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Initial Margin for Crypto Currencies Risks in Uncleared Markets

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ABSTRACT: We examine prospective classification of crypto currencies risks within the ISDA Standardized Initial Margin Model (SIMM) framework for calculation of initial margin on trades sensitive to cryptocurrencies' risk factors in the uncleared market. Consistent with the view that cryptocurrencies are digital assets that fundamentally rely on distributed ledger technology (DLT) and induce financial risks that are significantly different from those in traditional risk classes like commodities or FX, we find that cryptocurrencies are best classified into a distinct risk class within SIMM that is split into two buckets – pegged and floating (unpegged) crypto currencies as risk factors - and suggest risk weights' calibration methodology within the cryptocurrencies risk class that is consistent with the existing approaches adopted in SIMM.

I. INTRODUCTION

In response to the great financial crisis of 2008-2009, which highlighted systemic risks of uncleared OTC derivatives and led to their regulation under the "Margin and Capital Requirements for Covered Swap Entities" (80 *Federal Register* 74840) – also known as the Uncleared Margin Rule (UMR) – in the U.S. and a gradual adoption of the BCBS/IOSCO framework (BCBS-IOSCO, 2013) for margin requirements on uncleared swaps worldwide, the International Swaps and Derivatives Association (ISDA) developed in 2013 the Standardized Initial Margin Model (SIMM), whose purpose was to provide a standardized method of calculating initial margin (IM) so that counterparties could easily and quickly agree on the amount of initial margin to be exchanged, on a daily basis, to compensate the 99th percentile of potential losses over a 10-day margin period of risk – the time estimate to close out and re-hedge positions with a defaulting counterparty – in case of a counterparty default. Due to the model's intended adoption across a wide range of participants in the uncleared derivatives market – many of whom are constrained by scarce technological and labor resources – and the need for frequent exchanges of IM, industry-wide implementation of sophisticated dynamic IM models was impractical, so ISDA SIMM – a piece-wise static (as recalibrated only semi-annually, and prior to 2025, annually), sensitivities-based parametric Value-at-Risk-type model – became the industry's answer for collateral IM exchange in the uncleared derivatives market. However, conceived for the needs of the traditional financial market at the time when market capitalization of crypto assets was barely breaking one billion U.S. dollars, SIMM so far lacks an ability to calculate IM for crypto-sensitive financial assets despite exponential growth of the crypto market, with the total crypto market capitalization reaching four trillion U.S. dollars today.

As crypto market matures, gaining significance in terms of mainstream adoption, market cap and regulatory oversight, there is an increasing need to incorporate cryptocurrency risks in the ISDA SIMM model – the de facto industry-wide initial margin model accounting for over 90% of all IM collected and posted in the uncleared market, with total IM collected stabilized at around $431 billion in both 2023 and 2024. SIMM currently (in its version 2.8) assigns every deal to one of the four product classes (rates/FX, equity, credit, and commodity) and the deal's risk factors to six risk classes: interest rates, FX, equities, commodities, credit qualifying, and credit non-qualifying classes. Each risk class is further subdivided into multiple buckets, for which the risk weights for delta and, as appropriate, vega (in the case of instruments with sensitivity to implied volatility), curvature (for instruments with optionality), and base correlation (for credit instruments with sensitivity to correlation between defaults of different credits within an index or a basket) are calibrated from a total of four years of historical data (of which 25% comes from a continuous period of significant stress specific to that risk class, and the rest -- from the most recent 3 years that may be augmented with extra quarters if significant stress occurred in that period) and are used to weigh sensitivities of a given deal, with weighted sensitivities factored with calibrated relevant inter-bucket and intra-bucket correlations, to compute the deal's delta margin and, where applicable, vega margin, curvature margin, and base correlation margin components. For a set of deals in the same netting set that are within the same product class, the latter margin components are then added together for all such deals to produce the initial margin amounts at each risk class level. Within each product class, the risk-class level IMs are then aggregated as follows:

$$SIMM_{product} = \sqrt{\sum_r IM_r^2 + \sum_r \sum_{s \neq r} \psi_{rs} IM_r IM_s}\,,$$

where IM_r is the initial margin amount at risk class r and ψ_{rs} is the correlation between risk classes r and s. The SIMM IM at a netting set level is then obtained by simply adding product-class level IMs across all the product classes (and netting-set level IM can be aggregated further across netting sets with a given counterparty to produce the counterparty-level IM).

Thus, for computation of initial margin for crypto assets, SIMM's existing risk classes framework has to be augmented with a new crypto-specific risk class. In addition, we suggest creating a new crypto product class (that would allow for recognition of hedging benefits – depending on correlations – across crypto-specific risk factors) instead of trying to assign crypto assets to one of the SIMM's traditional four product classes. CoinMarketCap, a popular crypto tracking platform, currently tracks over 18,815 active cryptocurrencies. On the other hand, cryptocurrency market remains highly concentrated with the top dozen cryptocurrencies accounting for close to 90% of the total cryptocurrency market capitalization – with Bitcoin (BTC) alone accounting for 58.5% and Ethereum (ETH) accounting for an additional 12% of today's total crypto market cap (Slickcharts, 2025). Thus, from a representativeness point of view, taking a dozen of top cryptocurrencies (with a half being floating and the other half – pegged to fiat currencies) should be sufficient to reflect material cryptocurency risks in today's crypto market.

II. DATA

Our cryptocurrencies dataset consists of twelve major cryptocurrencies (six floating – Bitcoin (BTC), Binance (BNB), Ethereum (ETH), Cardano (ADA), Dogecoin (DOGE), XRP Ledger (XRP) – and six pegged – United States Dollar Coin (USDC), United States Dollar Tether (USDT), Dai coin (DAI), True USD (TUSD), Pax Dollar (USDP), and Gemini Dollar (GUSD)), selected based on their high market capitalization and trading volume, as recorded from CoinGecko, ensuring that the sample is both popular and representative of the broader crypto market. The summary statistics are presented in Table 1 below. The daily valuation data was retrieved from public sources – BitBo and CoinMarketCap.

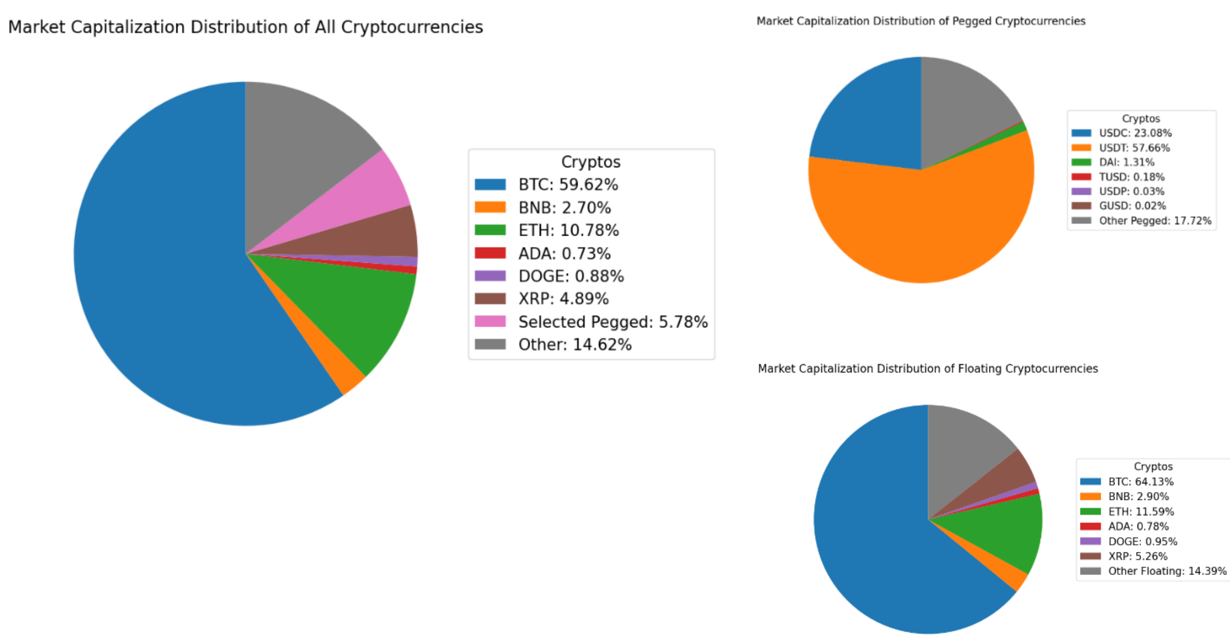
Table 1. Summary statistics of the twelve cryptocurrencies (six floating in the six top rows and six pegged in the six bottom rows) used as calibration instruments in the new crypto risk class.

