Volatility Scan Range (PSR)

The original CME SPAN consisted of 16 scenarios with PSR and VSR as given in Table 1. The scenario-based margin based on SPAN is set as the maximum of weighted loss over the risk array for a portfolio. This is called scan risk. Its parameters were aimed to provide a 95-99% coverage originally, but parameters can be set to provide any level of coverage.

[Table 1 about here]

For calculation of the final margin amount, SPAN allows for adjustments to scan risk towards what are called Intra-Commodity Spread, Inter-Commodity Spread, Super Inter-Commodity Spread and Inter-Exchange Spread Credit. After allowing for adjustments, the total margin is set as the sum of mark-to-market gain/loss in the position and the maximum of scan risk and the Short Option Minimum charge[2]

Even though exchanges are free to decide on the parameters, and CME has recently modified the definition of last two scenarios (see Table 2), all users of `SPAN` in the study continue to essentially use Table 1 to calculate the scan risk.

[Table 2 about here]

3.2 Alternatives to `SPAN`: Eurex

The popularity of `SPAN` notwithstanding, there are its criticisms in that the various spread adjustments are not only ad-hoc and cumbersome but also complex (Cotter and Dowd, 2006). Also, the way it has evolved over time makes its performance difficult to back-test (Alexander et al., 2019).

The most predominant exchange which does not uses `SPAN` to estimate margins is Eurex which uses its proprietary VaR-based portfolio margining approach called `Prisma`. Although initially only applied to interest rate and credit derivatives, since 2015 use of `Prisma` also covers ETDs. While the details of `Prisma` are not available publicly, based on its own publications, it provides more effective netting of risks than `SPAN` (Eurex, 2018). According to Eurex (2018), it uses a variant of filtered historical simulation based VaR to estimate margins while allowing for more general dynamics for implied volatility surface (beyond only parallel shifts covered in `SPAN`), break-down in correlations and the term structure of interest rates.

According to Eurex (2018), an important benefit and advantage of `Prisma` over `SPAN` is the integration of its margining with the default management process. As we discuss later, an important consideration in default management is how the positions are netted at the clearing member level and different jurisdictions have different requirements on that. `Prisma` divides positions into pre-defined "liquidation groups" which share common risk factors, and risk offsets are allowed only within a group. Also, margin period of risk for portfolios is aligned with the timelines implicit in the default management process.

Although Eurex's approach is arguably more modern and uses more sophisticated statistical machinery in handling multiple underlyings, it is also true that it was the VaR-based approaches that failed during the GFC (Salmon, 2009), and historical simulation is prone to dangers (Pritsker, 2006; Gurrola-Perez and Murphy, 2015). VaR is also known to be more risk sensitive than `SPAN`'s ad hoc way of dealing with correlations, and as argued before, a big plus in favour of `SPAN` is that it is coherent risk measure whose properties and limitations are better understood than any proprietary black-box model. At the same time, for CCPs which are also starting/going to clear OTC derivatives, Eurex's approach to handling multiple underlyings and tying the risk-based margining with the default management process is attractive

There have also been alternatives to `SPAN` offered in the literature. In one of the first studies on setting margins in the Finnish stock index futures market, Booth et al. (1997)

[2]See https://www.cmegroup.com/clearing/files/span-methodology.pdf for details.

proposed an extreme value theory based margining approach which provides theoretical margin violation probabilities which closely match the empirical distribution of returns. Similarly, Cotter and Dowd (2006) apply the Generalised Pareto distribution to return distributions for setting margins and argue spectral risk measures are superior in that they allow for reflecting a CCP's attitude towards risk.

More recently, Alexander et al. (2019) proposes median tail loss as an alternative to VaR and `SPAN` and using data for a variety of underlyings show that their proposed measure is as easy to implement and back-test. Dionne et al. (2015) proposes a liquidity adjusted VaR measure by taking into account the endogenous liquidity associated with order size. Lam et al. (2010) propose a margining scheme which relies on volatility forecasting which keeps the margin stable, at level desired by the CCP. However, although volatility forecasting remains an active area of research within financial econometrics, as Houllier and Murphy (2017) argue, practicalities of margining at CCPs necessarily require approaches which are more robust than complex.

An alternative proposed in the literature that has been actively adopted by CCPs, including Eurex, is the filtered historical simulation VaR (Barone-Adesi et al., 1999). Gurrola-Perez and Murphy (2015) interprets it as an estimate of VaR risk conditional on more recent market conditions. While not something we explore in this study, FHS has been criticized for leading to margins which are more procylical than its 'unfiltered' counterparts.

Despite the move to more sophisticated VaR-based approaches for calculating margins for OTC products and selectively for exchange-traded derivatives, `SPAN` remains in use by more than 50 exchanges and regulatory bodies around the world. Clearing members and market participants still find it familiar and easy to understand despite its unwieldiness (Burnham, 2018). While copulas are probably the best way to analyze with multiple underlyings, that is outside the scope of our paper. As our modest contribution, given `SPAN`'s popularity worldwide as the margining model for ETDs, we proceed to discuss `SPAN` in detail for a single underlying.

3.3 Sensitivity to changes in `SPAN` parameters

Our focus here is on the three parameters underlying the calculation of scan risk, namely the specifications of PSR and VSR and design of the scanning grid.

To understand the sensitivity of each choice, the calculation of risk arrays and estimation of scan risk for all the portfolios is made in the sense of partial derivatives, so for the most part the three `SPAN` parameters are changed one at a time.

In particular, the review of calculation of risk arrays is done for select portfolios of futures and options on Hang Seng Index 200 of HKEx on May 14, 2019 (Table 3). The contracts considered have expiries on May 30 (14 days to maturity), June 27 (44 days to maturity) and September 27, 2019 (136 days to maturity). All valuation across the 16 scenarios are done using the Black (1976) model assuming that options are priced consistently with respect to corresponding futures contracts. The prevailing Hong Kong Libor rate is used as a proxy for rate of interest (using linear interpolation).

[Table 3 about here]

Margins at HKEx, just like in CME, are set in absolute terms. For the purpose of analysis here, however, it is useful to work in terms of number of shifts of standard deviations. The current margin on HSI futures is set at close to 90000.[3] With a contract size of 50, historical daily volatility of returns on HSI of about 1.0 - 1.5% (depending on the sample), spot price of close to 28000, this translates to a margin of 4 - 5 times daily volatility. A factor of 5σ then forms the base case for our comparisons. In particular, the scan risk is compared for each portfolio under different choices of a) volatility factor: 4, 5, 6, and 7, b) VSR shifts: 6%, 8%, 10%, 12% and c) fineness and number of scenarios in the scanning grid.

Table 4 represents comparison of scan risk for the 12 portfolios for volatility scaling factor (VSF) set at 3, 4, 5 and 6 respectively. For each choice of VSF, the location of the scan risk (maximum loss over the risk arrays) is also identified. So, for example, for portfolio number 11 with VSF set at 6 (column 5), the maximum loss was at -6σ and so on. For most cases, the maximum loss occurs at $\pm 1 \times$ VSF and not at $\pm 2 \times$ VSF because of the less than 1 weight (of 0.35) on the last two scenarios.

[Table 4 about here]

Broadly the impact of VSF on scan risk is clear: the higher the scaling factor higher the scan risk (except for calendar spreads where the long and short positions are being offset differently with time). This is expected, as a higher volatility scaling factor allows capturing extreme/stress events beyond $\pm 5\sigma$. The impact is the largest for short options positions.

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Table 5 represents comparison of scan risk for the 12 portfolios for volatility shift (VSh) for VSR calculation set at 6%, 8%, 10% and 12% respectively. As earlier, for each choice of VSh, the location of the scan risk (maximum loss over the risk arrays) is also identified. So, for example, for portfolio number 11 with VSh set at 10% (column 5), the maximum loss was at -5σ and so on (these results are conditional on VSF set at 5.) Again, as earlier, the impact of large change in level of volatility is the largest on portfolios with short options positions.

[3] Source: `https://www.hkex.com.hk/Services/Clearing/Listed-Derivatives/Risk-Management/Margin/Margin-Tables?sc_lang=en`

[Table 5 about here]

Both the earlier sensitivities are estimated in the sense of partial derivatives, i.e. one change at a time. Next the comparison is made by changing both VSF and VSh together for the following combinations: $(5, 8\%)$, $(5, 10\%)$, $(6, 8\%)$ and $(6, 10\%)$. The results are presented in Table 6. There is clearly no secular evidence on relative importance of either the VSF or VSh for portfolios with short positions - for some portfolios extremes seem to matter more (high VSF), and for others level of volatility is more important (high VSh). It should be added that a $\pm 12\sigma$ move and a jump in volatility by 10% in one day are by definition extreme/stress events with low ex-ante probabilities. Nevertheless, scan risks under such extreme scenarios are useful reference points.

[Table 6 about here]

The design of scanning grid affects how finely and uniformly risk arrays are calculated. The standard list of scenarios as in Table 1 has steps of $\pm 1/3$ to ± 1. There are a variety of ways in which one could modify the scanning grid, but from a CCP point of view there is a clear trade-off between practicality and robustness on one hand and precision on the other. Keeping that in mind two modifications are considered:

1. *Making the grid finer*: Here we consider fineness of $\pm 1/3$, $\pm 1/5$, $\pm 1/10$, $\pm 1/30$. Given the gaps with which strikes are set in practice, going finer than $1/30$ is probably an overkill.

2. *Making the grid more uniform*: In the standard `SPAN` grid after ± 1, the final two scenarios are ± 2 with weight 0.35. A more uniform grid could consider scenarios between 1 and 2 with declining weights. However, if the weights are chosen to decline uniformly beyond ± 1, the weights on extreme events at ± 2 scenarios would decline with the fineness of the grid. To prevent this from happening for this exercise, a lower bound of 0.35 is set for scenarios beyond ± 1 to facilitate comparison with existing practices. As an illustration, Table 7 presents a uniform grid with a fineness of $\pm 1/5$.