Name	Trading Volume	Market Capitalization	Start Date in Our Data	End Date in Our Data	Source
BTC	47,651,779,339	2,357,505,109,332	2013-01-01	2025-07-17	BitBo
ETH	55,014,727,363	426,229,665,454	2015-08-11	2025-07-17	CoinMarketCap
XRP	10,910,775,902	193,316,833,394	2013-08-05	2025-07-17	CoinMarketCap
BNB	2,494,844,905	106,643,889,562	2017-07-26	2025-07-17	CoinMarketCap
DOGE	12,527,195,381	34,778,699,738	2013-12-16	2025-07-17	CoinMarketCap
ADA	2,121,665,898	28,852,009,245	2017-11-09	2025-07-17	CoinMarketCap
USDT	160,916,462,044	160,296,240,201	2018-10-09	2025-07-17	CoinMarketCap
USDC	11,396,661,980	64,166,332,095	2018-10-09	2025-07-17	CoinMarketCap
DAI	144,053,206	3,653,971,165	2019-11-12	2025-07-17	CoinMarketCap
TUSD	20,595,330	494,767,339	2018-10-09	2025-07-17	CoinMarketCap
USDP	2,785,816	69,931,582	2018-10-09	2025-07-17	CoinMarketCap
GUSD	173,453,860	48,728,737	2018-10-09	2025-07-17	CoinMarketCap

As illustrated in Figure 1 (below), both the floating and pegged cryptocurrency markets are very concentrated, and, collectively, market capitalization of floating cryptocurrencies far outweighs that of pegged cryptocurrencies / stablecoins. (On the other hand, in terms of trading volume, as evidenced by Table 1, USDT far outweighs the rest.)

Since SIMM methodology generally relies on pseudo-indices to determine calibration periods for each risk class, a crypto index (or several indices) representative of the behavior of the entire risk class of crypto currencies should ideally be chosen. Among available crypto indices, BGCI stands out for the following reasons: it was one of the earliest comprehensive benchmarks (launched on May 3, 2018), earlier than its alternatives such as the Nasdaq Crypto Index (2021), the CoinDesk 20 Index (2024), and the S&P Cryptocurrency Broad Digital Market Index (2021). In addition, its monthly rebalancing, as compared to the quarterly schedule of the other mentioned indices, and strict eligibility rules (requiring assets to qualify for three consecutive months and applying a 35% cap and 1% floor on weights) allow to reduce additional spikes in volatility due to rebalancing and keep it reflective of the broader cryptocurrencies market (without allowing Bitcoin to overly dominate the index).

Figure 1: Cryptocurrency Market Concentration (as of August 2025): The left pie chart shows market capitalization of selected crypto currencies as a percent of overall crypto market cap. It shows that, overall, market cap of floating cryptocurrencies far dominates that of pegged cryptocurrencies, and the twelve crypto currencies selected in this paper account for 85% of the total crypto market capitalization. The top pie chart on the right shows the six selected pegged crypto currencies as percent of total pegged crypto market by market cap. The pegged (stablecoin) cryptocurrency market is very concentrated: it is heavily dominated by USDT, with USDC coming as a remote second. The bottom chart on the right is similar but is for the floating crypto market. It shows selected floating crypto currencies as percent of total floating crypto market. The floating cryptocurrency market is very heavily dominated by Bitcoin, with ETH coming as a far behind second.



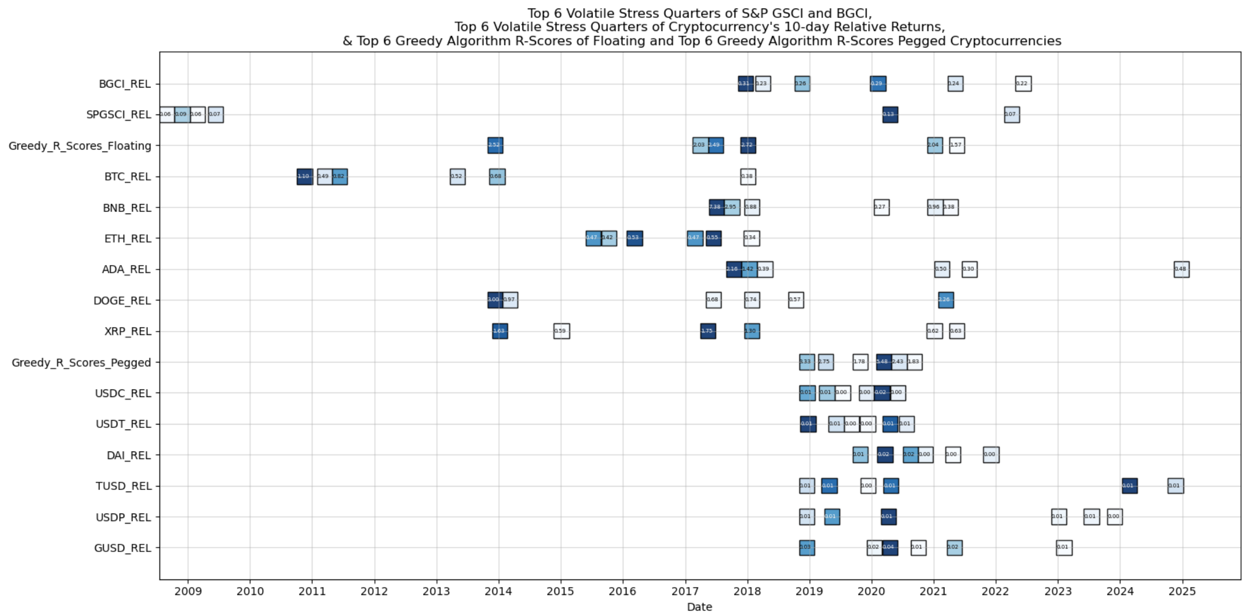
Another index used in this analysis is S&P GSCI, which ISDA employs as a single commodity index in SIMM to calibrate stress period in commodity risk class. Both BGCI and S&P GSCI data were retrieved from the Bloomberg Terminal: the BGCI series starts on 2017-08-02 and the S&P GSCI series starts on 2008-01-02, with both series spanning through 2025-07-17.

III. POTENTIAL RISK CLASS ASSIGNMENT OF CRYPTOCURRENCY BUCKETS IN SIMM

Although the U.S. Commodity Futures Trading Commission (CFTC) classifies a number of the more material cryptocurrencies (most notably, Bitcoin, Ethereum, but also others like Litecoin, Tether, etc.) as commodities (CFTC, 2017) subject to the Commodity Exchange Act – with the classification re-affirmed most recently by the US District Court in judgment for the CFTC in *Commodity Futures Trading Commn. v. Ikkurty* (2024 WL 3251348), we show that assignment of cryptocurrencies risks to the existing commodities risk class within SIMM is inadvisable due to a very different risk profile of cryptocurrencies' risk factors in comparison to traditional commodities risk factors and recommend placing crypto risks in a separate risk class.

Calibration of risk weights within each risk class in SIMM requires a determination of an additional stress period using the so-called "Stress Balance Method," which relies on identification of the top 10% of the most volatile, disjoint quarters (since Jan 2, 2008 through the last day of the current calibration period) for a pseudo-index representing that risk class. For the commodities risk class, the pseudo-index is S&P GSCI. As shown in Figure 2, a comparison of the top six most volatile quarters of S&P GSCI 10-day relative returns with the top six most volatile quarters for 10-day relative returns of the selected twelve cryptocurrencies' calibration instruments – six most material pegged cryptocurrencies and six most material floating cryptocurrencies – shows that neither the pegged nor unpegged cryptocurrencies have a similar stress periods profile as the commodities pseudo-index S&P GSCI as only one of GSCI's top six stress quarters falls close to the cryptocurrencies' top six stress quarters.

Figure 2. Comparison of top six most volatile quarters of 12 crypto instruments as well as of the commodities index S&P GSCI and the Bloomberg Galaxy Crypto Index (BGCI)



In addition, Figure 2 also confirms that the top six floating (unpegged) crypto-currencies (BTC, BNB, ETH, ADA, DOGE, and XRP) have a distinctly different clustering of the most stressful / volatile quarters than the (bottom six) pegged crypto-currencies/stablecoins (USDC, USDT, DAI, TUSD, USDP, GUSD), suggesting that the assumed split into two cryptocurrencies' buckets based on pegged vs. unpegged nature was the right call. Among potential candidates for a crypto (pseudo)index used for determination of a separate cryptocurrency risk class stress period is Bloomberg Galaxy Crypto Index (BGCI), which tracks well four of the most volatile quarters among the selected floating cryptocurrencies. However, given the differences in stress quarters' distribution across floating versus pegged cryptocurrencies, one may either use a second "pseudo-index" (say, USDT) to determine a separate stress period for pegged currencies or rely on ISDA's new "greedy"[1] algorithm (applied across all twelve selected calibration instruments) to determine the calibration period(s) for the floating and pegged cryptocurrencies' buckets.

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[1] The "greedy" algorithm is used here with permission of ISDA, and ISDA reserves full rights to the algorithm. It works as follows: Suppose there is a set of N time series over a period T, and one wants to select n most stressed, disjoint time intervals of fixed length m for that set of time series. Then take a rolling window i of length m (starting at the beginning of period T), compute the corresponding R-score R(i) defined by equation (1), then shift the window to the right by one day, compute the corresponding R-score again, and so on, until the last day of the rolling window coincides with the last day of period T. Then rank the resulting R-scores in decreasing order and pick the period i_1 with the highest R-score. Then discard any periods i of length m that overlap with i_1. Then from those left, find the period i_2 with the next highest R-score. Then discard any periods i of length m overlapping i_2. Then repeat this process until i_1, i_2, …, i_n are selected. In this paper, the algorithm is used to determine top six stress quarters for a given risk bucket or risk class (instead of a pseudo-index, like it is currently done in SIMM), with the set of time series being the set of calibration instruments in that risk bucket or risk class. If some of these six most stressed quarters fall in the recent 3-year period, the additional stress period gets reduced to a smaller number of quarters, say, s (like is currently done in SIMM). Then the "greedy" algorithm is used *again* to find a *continuous* single period of s quarters in length (with the highest R-score) to determine the additional stress period (which together with the recent period is then used for calibration of risk weights in that risk bucket or risk class).

(The “greedy” algorithm was introduced in SIMM version 2.8 for determination of a global stress period and is currently *not* used in SIMM for calibration period selection for individual risk classes, likely due to being too computationally costly for application in buckets/risk classes with thousands of calibration instruments). However, since cryptocurrencies’ buckets have few calibration instruments due to crypto industry’s concentration, the “greedy” algorithm is feasible to use for the crypto risk class and, as Table 5 subsequently illustrates, it provides superior results for calibration period determination for delta risk weights of the two cryptocurrencies’ buckets relative to the other methods considered.

To see the effect of placing cryptocurrencies risk factors into a separate risk class versus placing them into two additional buckets within the existing commodities risk class, we compare the corresponding calibrated delta risk weights of cryptocurrencies’ buckets based on differing calibration periods used for the two cases, while keeping the overall method of calibration the same. In SIMM 2.7+2412 (used by the industry during the half-year starting on July 12, 2025), the calibration of the commodities risk class is based on the calibration period comprised of two distinct periods: a 3-quarter stress period from September 13, 2008 through June 12, 2009 and the “recent period” from October 1, 2021 through December 31, 2024. If two new cryptocurrencies’ buckets (pegged and unpegged) are added to that calibration, the resulting calibrated delta risk weights are as follows:

Table 2. Delta risk weights of commodity risk class buckets based on SIMM 2.7+2412 calibration period with additional 2 crypto buckets in commodity risk class.

Bucket	Description	Delta Risk Weight
1	Coal	48
2	Crude	21
3	Light Ends	23
4	Middle Distillates	20
5	Heavy Distillates	24
6	North American Natural Gas	33
7	European Natural Gas	61
8	North American Power	37
9	European Power and Carbon	64
10	Freight	45
11	Base Metals	21
12	Precious Metals	17
13	Grains and Oilseed	16
14	Softs and Other Agriculturals	17
15	Livestock and Dairy	10
17	Indexes	16

18	Crypto Floating	58
19	Crypto Pegged	1

(Note: Bucket 16 is skipped as its delta risk weight is not calibrated but set to be the maximum risk weights of buckets 1-15. Note also that the more precise calibrated delta risk weight for bucket 19 (pegged crypto) is 0.72 but, since SIMM uses rounded to the nearest integer risk weights, its delta risk weight is rounded to 1.)

Table 2 illustrates that, when placed in the commodities risk class, the floating cryptocurrency bucket has one of the top three delta risk weights in that risk class (and much higher than that of gold/precious metals with which crypto are often compared as a store of value), while the pegged cryptocurrency bucket naturally has a very low risk weight. Yet, as we will see soon, these calibrated delta risk weights for crypto are poorly estimated due to the fact that stress periods for cryptocurrencies are very different from those of traditional commodities.

Indeed, suppose cryptocurrency risk factors are put in a separate risk class with individual calibration periods for each of the two buckets (owing to the stark differences between the two). Then the new delta risk weights for cryptocurrency buckets depend on whether BGCI (or some other representative crypto index) is used for the cryptocurrency risk class overall or whether the "greedy" algorithm is used to determine the stress periods for each of the two buckets separately because, as shown in Table 3, the stress period for the pegged cryptocurrency bucket shifts as a result.

Table 3. Estimated calibration period for crypto risk class based on either BGCI or the "greedy" algorithm for the observation period in SIMM 2.7+2412.

Calibration Period Based on Either BGCI or "greedy" algorithm				
	Based on BGCI		Based on "greedy" algorithm	
	Additional Stress Period	Recent Period	Additional Stress Period	Recent Period
Crypto Floating	Nov 22, 2017 – Nov 21, 2018	Jan 1, 2022 – Dec 31, 2024	Nov 29, 2016 – Nov 28, 2017	Jan 1, 2022 – Dec 31, 2024
Crypto Pegged	Nov 22, 2017 – Nov 21, 2018	Jan 1, 2022 – Dec 31, 2024	Apr 23, 2019 – Apr 22, 2020	Jan 1, 2022 – Dec 31, 2024

The calibration periods for a cryptocurrencies' bucket's delta risk weight are obtained by first identifying top 10% of the most volatile quarters for each of the 13 time series (10-day relative return of BGCI and 10-day relative returns of each of the twelve crypto currencies (BTC, BNB, ETH, ADA, DOGE, XRP, USDC, USDT, DAI, TUSD, USDP, GUSD)) for the historical period (in SIMM 2.7+2412) from Jan 2, 2008 through Dec 31, 2024. The latter historical period covers 17 years (or 68 quarters), so top 10% of the most volatile (disjoint) quarters consists of six most volatile quarters. Unlike ISDA has done for the traditional risk classes, we choose to round the number of most volatile quarters down rather than up because there were no cryptocurrencies in 2008, while in 2009, BTC was the only one launched and with no standard pricing until mid-2010 (with all the other cryptocurrency instruments launched some years later). Next, we find how many of the six most stressed/volatile quarters fall in the "recent" 3-year period of 2022-2024. For BGCI, the number of "recent stress" quarters is 0, so the "recent" period is from Jan 1, 2022 through Dec 31, 2024, and the number of non-recent stress quarters must be 4, so the stress period for BGCI is obtained by finding a continuous year (continuous period of 365 calendar days) prior to 2022 with the highest volatility of returns. Similarly, for the "greedy" algorithm approach, the number of "recent stress" quarters is 0 for both pegged and unpegged (floating) crypto (as seen in Table 4), so the stress period for each bucket is obtained by finding (using a rolling by a day window) a continuous year prior to 2022 with the largest cumulative R score, where

$$R(i) = \sum_k \frac{vol(k,i)}{MaxVol(k)}, \qquad (1)$$

where i is a rolling 1-year period prior to 2022, k is an instrument in a given bucket, vol(k,i) is the average daily volatility of the kth instrument's returns over period i, and MaxVol(k) is the maximum of the average daily volatility of the kth instrument's returns over all 1-year periods prior to 2022. It is worth noting that, as is clear from Table 4, although R scores from the greedy algorithm can be compared for the same fixed set of instruments across time (with higher R scores generally representing a more volatile period for that set of instruments), they should not be compared across different sets of instruments (as evidenced by the fact that R scores for a set of pegged crypto instruments are often higher than R scores of a set of floating/unpegged crypto instruments).