[Table 7 about here]

Figures 1 and 2 presents comparisons of scan risk over a uniform grid steps of $\pm 1/3$ and $\pm 1/30$ (results with other finer gradations available on request). For all portfolios plotted in the two figures, VSF is set at 6 and VSh is set at 10% except for the 'Margins Base Case' case where VSF is set at 5 and VSh is set at 6%, which is considered to provide a reference point for comparisons with the existing grid with sixteen scenarios.

In both Figures 1 and 2, the following are plotted:

- Negative of the payoff function from the portfolio: '-Payoff', as cross $\times$
- Risk array with the uniform grid: 'Risk Array Uniform Grid', as a circle as $\circ$
- Scan risk with the default grid: 'Margins Default Grid', as a filled square ■
- Scan risk with the default grid, VSF of 5 and VSh of 6%: 'Margins Base Case', as a filled triangle ▲

- Scan risk with the uniform grid: 'Margins Uniform Grid', as filled circle ●

[Figure 1 about here]

[Figure 2 about here]

For all cases where a) either extremes are important (portfolios 9 to 12) or low volatility is important (portfolio 6) the impact shows up. For portfolio 6 for instance (short butterfly), at a fineness of $\pm 1/3$ in Figure 1 does not even allow the payoff to reflect that it is a butterfly payoff with the middle strike lying within the coarsely designed grid. Only a finer grid as in Figure 2 ($\pm 1/30$) reflects that portfolio 6 is indeed a short butterfly. A similar observation was made by Varma (2009).

In addition, note that for all short option positions potential losses are larger than the margin in all cases considered. This explains the need for an additional 'top-up' for short positions/portfolios, like the Short Option Minimum Charge currently being imposed by all CCPs using `SPAN` for ETDs.

Note that a finer grid does not necessarily imply that margins would also be always necessarily higher. The weights applied along the scanning grid matter equally. For portfolio 11 for example, scan risk with a finer grid is a bit lower compared when a coarse grid is used because of the higher weight. Nevertheless, the scan risk is higher in both the cases when compared to the default scanning grid with existing VSF and VSh.

While the analyses to sensitivity of margins to `SPAN` parameters shows that given the design of `SPAN`, certain positions (like short butterfly) may be designed to "fall between the cracks" and escape stringent margins. At the same time, we have shown that it is indeed not difficult to improve `SPAN` parameters and fix its observed inadequacies. Of course, it needs to be mentioned that we have ignored spread adjustments in our analysis.

4 Gross versus net margins

In 2015, European Securities and Markets Authority (ESMA), a European Union regulatory body issued a discussion paper (ESMA, 2015) on whether EMIR should take lead from the US CFTC and revisit their MPOR requirements for ETDs - the time horizon for liquidation assumed in the event of default. At the time, EMIR required an MPOR of at least 2 days for ETDs and at least 5 days for OTC derivatives. While EMIR's concern was that an MPOR of 1 day required by the US CFTC may give rise to regulatory arbitrage,[4] the issue of MPOR is intimately tied to 'how' CCPs collect margins.

As the regulations have evolved, the US based CFTC requires that margins from clients at the level of clearing members be grossed (without netting) and deposited with the CCP. On the other hand, the ESMA allows for both gross and net margin systems, though net margins remains the predominant mode. While details differ, other than US CFTC mandated gross margining, all other CCPs considered in the study permit net margining system under

[4]In 2016 ESMA reduced to MPOR of 1 day for ETDs; see https://www.esma.europa.eu/press-news/esma-news/emir-esma-proposes-one-day-margin-period-risk-ccp-client-accounts

different account structures.[5] Gregory (2014) provides a detailed description of variety of account structures popular in US and Europe.

Although there is no previous research on this topic to our knowledge, whether a clearing member collects margins on a gross versus net basis has important implications for both the margins collected at the CCP as well as the default waterfall. We restrict our attention here to the implications of gross versus net margins. Our contribution on this aspect is related to the work of Ghamami (2015) and Bielecki et al. (2018) who study the dynamics of default waterfall process.

4.1 Impact of gross versus net margins for different MPOR: The context

In a gross margin system, the CCP collects margins from the clearing member based on the sum of individual margins required based on each client's position, without netting of exposures between clients. In a net margin system, on the other hand, the CCP collects margins based on the netted exposures in the clearing member's account. Note that the clearing members themselves are permitted to collect margins from their clients on a gross basis, so in a net margin system members get to retain more of the client's margins compard to in a gross margin system. Figure 3 provides a schematic comparing the gross versus net margining system.

[Figure 3 about here]

For example, if client A has bought 500 shares and client B of the same clearing member has sold 300 shares, the net position of the clearing member is 200 shares long. In a net margin system, the CCP collects margins only the net position of 200 shares. In a gross margin system, the CCP collects margins on the aggregate gross positions of all clients; in the above example, that would be 800 shares (500 long plus 300 short). We make a number of reasonable simplifying assumptions to analyse the difference between the two systems:

- The CCP charges equal margins on long and short positions. This is what is commonly observed in practice, though the skewness of the log normal distribution can be used to justify somewhat greater margins on short positions than on long positions. The measure proposed by Alexander et al. (2019), for example, allows for that.
- The clearing member has no significant outside liabilities, or such liabilities are junior to the client obligations. For regulatory and other reasons, the clearing member is typically a separate ring fenced legal entity. During the bankruptcy of Lehman Brothers, for example, the broker dealer subsidiary was relatively insulated from the problems at the parent.
- The clearing members' risk management is more lenient than that of the CCP particularly for large clients. Consider the earlier net margin example of a clearing member with two clients who are respectively 500 shares long and 300 shares short. The clearing members' risk management system would require collateral from both clients to back their respective positions. If the collateral demanded by the clearing member

[5] Since LCH also operates in US jurisdiction, it has to offer both to meet CFTC regulations

were at the same level as what the CCP itself demands, then the distinction between gross and net margin by the CCP would become quite muted: absent any operational risk at the clearing member level, the system as a whole would have more or less the same level of protection in both cases. In practice, clearing members charge significantly lower level of margins from their largest clients. It is not uncommon even in the gross margin case, for the clearing member to collect lower margin from some clients, and deposit margins with the CCP out of its own resources. In a net margin case, the clearing member is even more likely to be lenient since it does not have to fund the difference. The structural reason for the difference in behaviour of CCPs and clearing members is that CCPs are designed and managed to make the probability of failure extremely remote; they usually target a triple 'A' rating ('AAA' or 'Aaa'). Clearing members by contrast might target only a single 'A' credit rating. Gross Margins will therefore be more of a Defaulter Pays Model than Net Margins.

- In the gross margin case, we assume that (a) the novation by the CCP extends only to the clearing member and not to the ultimate clients, but (b) the CCP is not allowed to impose initial margin haircuts on non defaulting clients of the defaulting clearing member to cover its default losses. The actual outcome in this situation would depend both on the bylaws of the CCP and on the segregation/commingling models used by the clients, but our assumption is a reasonable middle ground between the two extremes of client level novation and initial margin haircutting.

4.2 Idiosyncratic default by a large client: A Monte Carlo investigation

In this section, we discuss the scenario where a large client of a clearing member defaults idiosyncratically. In other words, we assume that the default is not accompanied by significant defaults by other clients at this or other clearing members. Of course, default by a large enough client is likely to lead to a default by that clearing member. Moreover, as the recent Nordic power spread default episode demonstrates (Nasdaq, 2018), even such localized defaults can blow a large hole in the resources of the CCP.

As already mentioned, the greater margin leniency of the clearing member as compared to the CCP makes the net margin system more reliant on Loss Allocation (Non Defaulter Pays). This takes several forms:

- In the first instance, the clearing member's capital would be used to cover the default loss. This is the skin in the game that prevents the clearing members from becoming too lenient in the margins that they collect from clients.
- If the loss is large enough to cause the clearing member itself to default, then non defaulting clients of this member will suffer at least the equivalent of variation margin haircutting since the novation by the CCP is at the clearing member level. In our example of a clearing member with two clients X and Y who are respectively 500 shares long and 300 shares short, suppose that the stock price falls and client X (the long) defaults, and the clearing member also defaults. Then client Y who is short will not be able to collect the profits on her trades because her clearing member is

bankrupt. Economically, this is the same as a Variation Margin Gains Haircutting (VMGH), and we refer to this below as (implicit) VMGH though the term VMGH is typically used only when it is imposed by the CCP under its own rules (outside a normal bankruptcy process).

- If the clearing member defaults and client Y was using a completely commingled model, she could also suffer the equivalent of an initial margin haircut. The defaulting clearing member might be unable to return the margins posted by her. We will ignore this risk in our analysis.

To quantify these channels of loss allocation, we need to choose values for a large number of parameters:

- `n` (ten million): The sample size for Monte Carlo simulations. We are not aware of any analytical formulas for the quantities that we are interested in. We do not attempt any analytical approximations as these might not be reliable so far out in the tails. The raw sample size has to be reasonably large to get enough sample of default observations. A raw sample of ten million gives us a sample of 1000 defaults even if the default probability is only 1 basis point (0.01%).

- `t_df` (4): We need a statistical model of return distributions and the correlation (more broadly, the dependence structure) between the returns on defaulter and non defaulter positions. As discussed in 4.2.1 below, we use student-t marginal distributions and a student-t copula with same degrees of freedom (`t_df`) in both.

- `pos_D` (1 million): The defaulter position size. Since we assume margins to be linear in position size, a large position size is mainly for convenience of displaying and interpreting the results. If we use small numbers like 1 or 1000, the expected loss numbers will be tiny fractions.