Table 4. Top six most stressed quarters (as measured by cumulative R scores) for 10-day relative returns for the two cryptocurrencies' buckets (each with six instruments).

Instrument	Quarter Start	Quarter End	R score in quarter
Floating Crypto bucket with "greedy" algorithm	11/08/2017	02/06/2018	R_score: 2.72
	09/21/2013	12/20/2013	R_score: 2.52
	05/16/2017	08/14/2017	R_score: 2.49
	11/21/2020	02/19/2021	R_score: 2.04
	04/02/2021	07/01/2021	R_score: 2.03
	05/19/2015	08/17/2015	R_score: 1.57
Pegged Crypto bucket with "greedy" algorithm	03/04/2020	06/02/2020	R_score: 5.48
	07/19/2018	10/17/2018	R_score: 3.33
	11/26/2019	02/24/2020	R_score: 2.75
	10/24/2018	01/22/2019	R_score: 2.43
	06/19/2020	09/17/2020	R_score: 1.83
	04/25/2019	07/24/2019	R_score: 1.78

Once the additional one year of stress is determined through both methods (by the pseudo-index BGCI method and by the cumulative R scores via greedy algorithm), we calibrate delta risk weights for cryptocurrencies' buckets by finding the median – across all six instruments in each bucket – of the maximum of absolute values of the 1^{st} and 99^{th} percentiles of the 10-day overlapping relative returns of each instrument over the 3-year recent period plus the year of stress. The resulting calibration of delta risk weights for pegged and unpegged cryptocurrencies' buckets, as shown in Table 5, illustrates that once stress period selection is specific to each cryptocurrency bucket, the delta risk weights for cryptocurrencies' buckets rise by at least a factor of two (relative to being kept in the commodities risk class).

Table 5. Comparison of delta risk weights of pegged and floating crypto buckets placed in a separate crypto risk class versus in the commodity risk class, depending on which method (BGCI or greedy algorithm) is used to select the calibration period.

Crypto Bucket's delta risk weight	In Commodity Risk Class	In Crypto Risk Class with calibration period based on BGCI volatility	In Crypto Risk Class with calibration period based on R scores from greedy algorithm
Floating Crypto	58	132	132
Pegged Crypto	1	1	2

In other words, Table 5 shows that placing crypto buckets in commodity risk class significantly underestimates delta risk weights of the crypto buckets (with delta risk weights being at least twice smaller than when a separate cryptocurrency risk class is used). On the other hand, Bloomberg Galaxy Crypto Index appears to capture volatility of floating crypto currencies very well but does not work nearly as well to represent pegged crypto currencies. Overall, the calibration of floating crypto and pegged crypto buckets based on calibration periods determined separately for each bucket using the "greedy" algorithm produces the most reliable result (of the three approaches considered here) in view of the stark differences between the risks of the two crypto buckets and their significant differences from the risks of traditional commodities.

IV. CORRELATIONS

All the correlations (cross-risk classes correlations ψ_{rs}, as well as inter-bucket and intra-bucket ones) used in ISDA SIMM are estimated using (nonparametric) Kendall's correlation coefficient τ_B that is then converted to Pearson correlation coefficient estimate through $\sin(0.5\pi\tau_B)$ transformation as proposed in Kendall's book. The initial non-parametric approach (in the form of Kendall's correlation) is adopted in SIMM to make the estimation less sensitive to outliers, but SIMM model still aims to capture linear relationships between risk factors rather than monotonic ones (due to the underlying variance-covariance structure of decompositions in

SIMM), so the given (scaled) sine transformation provides an estimate of the Pearson correlation once the influence of outliers is accounted for. Another popular non-parametric correlation – rank-based Spearman's correlation – is, in general, statistically less preferable than Kendall's due to its downward bias and slower convergence to Gaussian distribution with sample size. To see a more explicit comparison of different types of correlation and their robustness properties, consider an MA(1) process of the form: $X_t = \varepsilon_t + \alpha\varepsilon_{t-1}$, where ε_t are i.i.d. $N(0, \sigma_\varepsilon^2)$, and a second time series Y, which is a linear function of X plus white noise: $Y_t = \phi X_t + \delta_t$, where δ_t are i.i.d. $N(0, \sigma_\delta^2)$, with (δ_t) process independent of (ε_t) process. Then the true correlation parameter between X and Y is given by:

$$E((X_t-E(X_t))(Y_t-E(Y_t)))/[Var(X_t)Var(Y_t)]^{1/2} = \phi E(X_t^2)/[(E(X_t^2)\{\phi^2 E(X_t^2)+ \sigma_\delta^2\}]^{1/2}$$

$$= \phi/[\phi^2+ \sigma_\delta^2/\{(1+\alpha^2)\sigma_\varepsilon^2\}]^{1/2},$$

so if $\phi=0$, the true contemporaneous correlation between processes X and Y is zero (as expected), while if $\phi\neq 0$, the true correlation parameter is $\mathrm{sign}(\phi)/[1+\sigma_\delta^2/\{\phi^2(1+\alpha^2)\sigma_\varepsilon^2\}]^{1/2}$, with function sign(x) set to 1 for positive x and -1 for negative x. (Naturally, as $\sigma_\delta^2 \to 0$, Y becomes just a linear function of X, so the correlation converges to 1 for $\phi>0$ and -1 for $\phi<0$.) For example, taking a simple example of $\sigma_\varepsilon = \sigma_\delta = 1$, $\phi=0.8$, and $\alpha=0.4$ gives a theoretical true correlation of $1/(1+1/[\{0.64(1+.16)\}]^{1/2} = 0.6527472$. To see the behavior of sample correlation coefficients (Pearson, Spearman, Kendall, and Kendall's conversion to Pearson), we simulate the corresponding time series X and Y (of n=100 time points each) and compute all four types of sample correlations. Then in the X series, we replace one of the observations with an outlier that is $10\sigma_\varepsilon$ in size. Afterwards, in the Y series, we replace one of the observations with an outlier that is $-15\sigma_\delta$ in size (as shown in Figure 3). Then we recompute all four types of sample correlations. Then we repeat this simulation N=1000 times and compute the average of each of the four correlation types before and after inserting two outliers. The simulation results are summarized in Table 6 and show that the scaled sine transformation $\sin(0.5\pi\tau_B)$ of Kendall's sample correlation (converted to Pearson's coefficient) is both accurate and more robust than the other alternatives.

Figure 3. A simulated run of MA(1) process X and process Y, which is a linear function of X plus independent white noise, over a hundred timepoints, where one outlier (marked by a red upward dot) is inserted in X and one outlier (marked by another red dot) is inserted in Y.

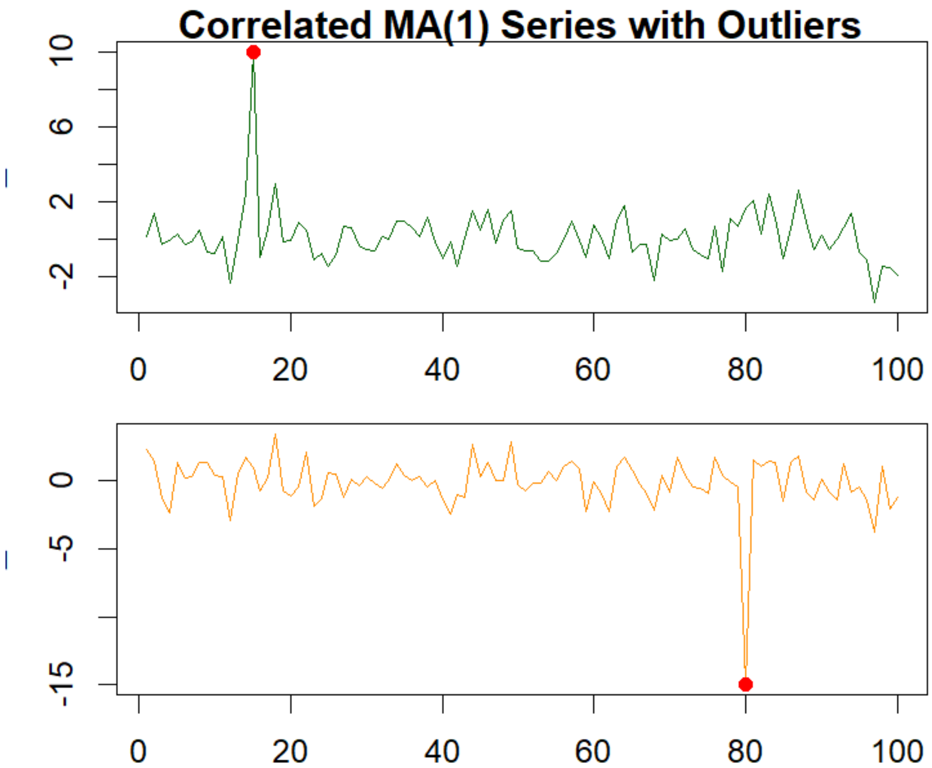


Table 6. Comparison of Pearson's, Spearman's, Kendall's, and Kendall's-transformed-to-Pearson sample correlation coefficients between simulated time series X and Y (with n=100 time points each and N=1,000 simulation runs), where X is MA(1) and Y is a sum of ϕX (with ϕ=0.8) plus independent white noise, before and after adding a couple of outliers (as in Figure 3).

True correlation is 0.6527472	Average Pearson's r	Average Spearman's ρ	Average Kendall's τ_B	Average $\sin(0.5\pi\tau_B)$
No outliers	0.6503504	0.6292351	0.4528388	0.6504231
With outliers	0.3170934	0.6051634	0.4354695	0.6295742

Table 6 illustrates the high sensitivity of the classical sample Pearson's correlation to outliers as Pearson's correlation coefficient drops below half of its original value (from 0.6503504 to 0.3170934) once a couple of outliers is introduced. In contrast, the three columns with non-parametric correlations show little change in response to the insertion of outliers. (In addition, the non-parametric versions of sample correlation are expected to be more robust than the Pearson's correlation once the Gaussian assumption for X and Y is dropped.) Further comparison of each of the four sample correlation coefficients with the true population correlation (of 0.6527472) shows that Kendall's-transformed-to-Pearson sample correlation coefficient (in the last column) is highly accurate relative to the other common estimates of correlation, and this overall result generally remains stable when various parameters of the simulation (including the number of simulation runs, the length of time series, the coefficients and the order of the moving average process X, linear coefficient ϕ in Y, and the volatilities of noises) are perturbed. Hence, ISDA's choice of correlation estimate – based on the specified conversion of Kendall's coefficient to Pearson – appears to be optimal from the combined accuracy and robustness points of view and is therefore adopted in the rest of this paper.

Proceeding with intra-bucket correlations of the two cryptocurrencies' buckets based on the 3 recent years (2022-2024) plus one year of stress, where a single stress period is selected for the entire crypto class using the "greedy" algorithm (which results in the 11/27/2017 – 11/26/2018 additional stress period), produces estimated intra-bucket correlations shown in Table 7, with intra-bucket correlation for the floating crypto bucket being significantly higher than the one for the pegged crypto bucket (the latter is very low suggesting that once the pegging to USD is accounted for, the rest of the variation across pegged instruments is rather idiosyncratic).

Table 7. The calibration of intra-bucket correlations in the crypto risk class based on the recent period of three years (2022-2024) plus one year of stress (the latter is found by computing R scores across all twelve calibration instruments in the crypto risk class and applying the "greedy" algorithm to determine a single year of additional stress for the crypto risk class).

Crypto Bucket	Kendall-to-Pearson intra-bucket correlation	Recent period	Additional stress period
floating	73%	1/1/2022 – 12/31/2024	11/27/2017 – 11/26/2018
pegged	14%		

However, although the above identification of a single calibration period for the entire crypto risk class is consistent with the approach adopted in ISDA SIMM, it is far from ideal for pegged crypto bucket because the stress period of 11/27/2017 to 11/26/2018 includes only one month when "pegged" crypto had trading data. Given this data limitation, like in the case of delta risk weights, it may still be advisable to calibrate individual calibration periods for the two cryptocurrencies' buckets. In the latter case, the new intra-bucket correlations are revised in accordance with Table 8 (with the intra-bucket correlation for floating crypto bucket staying unchanged, but with the intra-bucket correlation for pegged crypto bucket rising by about 6%).

Table 8. The calibration of intra-bucket correlations in the crypto risk class based on separate calibration periods for the two buckets (each calibration period is selected based on "greedy" algorithm applied to six instruments in each crypto bucket).

Crypto Bucket	Kendall-to-Pearson intra-bucket correlation	Recent period	Additional stress period
floating	73%	1/1/2022 – 12/31/2024	11/27/2017 – 11/26/2018

pegged	20%	1/1/2022 – 12/31/2024	4/23/2019 – 4/22/2020

Note that instead of using the “greedy” algorithm as in Table 8, one could use BGCI as a pseudo-index for determination of the calibration period for floating crypto bucket and USDT as a “pseudo-index” for pegged crypto bucket, but the resulting intra-bucket correlations would stay close to those in Table 8. (As before, using a single pseudo-index like BGCI for the entire crypto class is inadvisable since the stress period ends up including only about one month of pegged crypto data, so it’s not representative of the stress period for pegged cryptocurrencies.) Note also that the stress period for the floating crypto bucket in Table 8 is different from the stress period in the fourth column in Table 3, even though both are based on the “greedy” algorithm for individual crypto instruments in the floating bucket, because delta risk weight calibration requires only a single instrument to be available in a bucket (and Bitcoin started much earlier than the other floating crypto instruments), whereas intra-bucket correlation calibration requires availability of at least two instruments, so the time horizons within which a stress period selection takes place are necessarily different in the two cases.

To determine the inter-bucket correlation between floating and pegged crypto buckets, we compute pairwise correlations between each instrument in the floating crypto bucket and each instrument in the pegged crypto bucket and take the median of all such correlations (this is consistent with the approach taken in SIMM for the other risk classes). To avoid computing 6^2=36 separate calibration periods for each pair of instruments, we select the calibration period based on BGCI and USDT as pseudo-indices. Noting that none of the top six most volatile (in terms of R scores) quarters of BGCI and none of the top six most volatile quarters of USDT fall within the 3-year recent period of 2022-2024, we select a continuous, one-year additional stress period that falls within the period of 10/23/2018 (start date of USDT returns time series to ensure that both USDT and BGCI return time series are available) to 12/31/2021 (the last day before the start of the 3-year recent period). That additional 1-year stress period can be chosen by maximizing the sum of R scores of BGCI and USDT. (This represents a slight departure from ISDA SIMM’s methodology in other risk classes where the calibration period for inter-bucket correlations coincides with the calibration period for delta risk weights in that risk class. This is because we have chosen to use *separate* calibration periods for delta risk weights for the two crypto buckets, given how different the two crypto buckets stress periods are and the shorter availability of data for pegged cryptocurrencies versus the floating cryptocurrencies. As a result, a separate single calibration period had to be chosen to compute the inter-bucket correlation between the floating and pegged crypto buckets.)

Table 9. The calibration of inter-bucket correlation between the floating and pegged crypto buckets based on the stress period obtained using the "greedy" algorithm that maximizes the sum of R scores for BGCI and USDT pseudo-indices.

Pearson	Spearman	Kendall	Kendall-to-Pearson conversion	Additional stress period (mm/dd/yyyy)	Recent period
−2%	−3%	−2%	−4%	11/10/2018 – 11/09/2019	01/01/2022 – 12/31/2024

We included all four types of correlation in Table 9 to double-check the consistency of signs and variability of inter-bucket correlations of different types. The results show that the inter-bucket correlation between floating and pegged crypto is slightly negative and very close to zero regardless of the specific type of correlation coefficient used. Given that these sample correlations are estimates (subject to estimation errors) and extremely close to zero, we suggest setting the inter-bucket correlation between the floating and pegged crypto buckets to zero.