- `pos_ND_ratio` (1): The ratio of (a) gross positions of non defaulting clients of the clearing member to (b) gross positions of the defaulting client. If this is small, then there is very little netting at the clearing member level, and the whole problem of net margin becomes irrelevant.

- `vol_D` (0.3): Volatility of defaulter returns. Since we assume margins to be linear in risk (as measured by standard deviation), this variable like `pos_D` simply scales the results.

- `vol_ND` (same as `vol_D`): Volatility of non defaulters positions. The effect of this variable is similar to that of `pos_ND_ratio`.

- `corr` (-0.4 to -0.3): Correlation of defaulter and non defaulter returns. The more negative the correlation is, the greater the netting benefit. Netting becomes very small if `corr` is positive or close to zero.

- `client_NW_sigmas` (1): Net worth of defaulting client in number of standard deviations. Even a client targeting high levels of leverage would maintain some level of net worth to avoid premature close out of position. Since this net worth would depend on the riskiness of the position, we measure this in number of standard deviations.

- `CM_NW_sigmas` (1): Clearing member net worth in number of standard deviations. This is partly governed by the rules of the CCP, and partly by the clearing member's own risk management.
- `CCP_margin_sigmas_GM` (7): CCP Margin in number of standard deviations. This value is borrowed from Menkveld (2017) who in turn bases it on the actual data from a large CCP.
- `CCP_net_margin_ratio` (1 to $\sqrt{2}$): CCP net margin to gross margin ratio. The value of 1 is useful to compare net margins with gross margins without any other change in the risk management system. The value of $\sqrt{2}$ covers the case of a CCP that uses an MPOR of 2 to compensate for net margins.
- `CM_margin_sigmas` (5): Minimum margin collected by clearing member from client when CCP charges low margin due to net margin.

When we set the correlation to -0.4 and assume a `CCP_net_margin_ratio` of 1 (net margins are levied at the same rate as gross margins), we find that the default probability more than doubles from less than 5 basis points under gross margins to more than 10 under net margins (see Table 8). The expected loss for the CCP also more than doubles under net margins. In addition, the loss (implicit VMGH) suffered by non defaulting members of the clearing member also more than doubles.

[Table 8 about here]

We also observe that under both gross and net margins, the VMGH losses of non defaulting members are about 1.75 times the losses suffered by the CCP. Non defaulting members thus have a lot of skin in the game, though in some jurisdictions, they may be able to recover some of these losses through default funds set up by the industry or the government (for example, the SIPC in the US).

Our next results show that an MPOR of 2 can significantly compensate for the laxity of net margins. Under our base case assumption of a correlation of -0.4, however, this $\sqrt{2}$ scale up of margins is not sufficient to fully offset the weakness of net margins.

Finally, we reduce the magnitude of the correlation to -0.3 and find that an MPOR of 2 provides a rough offset for net margins. At this level of correlation, gross margin with MPOR of 1 and margin with MPOR of 2 are more or less equivalent in all respects (probability of default, expected loss to the CCP and expected VMGH for non defaulting clients).

4.2.1 Correlation and copulas

Particularly after the GFC, finance theory has veered round to the view that the dependence between two underlyings is non linear. Non linear dependence can account for the high correlation of extreme movements and the modest correlation of mild movements. It can also account for asymmetric dependence relationships where the dependence is different in rising and falling markets. Correlations are a poor measure of non linear dependence. For example if x lies between -1 and $+1$ and $y = x^2$ then x and y are uncorrelated though y is perfectly dependent on x.

Copulas provide the mathematical machinery to model dependence which may be non linear. The linear correlation is also represented by a copula: specifically the Gaussian copula postulates a linear relationship between two variables). The Gaussian copula has the property that if the correlation is zero then the two variables are unrelated. This is shown in the scatter diagram in which presents a circular pattern. There are hardly any instances of a simultaneous extreme movement in both variables. Figure 4 is a visual depiction of the well known fact that the Gaussian copula implies negligible tail dependence.

This must be contrasted with the non linear dependence of the t-copula shown in Figure 5. Here also the correlation is zero signifying the absence of a linear relationship. The two variables are individually normally distributed as in the earlier diagram. However, there is a non linear dependence. The scatter plot looks like a square and simultaneous extreme movements in both variables are seen. If we were modelling the relationship using correlations, then in times of market stress, it would appear that two previously uncorrelated variables have become highly correlated. In fact, the dependence relationship has been stable but was non linear to begin with.

To use copulas, we must fit a marginal distribution to the returns for each underlying and apply the copula to these marginals. Marginal distributions of asset returns are known be fat tailed; the Gaussian distribution is quite inappropriate for risk management purposes. One possibility is to use a tractable fat tailed distribution like the student-t. More realistically, CCPs can and do use historical data (including data from stressed markets) to fit an empirical distribution. Empirical copulas are harder to estimate, and it is easier to use an analytical copula that fits the stylized facts of empirical finance. The t-copula is one of the most suited for this purpose.

In our analysis, we use both t-marginals and t-copulas. The degrees of freedom of the marginals and the copulas need not be the same, but for simplicity, we have used the same degrees of freedom for both. In this case, we can simplify the simulations by sampling from the multivariate t distribution. It is not too hard to modify the code to use a different marginal distribution.

4.3 Impact of gross margins in the context of crowded trades

In this section, we discuss the impact of gross margins in the scenario of 'crowded trade' (Menkveld, 2017) where many clients of many clearing members have taken large long and short positions in the same underlying. When there is an extreme price movement in this crowded asset, many clients suffer large losses and may default. If the trade is sufficiently crowded, several clearing members may also default as a consequence of defaults by many of their members even if gross margins are used. This is a systemic risk event for the CCP that might not be captured by the standard 'Cover 2' approach to CCP risk management (Capponi et al., 2018). Our goal is to analyse the extent to which net margins can amplify and aggravate this risk.

For an intuitive understanding of how net margins become problematic in a crowded trade scenario, it is instructive to begin with a toy model that assumes:

- Each clearing member has a large number of clients
- The clients of each clearing member are equally likely to be long or short the crowded asset.
- The position size of individual clients follows a thin tailed distribution.

Under these conditions, the law of large numbers and the central limit theorem guarantee that each clearing member's net position is close to zero and the net margin payable to the CCP is practically zero. Under our standard assumption that clearing member risk management is relatively lax, it is very likely that a large number of clearing members will fail and the CCP would have to rely almost entirely on the default fund and its own capital to cope with an extreme price move in the crowded asset.

To model the situation more realistically, we drop all of the above simplifying assumptions and replace them with the following:

- Each clearing member has a small number of clients (say 25) who take significant speculative positions (for example, institutions, hedge funds, high net worth individuals).
- The probability that clients of a clearing member take long or short positions in the crowded asset varies across clearing members. Some members might have a lot of bullish clients while some others might have a lot of bearish clients. Specifically, we assume that the probability 'p' that a client of a specific clearing member is bullish follows the beta distribution. We set the two shape parameters of the beta distribution equal to each other to ensure that the distribution is symmetric. If the shape parameter is greater than or equal to unity, the beta distribution is unimodal and symmetric around mode of $p = 0.5$. A low value of the shape parameter spreads out the distribution (the limiting value of unity means that p is uniformly distributed between 0 and 1). Values of the shape parameter below unity lead to a symmetric bimodal distribution with peaks at 0 and 1.
- The position size (disregarding the sign) of individual clients follows an extremely fat tailed distribution. Specifically, we choose the Pareto distribution which is commonly used to model the distribution of income and wealth. If the shape parameter (power law exponent) of the Pareto distribution is set to 1.15, then 20% of the clients account for 80% of the positions. This is the value that is commonly observed in wealth distributions in many countries.

Since this model is not analytically tractable, we use Monte Carlo simulations to estimate the effect of net margins. Our simulation results show that under our assumptions, the net margins collected by the CCP is on average less than 20% of what it would collect under gross margins. Clearly even a $\sqrt{2}$ scale-up induced by an MPOR of 2 would go only a small way towards offsetting this large difference.

Because of the fat tails of the the Pareto distribution, there is a lot of variability in the ratio of net margins to gross margins as shown in Table 9.

[Table 9 about here]

5 Conclusion

With the evolving regulations, the CCPs today have become integral to all developments of modern financial market infrastructure governed by the CPSS-IOSCO PFMI standards adopted by the Group of Twenty countries in 2012.

The PFMI document contains 24 principles that apply to all areas of clearing, ranging from legal and governance issues to margins and credit risk management, so any study attempting to review of risk management in CCPs needs to restrict its focus. In our study we have looked at the the risk management practices of select large CCPs across jurisdictions as they relate to their use of risk-based margin models and collection of margins, in particular whether margins are collected by CCP from clearing members on gross versus net basis.

All the CCPs considered here except Eurex use some variant of `SPAN` to evaluate the risk of a portfolio of positions and compute the applicable margins for ETDs. While `SPAN` is known to be a coherent risk measure (Artzner et al., 1999), it is also a very old system that has not been updated to reflect the massive improvements in computing power and the increasing complexity of trading strategies. Eurex on the other hand uses a different methodology (`Prisma`) which is arguably more modern. On the flip side, `Prisma` is a proprietary methodology that is quite opaque compared to `SPAN`.

As reviewed here, although there are various alternatives offered to `SPAN` in the literature, either they remain untested for portfolios (Alexander et al., 2019) or are highly data/econometrics intensive (Cotter and Dowd, 2006; Lam et al., 2010). Despite its known and obvious limitations, given the popularity of `SPAN` for margining ETDs, a review of its parameters is important. In that light, we have critically reviewed `SPAN` margining model used in calculation of scan risk. A limitation is that this study does not look at the spread adjustments that are important to reducing margins within `SPAN`. Like with other studies in the literature, we have also not looked at portfolios straddling multiple asset classes.

Even so, the analyses to sensitivity of margins to `SPAN` parameters shows that given the design of `SPAN`, certain positions (like short butterfly) may be designed to "fall between the cracks" and escape stringent margins. At the same time, we have shown that it is indeed not difficult to improve `SPAN` parameters and fix its observed inadequacies.

We find that while large CCPs have broadly similar practices (partly ensured by compliance with PFMI regulations) with respect to collecting margins, with US based CCPs standing out for requiring margins to be collected on a gross basis (aggregate of margins on client wise positions). On the other hand, all other CCPs considered here allow for net margins - margin on the net position of all clients (though not exclusively). In the second part of the study, we provide a quantitative comparison not found elsewhere in the literature to our knowledge for evaluating the impact of gross versus net margins with MPOR alternatively set at 1 and 2.

The impact of a higher MPOR versus margining on a net basis might partially offset each other, and it is not obvious that either the erstwhile European MPOR of 2 or the US CCPs are more lax than the other. An important methodological contribution of our paper is to analyze the trade-offs in gross versus net margining in (a) the scenario where a large client of a clearing member defaults idiosyncratically and (b) in the scenario where defaults arise out of "crowded trades" (Menkveld, 2017). We have been able to find the conditions under which the higher MPOR does or does not offset the risks induced by net margins.

Table 1
SPAN risk array used by ASX, CME (original), HKEx and LCH

Number	PSR	VSR	Weight
1	0	1	1.00
2	0	-1	1.00
3	1/3	1	1.00
4	1/3	-1	1.00
5	-1/3	1	1.00
6	-1/3	-1	1.00
7	2/3	1	1.00
8	2/3	-1	1.00
9	-2/3	1	1.00
10	-2/3	-1	1.00
11	1	1	1.00
12	1	-1	1.00
13	-1	1	1.00
14	-1	-1	1.00
15	2	0	0.35
16	-2	0	0.35

Table 2
SPAN risk array used by CME (current)

Number	PSR	VSR	Weight
1	0	1	1.0
2	0	-1	1.0
3	1/3	1	1.0
4	1/3	-1	1.0
5	-1/3	1	1.0
6	-1/3	-1	1.0
7	2/3	1	1.0
8	2/3	-1	1.0
9	-2/3	1	1.0
10	-2/3	-1	1.0
11	1	1	1.0
12	1	-1	1.0
13	-1	1	1.0
14	-1	-1	1.0
15	3	1	0.3
16	3	1	0.3

Table 3
The twelve representative portfolios on HSI for comparing calculation of scan risk

No.	Portfolio	Strikes
1	Long futures	-
2	Short futures	-
3	Long call spread	28000, 28400
4	Short call spread	28000, 28400
5	Short butterfly 1	27800, 28200, 28600
6	Short butterfly 2	27800, 28200, 28600
7	Long futures and 50 call calendar spread	28000
8	Short futures and 100 put calendar spread	28000
9	Short call	28000
10	Short put	28400
11	Four short ITM calls and ITM puts	27400, 27600, 27800, 28000, 28400, 28600, 28800, 29000
12	Four short OTM calls and OTM puts	29000, 28800, 28600, 28400, 28000, 27800, 27600, 27400

Table 4
Impact on scan risk and its location of different volatility factor

Portfolio	VSF = 4	VSF = 5	VSF = 6	VSF = 7	Loc 4	Loc 5	Loc 6	Loc 7
1	699.91	874.89	1049.87	1224.85	-4.00	-5.00	-6	-7.00
2	699.91	874.89	1049.87	1224.85	4.00	5.00	6	7.00
3	163.74	172.21	175.95	177.37	-4.00	-5.00	-6	-7.00
4	233.93	278.66	313.73	341.54	4.00	5.00	6	7.00
5	15.56	17.76	22.27	26.91	4.00	5.00	6	7.00
6	70.90	71.01	68.99	65.01	1.33	1.67	2	2.33
7	6181.38	6020.07	6132.06	6185.12	-2.67	-1.67	-2	-2.33
8	9948.85	9887.86	9730.45	9475.66	1.33	1.67	2	2.33
9	956.14	1206.56	1470.43	1745.21	4.00	5.00	6	7.00
10	1013.87	1264.91	1520.62	1779.63	-4.00	-5.00	-6	-7.00
11	3093.96	3938.77	4877.88	5893.03	-4.00	-5.00	-6	-7.00
12	2534.34	3249.06	4061.00	4951.13	-4.00	-5.00	-6	-7.00

Note: VSF = Volatility scaling factor, Loc 3 = Location of scan risk with maximum loss across risk arrays with VSF = 3 and so on

Table 5
Impact on scan risk of different volatility shift applied

Portfolio	VSh = 0.06	VSh = 0.08	VSh = 0.10	VSh = 0.12	Loc 6	Loc 8	Loc 10	Loc 12
1	874.89	874.89	874.89	874.89	-5.00	-5.00	-5.00	-5.00
2	874.89	874.89	874.89	874.89	5.00	5.00	5.00	5.00
3	172.21	175.82	177.53	177.97	-5.00	-5.00	-5.00	-5.00
4	278.66	291.33	302.58	310.29	5.00	5.00	5.00	5.00
5	17.76	17.33	21.02	27.37	5.00	5.00	1.67	1.67
6	71.01	97.70	132.70	179.78	1.67	1.67	1.67	1.67
7	6020.07	7584.59	9149.60	10708.92	-1.67	-3.33	-3.33	-3.33
8	9887.86	12923.31	15965.55	19012.88	1.67	1.67	1.67	1.67
9	1206.56	1236.99	1269.23	1303.04	5.00	5.00	5.00	5.00
10	1264.91	1276.06	1289.71	1305.75	-5.00	-5.00	-5.00	-5.00
11	3938.77	4123.97	4325.42	4541.49	-5.00	-5.00	-5.00	-5.00
12	3249.06	3433.02	3633.13	3847.78	-5.00	-5.00	-5.00	-5.00

Note: VSh = Volatility shift, Loc 4 = Location of scan risk with maximum loss across risk arrays with VSh set at 0.04 and so on

Table 6
Impact on scan risk with alternative volatility scale factors and different volatility shifts applied

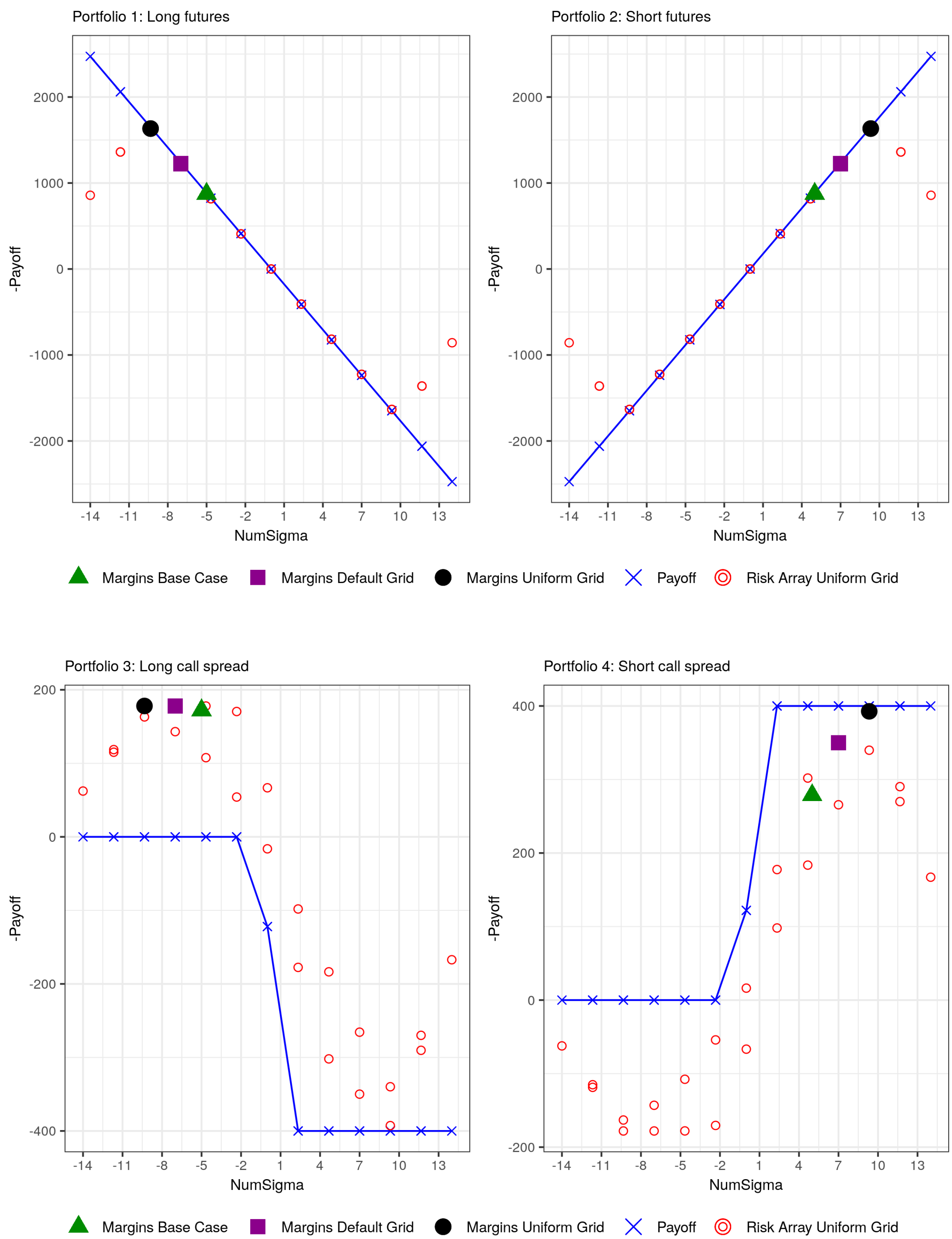
Portfolio	(5, 0.08)	(5, 0.10)	(6, 0.08)	(6, 0.10)	Loc 58	Loc 510	Loc 68	Loc 610
1	874.89	874.89	1049.87	1049.87	-5.00	-5.00	-6	-6
2	874.89	874.89	1049.87	1049.87	5.00	5.00	6	6
3	175.82	177.53	177.44	177.93	-5.00	-5.00	-6	-6
4	291.33	302.58	322.44	328.47	5.00	5.00	6	6
5	17.33	21.02	22.04	21.73	5.00	1.67	6	6
6	97.70	132.70	92.79	123.13	1.67	1.67	2	2
7	7584.59	9149.60	7641.42	9150.29	-3.33	-3.33	-2	-2
8	12923.31	15965.55	12771.70	15819.30	1.67	1.67	2	2
9	1236.99	1269.23	1495.90	1523.53	5.00	5.00	6	6
10	1276.06	1289.71	1528.53	1538.68	-5.00	-5.00	-6	-6
11	4123.97	4325.42	5025.30	5190.10	-5.00	-5.00	-6	-6
12	3433.02	3633.13	4206.82	4369.86	-5.00	-5.00	-6	-6