Finally, to determine the cross risk class correlations between the cryptocurrency risk class and each of the other six traditional risk classes, we suggest representing the cryptocurrency risk class via 10-day relative returns of two representative instruments: BGCI and USDT. Meanwhile, each traditional risk class in SIMM is represented by the 10-day returns across representative instruments currently adopted in ISDA SIMM and listed in Table 10.

Table 10: Cross risk class correlation representative instruments

Risk Class	Risk Factor(s)
Interest Rates	10-year swap rates of G4 currencies: USD, GBP, JPY, and EUR
FX	USD/JPY, JPY/USD, EUR/USD, USD/EUR, EUR/JPY, JPY/EUR, EUR/GBP, GBP/EUR, GBP/USD, USD/GBP, GBP/JPY, JPY/GBP
Equity	S&P 500, Nikkei 225, Euro Stoxx 50, FTSE 100
Credit Qualifying	5-yr CDX.NA.IG, CDX.NA.HY, iTraxx Europe and iTraxx Europe Crossover
Credit Non-qualifying	CMBX.NA.A, CMBX.NA.AA, CMBX.NA.AAA, CMBX.NA.BB, CMBX.NA.BBB-
Commodity	S&P GSCI
Cryptocurrency	BGCI, USDT

Two possible approaches to calibration of cross-risk class correlations can be explored (and are in line with the existing approaches taken in ISDA SIMM). One is, for a given pair of risk classes (i,j), take all possible pairs of representative instruments (with one instrument from risk class i and the second instrument from risk class j), compute the corresponding correlation for each such pair of representative instruments, and then compute the median of absolute values of such correlations (the correlations are Kendall's correlations converted to Pearson, as discussed earlier). Under this approach, assume first that the cryptocurrency risk class is represented by a single representative USDT. Then, as shown in Table 11, all cross-risk class correlations between crypto risk class and the traditional risk classes are very low.

Table 11. Cross risk class correlations between crypto risk class represented by USDT and the traditional six risk classes. The additional stress period was calibrated by using the "greedy" algorithm as the one-year period that maximizes the sum of R score for USDT and the average R score across representative risk factors from Table 10 for Risk Class 2.[2] [3]

Risk Class 1	Risk Class 2	Correlation parameter	Additional stress period (mm/dd/yyyy)	Recent period
Crypto-USDT	Commodity	5%	01/21/2020 – 01/20/2021	01/01/2022 – 12/31/2024
Crypto-USDT	Equity	6%	12/10/2019 – 12/09/2020	01/01/2022 – 12/31/2024
Crypto-USDT	IR	11%	10/24/2018 – 10/23/2019	01/01/2022 – 12/31/2024
Crypto-USDT	CreditQ	4%	10/26/2018 – 10/25/2019	01/01/2022 – 12/31/2024
Crypto-USDT	CreditNonQ	3%	06/18/2019 – 06/17/2020	01/01/2022 – 12/31/2024
Crypto-USDT	FX	12%	06/27/2019 – 06/26/2020	01/01/2022 – 12/31/2024

In particular, the low correlations in Table 11 between USDT and the commodity risk class and between the USDT and the equities risk class are further illustrated in Figure 4 using the scatter

[2] Unlike ISDA who uses the same calibration period – global stress period (Sept 13, 2008 to June 12, 2009 in SIMM 2.7+2412) plus global recent period – to calibrate *all* cross risk class correlations, we here calibrate individual stress periods across pairs of each crypto bucket with the other risk classes (plus add the 3-year recent period) for cross-class correlation parameter estimation not only because it generally results in more accurate correlations but, more crucially, because crypto markets did not yet exist during this ISDA SIMM global stress period.

[3] Although ISDA's "greedy" algorithm calls for a simple addition of R scores across instruments, we opt to average R scores across risk factors within each non-crypto risk class before summing them for different risk classes because, as is clear from Table 10, some risk classes contain only one risk factor, while others contain a lot more, so a simple addition of R scores across all the risk factors in a given pair of risk classes would bias the stress period selection towards a risk class with a higher number of representative risk factors.

plot matrices of USDT versus S&P GSCI and of USDT versus S&P 500 (one of the four risk factors in equities class).

Figure 4. Scatter plot matrix of USDT versus S&P GSCI showing very low correlation between the two.

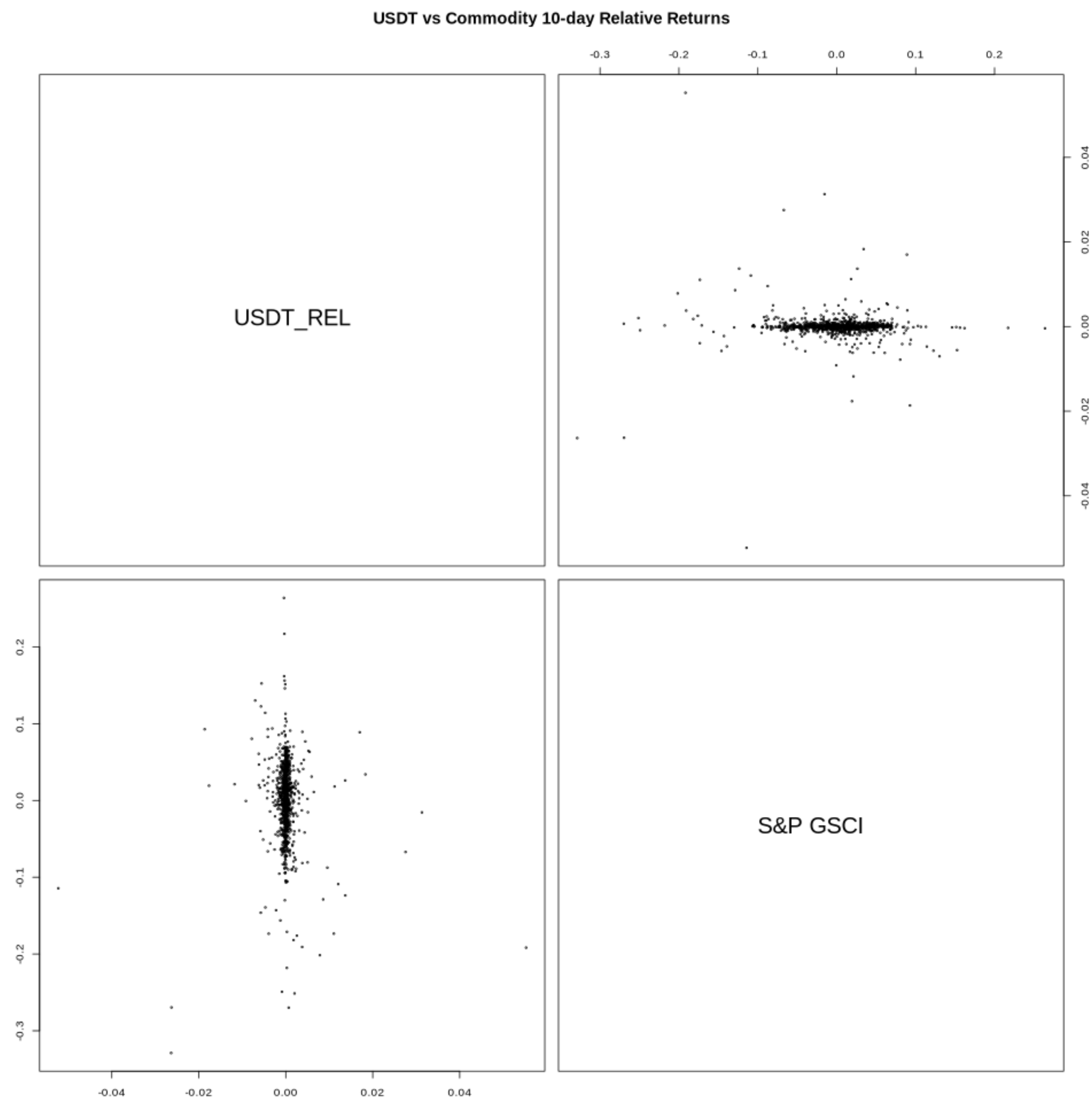
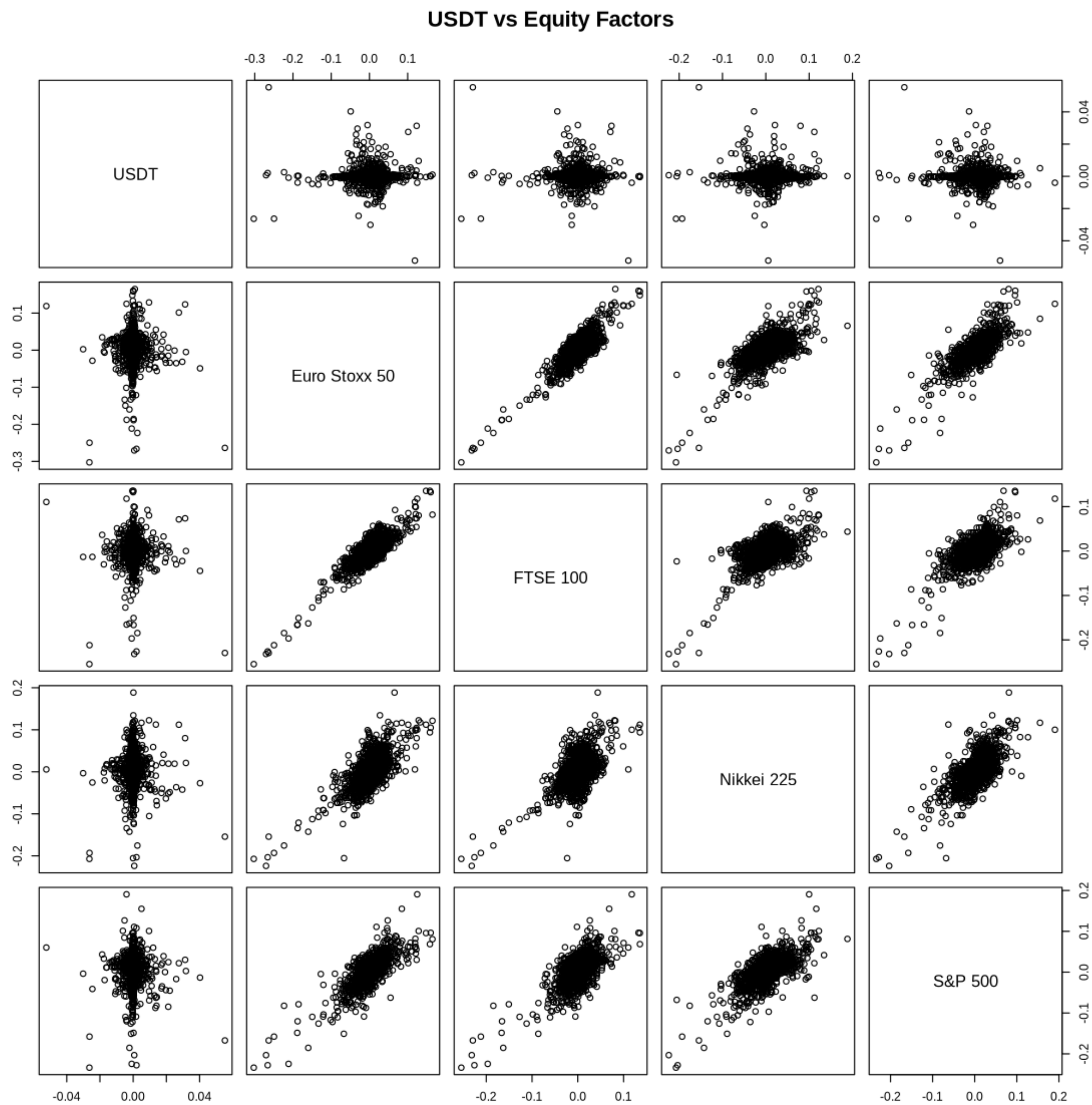