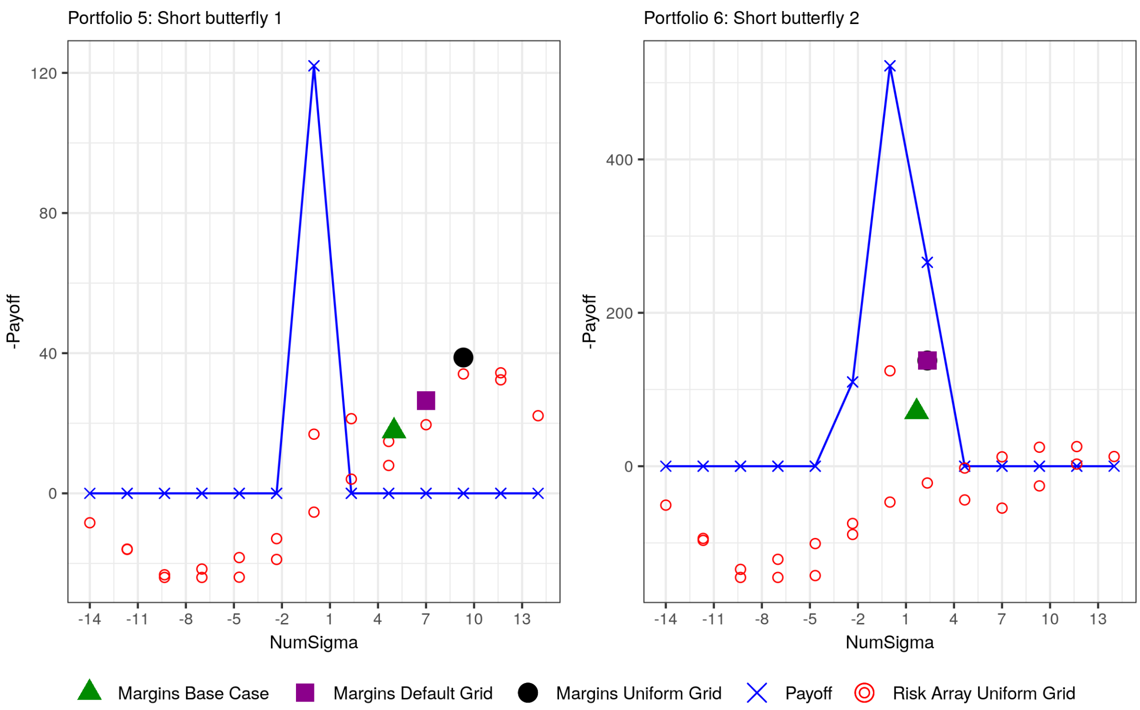
Note: (5, 0.08) = Volatility scaling factor set at 5 and volatility shift set at 0.08 and so on, Loc 58 = Location of scan risk with maximum loss across risk arrays with volatility scaling factor set at 5 and volatility shift set at 0.08 and so on

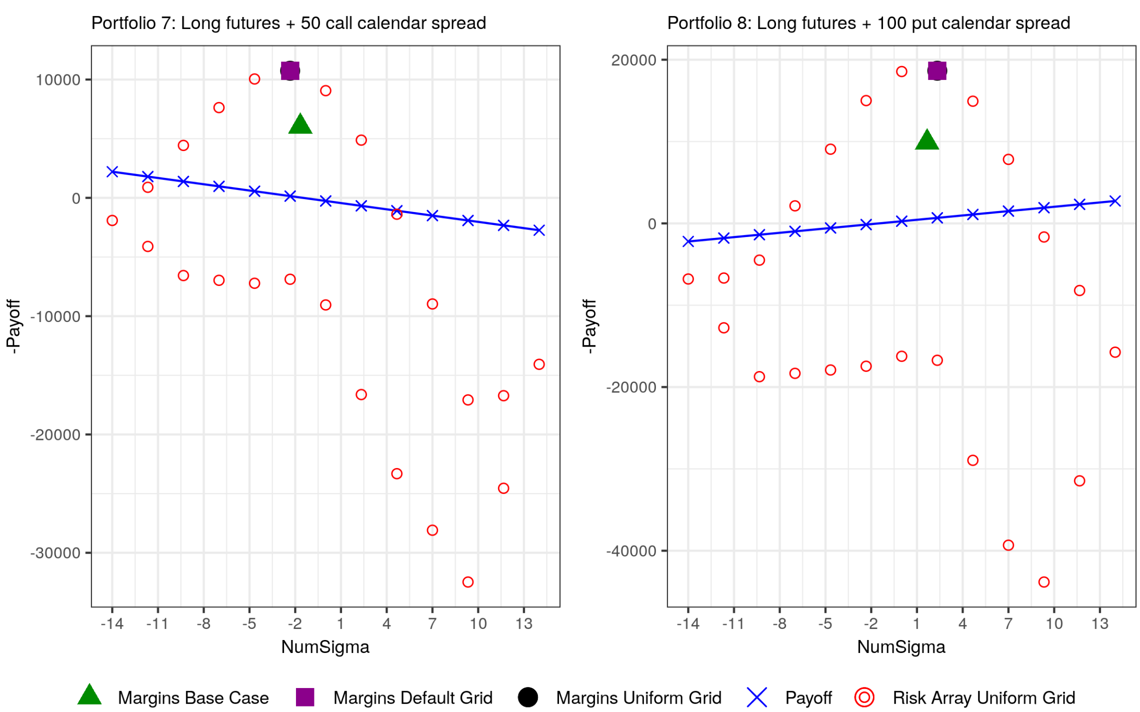
Table 7
Uniform scanning grid with a fineness of $\pm 1/5$

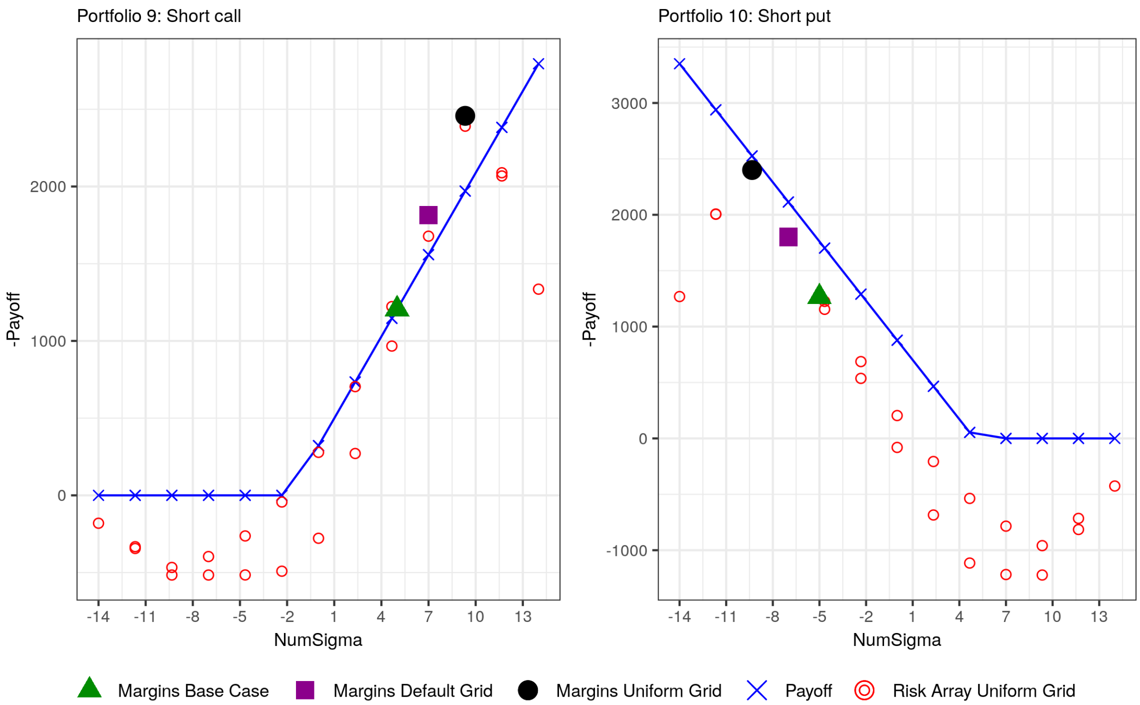
Num	PSR	VSR	Weight
1	0.0	1	1.00
2	0.0	-1	1.00
3	0.2	1	1.00
4	0.2	-1	1.00
5	-0.2	1	1.00
6	-0.2	-1	1.00
7	0.4	1	1.00
8	0.4	-1	1.00
9	-0.4	1	1.00
10	-0.4	-1	1.00
11	0.6	1	1.00
12	0.6	-1	1.00
13	-0.6	1	1.00
14	-0.6	-1	1.00
15	0.8	1	1.00
16	0.8	-1	1.00
17	-0.8	1	1.00
18	-0.8	-1	1.00
19	1.0	1	1.00
20	1.0	-1	1.00
21	-1.0	1	1.00
22	-1.0	-1	1.00
23	1.2	1	1.00
24	1.2	-1	1.00
25	-1.2	1	1.00
26	-1.2	-1	1.00
27	1.4	1	0.80
28	1.4	-1	0.80
29	-1.4	1	0.80
30	-1.4	-1	0.80
31	1.6	1	0.60
32	1.6	-1	0.60
33	-1.6	1	0.60
34	-1.6	-1	0.60
35	1.8	1	0.40
36	1.8	-1	0.40
37	-1.8	1	0.40
38	-1.8	-1	0.40
39	2.0	0	0.35
40	-2.0	0	0.35

Figure 1
Comparison of scan risk with default versus a uniform grid (fineness of $\pm 1/3$)




Portfolio 5: Short butterfly 1
Portfolio 6: Short butterfly 2
-Payoff
120
80
40
0
400
200
0
-14 -11 -8 -5 -2 1 4 7 10 13
NumSigma
Margins Base Case
Margins Default Grid
Margins Uniform Grid
Payoff
Risk Array Uniform Grid


Portfolio 7: Long futures + 50 call calendar spread
Portfolio 8: Long futures + 100 put calendar spread
-Payoff
10000
0
-10000
-20000
-30000
20000
0
-20000
-40000
-14 -11 -8 -5 -2 1 4 7 10 13
NumSigma
Margins Base Case
Margins Default Grid
Margins Uniform Grid
Payoff
Risk Array Uniform Grid


Portfolio 9: Short call
Portfolio 10: Short put
-Payoff
NumSigma
Margins Base Case
Margins Default Grid
Margins Uniform Grid
Payoff
Risk Array Uniform Grid

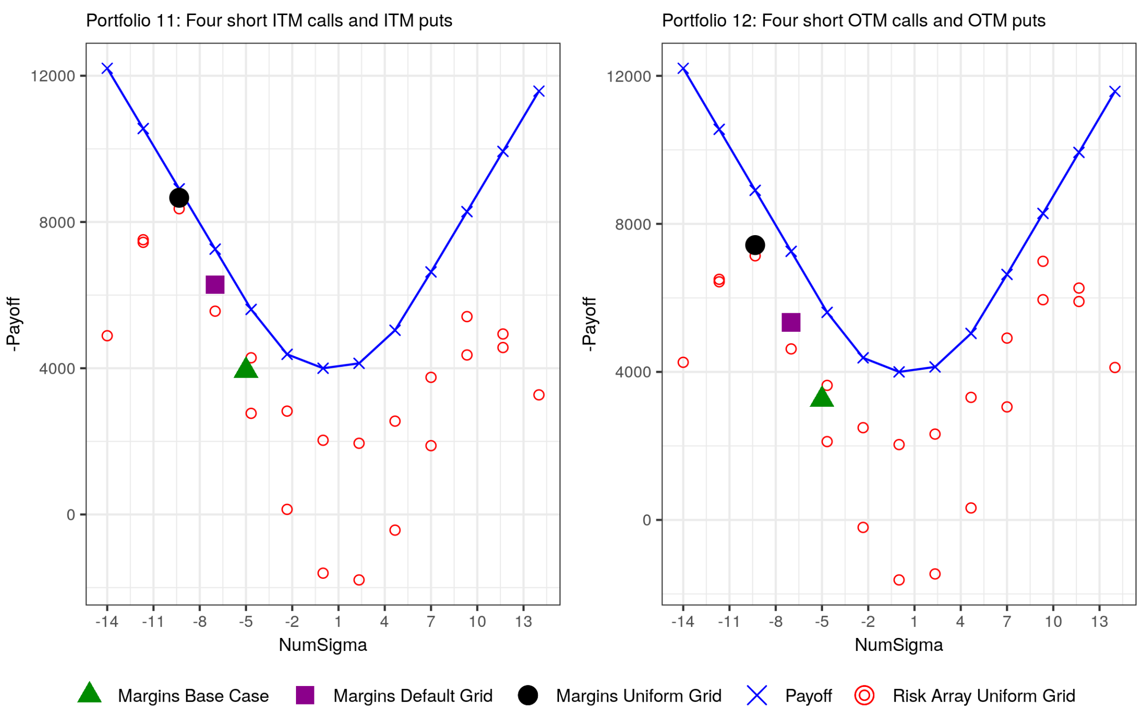
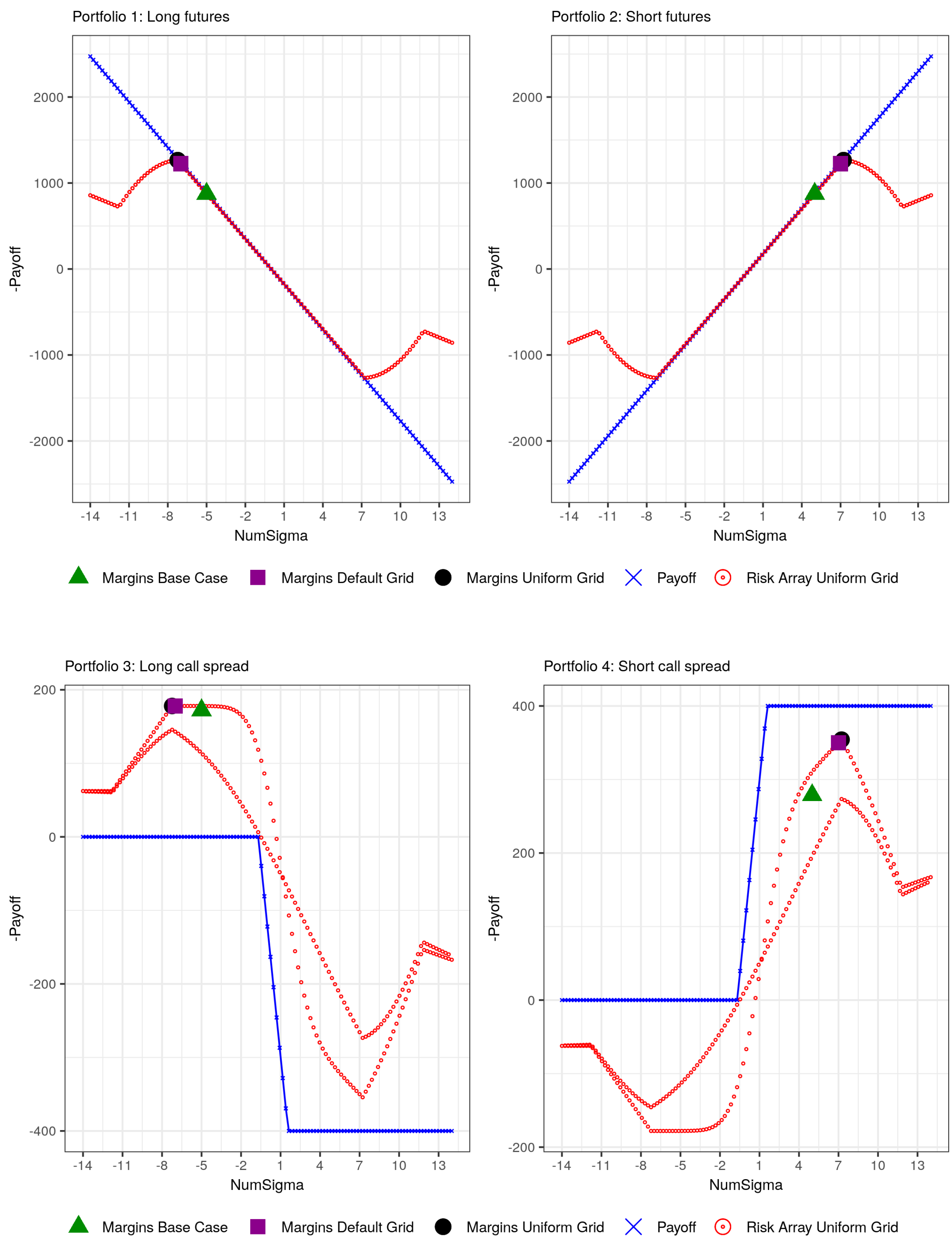
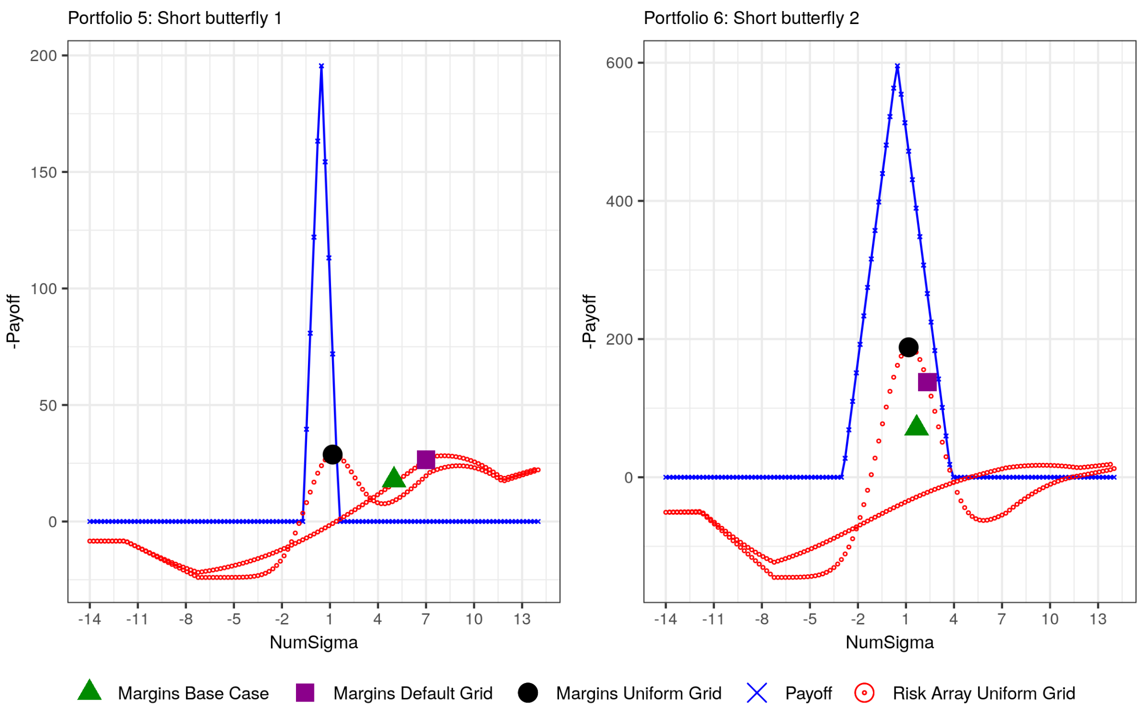
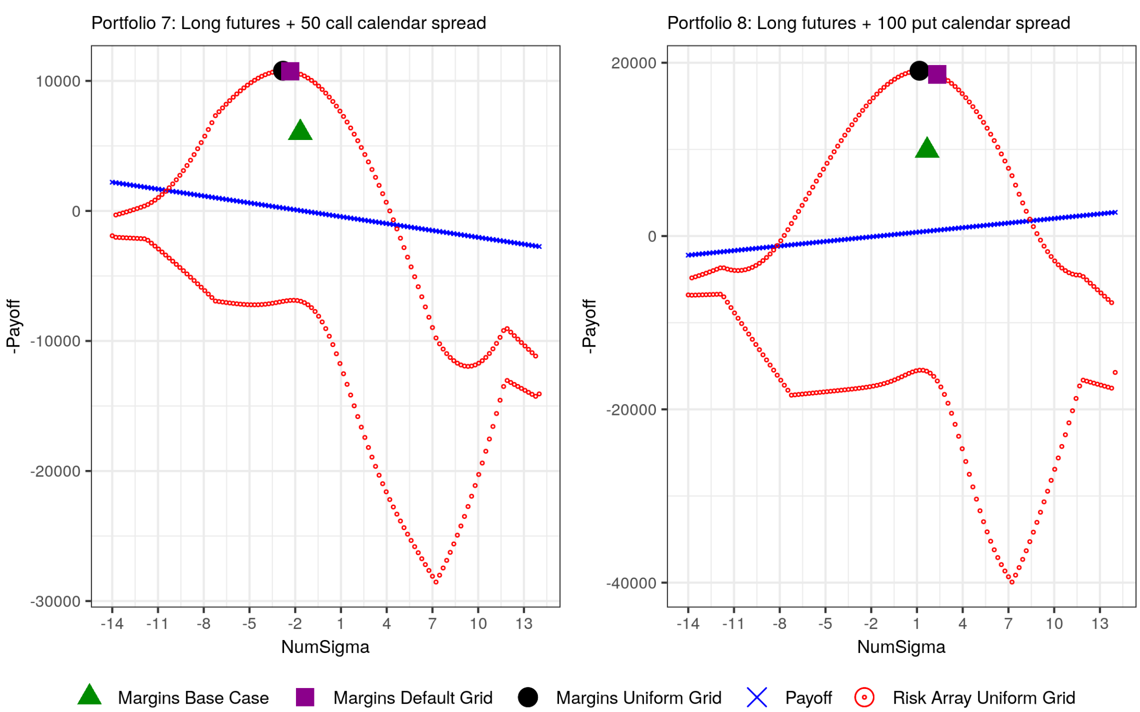
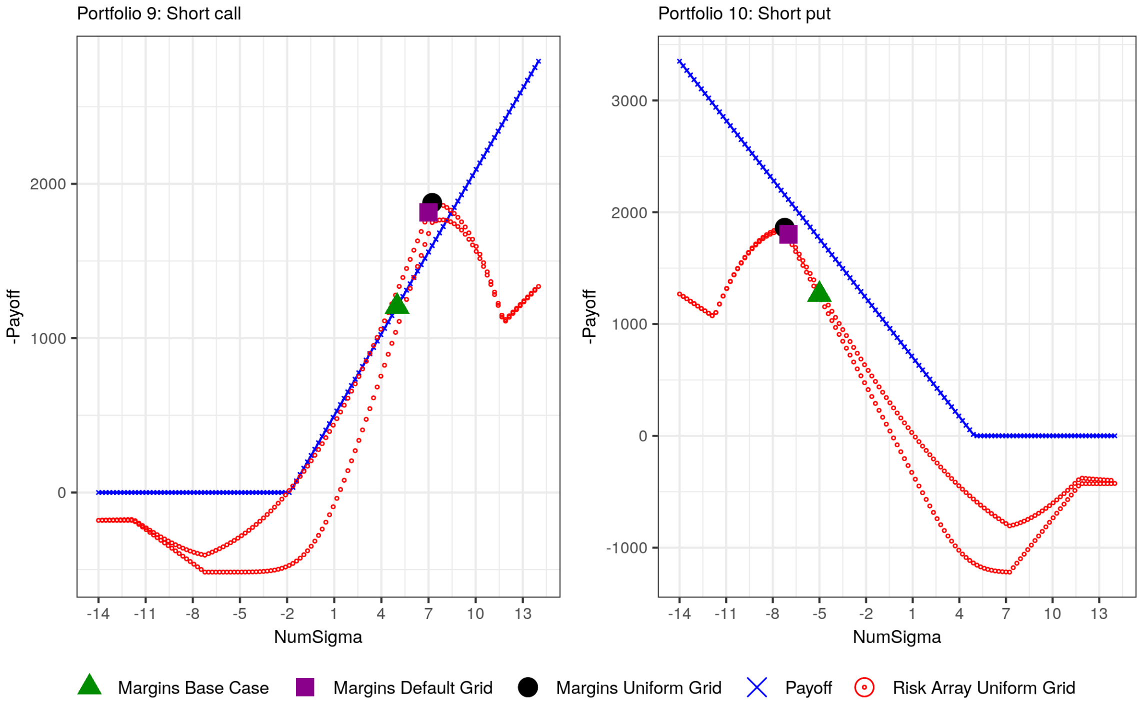