Figure 5. Scatter plot matrix of USDT 10-day relative returns versus equity indices' 10-day relative returns (as in Table 11) showing very low correlation between USDT versus representative equity indices (as evidenced by the top row or the left most column of the "matrix"). (This is in contrast to the strong positive correlations between the four equities indices evidenced by the sub-matrix of the second through the last rows and columns.)



On the other hand, if the cryptocurrency risk class is represented by BGCI (instead of USDT), the cross-risk class correlation parameters between cryptocurrency risk class and the traditional risk classes remain very low (and broadly similar, with mainly the correlation with FX risk class dropping in magnitude from 12% to 2%, while correlation with Credit Qualifying risk class rises from 4% to 11%). (These very low cross-risk class correlation parameters between crypto and the other risk classes remain robust with respect to taking other common types of correlation and to varying the stress period.)

Table 12. Cross risk class correlations between crypto risk class represented by BGCI and the traditional six risk classes.

Risk Class 1	Risk Class 2	Correlation parameter	Additional stress period (mm/dd/yyyy)	Recent period
Crypto-BGCI	Commodity	9%	11/28/2017 – 11/27/2018	01/01/2022 – 12/31/2024
Crypto-BGCI	Equity	2%	11/01/2017 – 10/31/2018	01/01/2022 – 12/31/2024
Crypto-BGCI	IR	13%	08/21/2017 – 08/20/2018	01/01/2022 – 12/31/2024
Crypto-BGCI	CreditQ	11%	11/29/2017 – 11/28/2018	01/01/2022 – 12/31/2024
Crypto-BGCI	CreditNonQ	2%	08/21/2017 – 08/20/2018	01/01/2022 – 12/31/2024
Crypto-BGCI	FX	2%	08/25/2017 – 08/24/2018	01/01/2022 – 12/31/2024

Here we can similarly illustrate low correlation parameters between floating crypto and commodities and equities risk classes through scatter plot matrices (in Figure 6) of floating crypto index BGCI versus S&P GSCI and in Figure 7 of BGCI versus S&P 500.

Figure 6. Scatter plot matrix of BGCI 10-day relative returns versus S&P GSCI 10-day relative returns (same period as in Table 11) visually showing very low correlation between the two.