Portfolio 11: Four short ITM calls and ITM puts
Portfolio 12: Four short OTM calls and OTM puts
-Payoff
NumSigma
Margins Base Case
Margins Default Grid
Margins Uniform Grid
Payoff
Risk Array Uniform Grid

Figure 2
Comparison of scan risk with default versus a uniform grid (fineness of $\pm 1/30$)




Portfolio 5: Short butterfly 1
Portfolio 6: Short butterfly 2
-Payoff
NumSigma
Margins Base Case
Margins Default Grid
Margins Uniform Grid
Payoff
Risk Array Uniform Grid


Portfolio 7: Long futures + 50 call calendar spread
Portfolio 8: Long futures + 100 put calendar spread
-Payoff
NumSigma
Margins Base Case
Margins Default Grid
Margins Uniform Grid
Payoff
Risk Array Uniform Grid


Portfolio 9: Short call
Portfolio 10: Short put
-Payoff
NumSigma
2000
1000
0
3000
-1000
-14 -11 -8 -5 -2 1 4 7 10 13
Margins Base Case
Margins Default Grid
Margins Uniform Grid
Payoff
Risk Array Uniform Grid

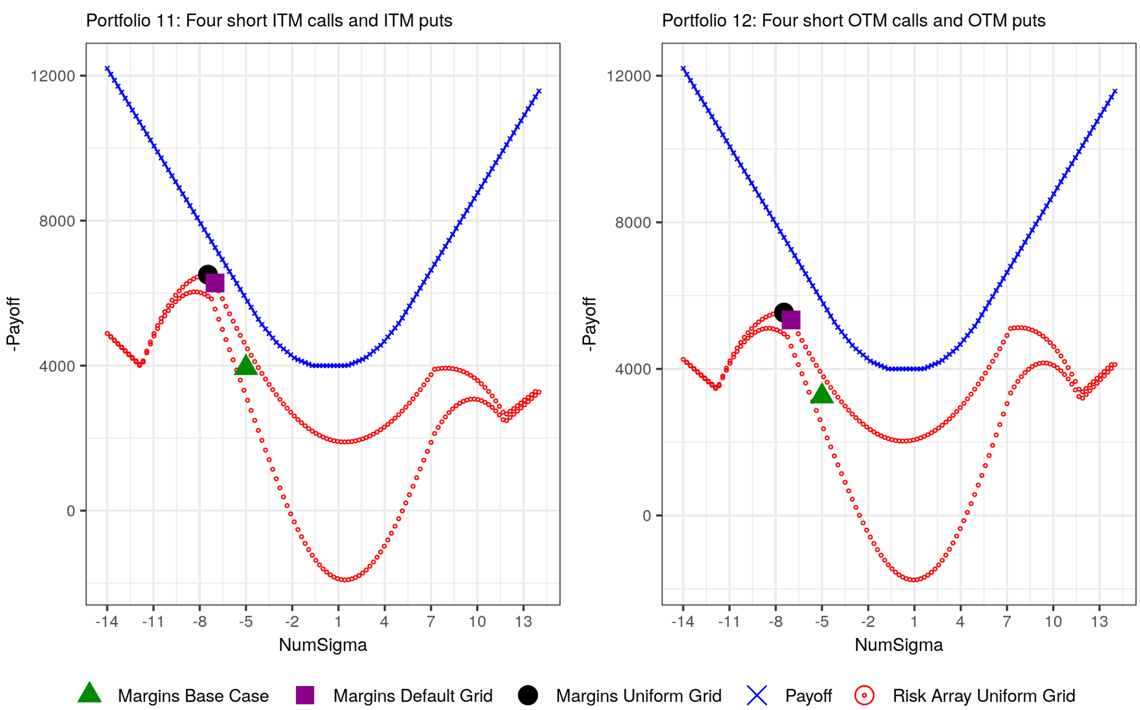

Portfolio 11: Four short ITM calls and ITM puts
Portfolio 12: Four short OTM calls and OTM puts
-Payoff
NumSigma
12000
8000
4000
0
-14 -11 -8 -5 -2 1 4 7 10 13
Margins Base Case
Margins Default Grid
Margins Uniform Grid
Payoff
Risk Array Uniform Grid