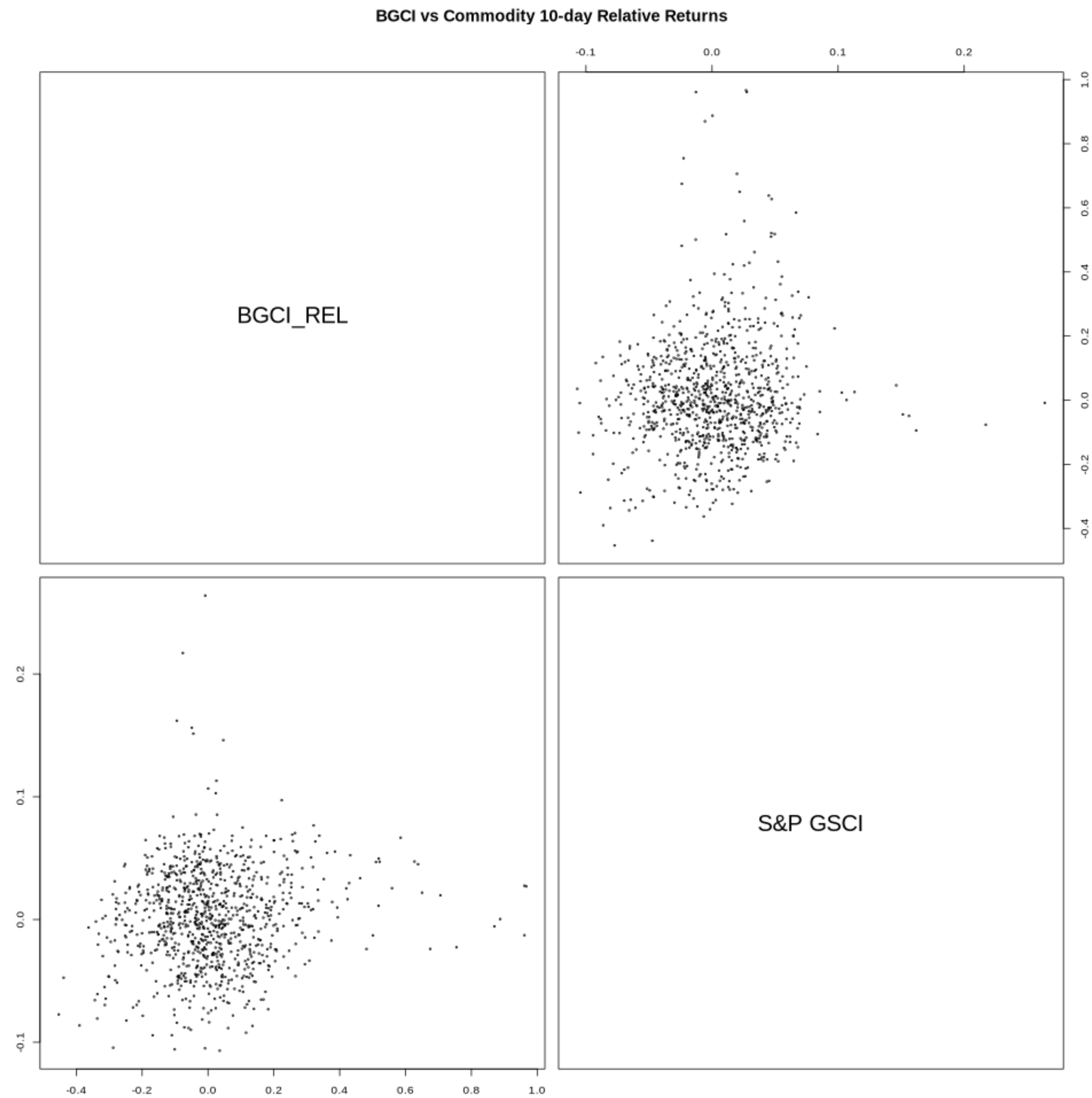
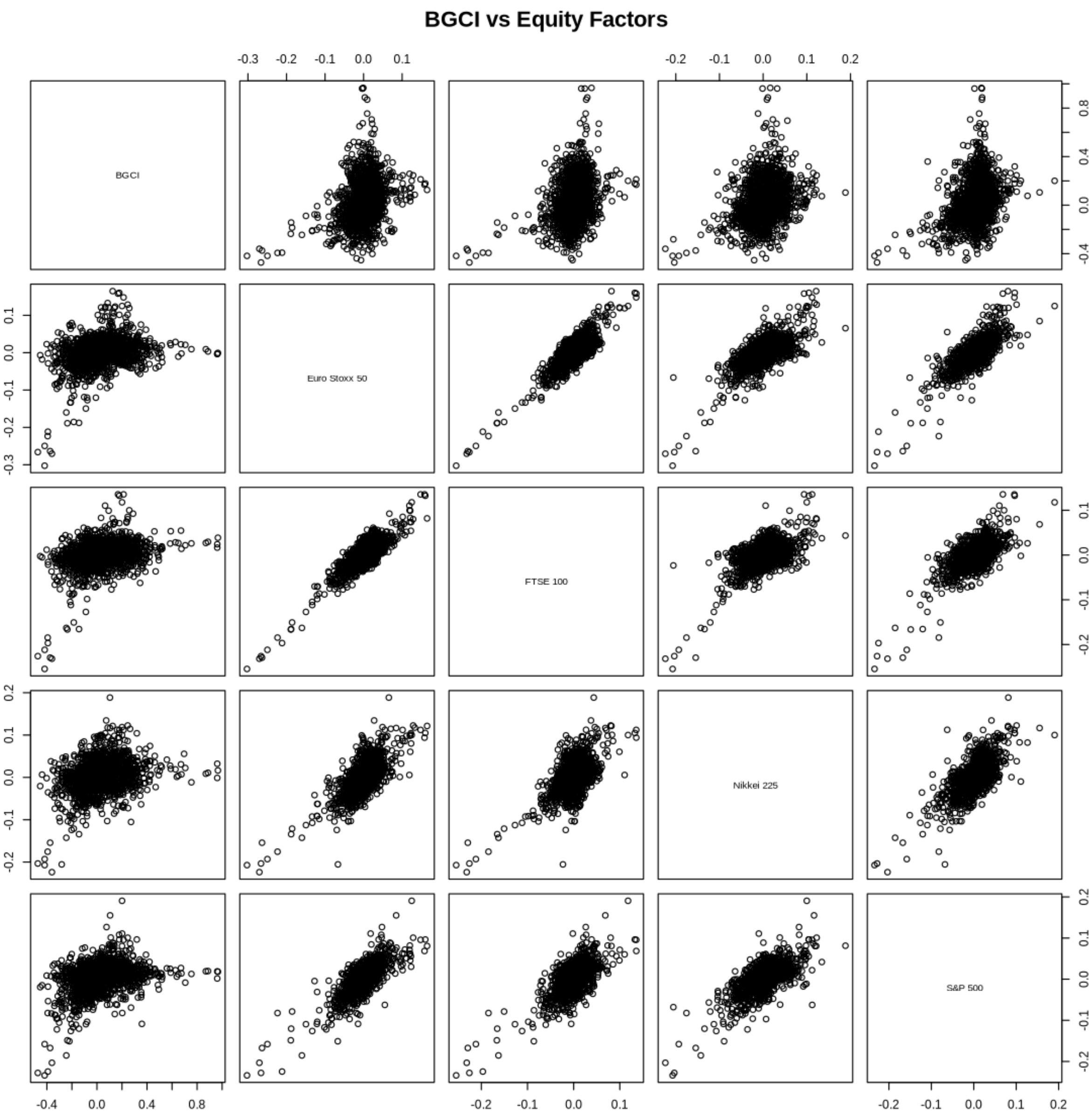


Figure 7. Scatter plot matrix of BGCI 10-day relative returns versus equity risk factors' 10-day relative returns (as in Table 11) visually showing (in the top row or left most column of the "matrix") very low correlations between BGCI and each (of the four) equity indices.



Given the similarly low correlation parameter values in Table 11 and Table 12 between the crypto risk class and the six traditional risk classes, these results suggest that correlations of crypto risks with other risk classes are low for both pegged and floating cryptocurrencies, and the use of both (at once) BGCI and USDT as two representative instruments for cryptocurrencies risk class would yield essentially the same results.

A second approach for cross-risk class correlation calibration is to build a single pseudo-index for each risk class (by taking a median of 10-day returns across all the representative instruments in each given risk class). Then the cross-risk class correlation parameter between each pair of risk classes could be set to equal the absolute value of correlation between respective pseudo-indices. This approach is less attractive for cryptocurrency risk class because USDT and BGCI have substantially different scales and stress periods, so averaging the two series is likely to yield a synthetic index that is not capable of capturing realistic cross-risk class correlations for either the pegged or the floating crypto cases.

V. CONCLUSIONS

Today's rapid development of crypto markets makes it necessary to incorporate new crypto product class and cryptocurrency risk class in the SIMM model to reduce counterparty risk associated with uncleared trading of derivatives sensitive to crypto risk factors. While conceptual hedging considerations suggest introduction of a separate crypto product class, it is the significantly different stress periods' profile, large underestimation of the cryptocurrencies' delta risk weights, and the extremely low cross-risk class correlations between cryptocurrency and the traditional risk classes that drive the need to separate cryptocurrencies' risk factors into a separate risk class rather than create crypto buckets within one of the already existing six risk classes. The proposed calibrations of delta risk weights in cryptocurrencies buckets and respective intra-bucket, inter-bucket, and cross-risk class correlations have the advantage of being simple to compute, robust to outliers and missing data, and consistent with the ISDA SIMM existing methodology. In addition, with crypto trading being highly concentrated in just a few instruments, and pegged and floating cryptocurrencies having substantially different stress period profiles, delta risk weights for the pegged versus floating cryptocurrencies' buckets should ideally be calibrated based on separate calibration periods (specific to each bucket). On the other hand, for the purposes of computing cross risk class correlations between crypto risk class and each of the six traditional risk classes, one could potentially use a pair of representative crypto indices (one from each of the floating and pegged crypto buckets, like BGCI and USDT in our approach) to calibrate a single correlation parameter (based on Kendall's correlation coefficient converted to Pearson for robustness against outliers) per each pairing of crypto risk class with a non-crypto risk class. Finally, this is the first systematic study in academic literature of inclusion of crypto risks into IM model, while keeping the model simple – and, thus, applicable industry-wide – and, at the same time, reflecting the unique risks associated with crypto.

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