Figure 3
Schematic comparing the gross versus net margining system

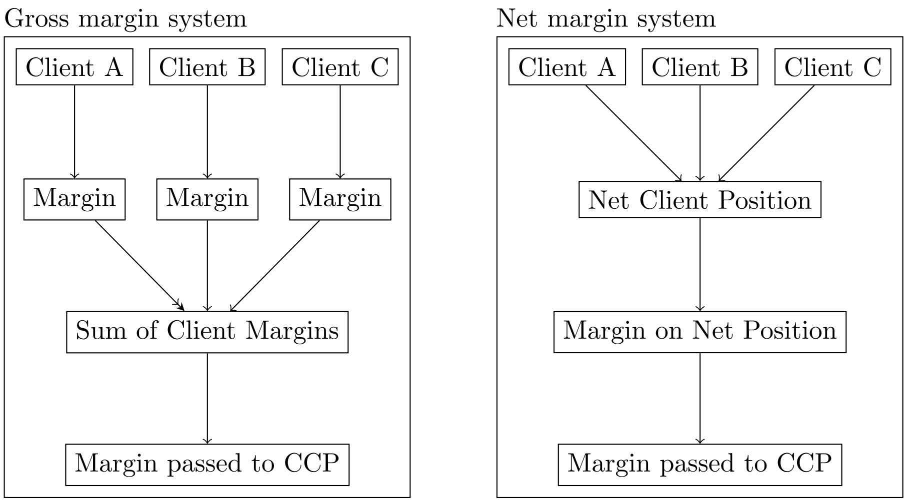


Table 8
Comparison of Gross and Net Margins

	MPOR=1(r=-0.4)	MPOR=2(r=-0.4)	MPOR=2(r=-0.3)
CM Default Prob bp (Gross)	4.34	4.29	4.18
CM Default Prob bp (Net)	11.00	6.86	4.30
CCP Exp. Loss (Gross)	399.20	398.27	388.87
CCP Exp. Loss (Net)	821.46	571.98	397.82
Implicit VMG Hair Cut (Gross)	705.39	726.13	586.78
Implicit VMG Hair Cut (Net)	1436.51	1028.13	600.65

Figure 4
Gaussian copula: Uncorrelated implies independent

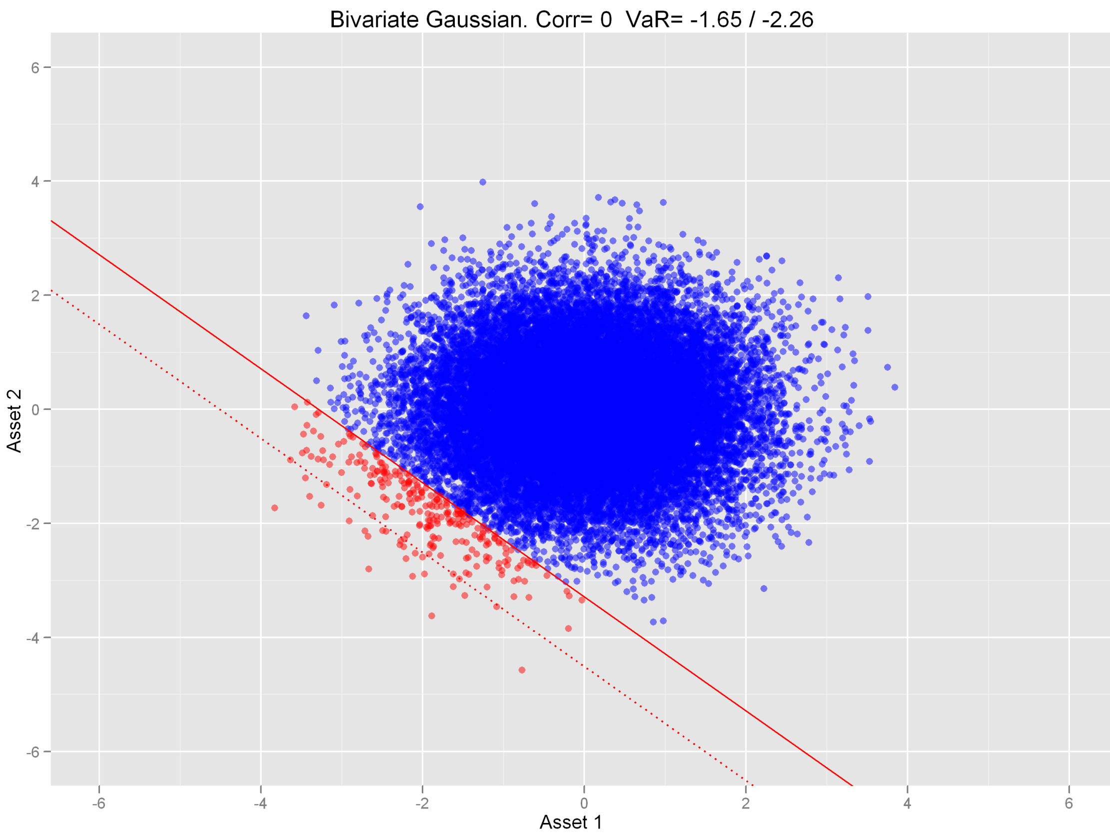


Figure 1: The Gaussian copula with zero correlation produces a scatter plot which is circular. There are very few observations involving simultaneous extreme moves of both x and y. The 99% and 99.9% VaR for an equally weighted portfolio of the two assets are 1.65 and 2.26 times the standard deviation of the individual asset.

Figure 5
t-copula: Uncorrelated assets show tail dependence

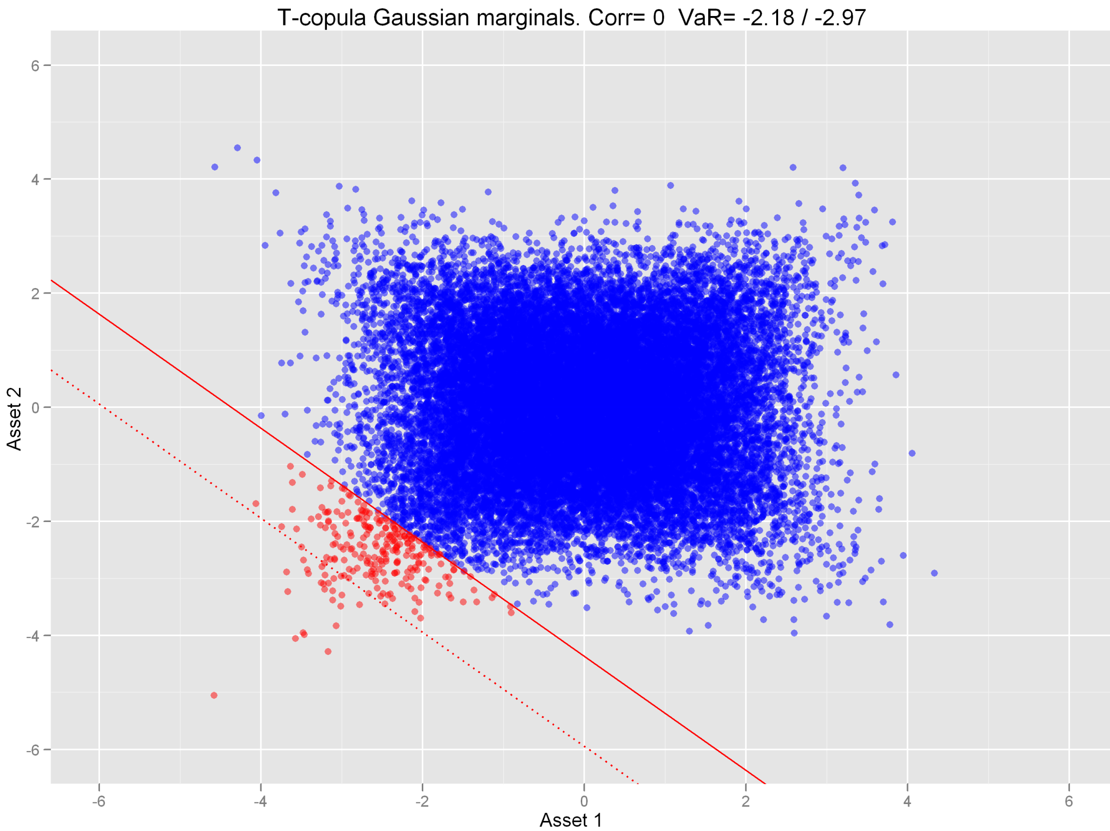


Figure 2: A t-copula with zero correlation produces a scatter diagram which looks like a square rather than a circular. The tail dependence is seen in simultaneous extreme moves in both x and y. The 99% and 99.9% VaR for an equally weighted portfolio of the two assets are 2.18 and 2.97 times the standard deviation of the individual asset.

Table 9
Ratio of net margin to gross margin for crowded trades

Min	Q1	Median	Mean	Q3	Max
0.01	0.07	0.16	0.21	0.3	0.86

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