Dependencies on PXE futures market: Pitfalls of correlation coefficient and copula function application

Igor Paholok

Abstract

Margin requirements derived from opened futures position plays a key role of the futures exchanges risk management. Assuming that the margin coefficient for each futures product was calculated correctly, we face another problem to solve: How to sum up margins requirements from different products to get an overall margin requirement per trading participant? The netting might be applied if we have the evidence of cross product price changes dependencies. This paper examines possibilities of dependencies measurement on PXE futures market, where no netting is applied in the process of margin requirement calculation. The pitfalls of Pearson’s correlation coefficient are illustrated and the copula function proposed as an appropriate alternative.

Key words

Pearson’s correlation coefficient, copula function, PXE, futures margining

1. Introduction

Studying and quantifying of reciprocal dependencies on financial, commodities and all other markets is the key issue of fundamental and stochastic modeling. Whenever we deal with more than one product in a portfolio, we need to operate with an interaction of products we hold. Portfolio effects have to be considered in the process of speculative decision making, creating of appropriate hedging strategy or quantifying Value at Risk figures etc.

Another good example of similar application is future margin netting. Margin requirements is usually quantified from the opened position of the trading participant on futures exchange markets. Margins are required by exchange/clearing house from the clearing members for each trading participant, non clearing member which belongs under particular clearing member. Similar proceeding is applied on the Power Exchange Central Europe, a.s. (PXE). In contrary with economic hypothesis of dependencies among different products existence, the netting or portfolio effect of margin requirements calculated separately for particular products, which is held by each trading participant, is not applied. Margin requirement for each product are summed up together without consideration of any possible interaction and without consideration whether we sum up only long positions or long and short position together.

The purpose of this paper is to examine relations between different futures products traded on PXE in order to identify possibility of margins netting application.

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Introduction continues with literature review and analysis of market and data characteristics. Relations quantification (including short methods theory descriptions) is then presented within three separated chapters: correlation coefficient, copula function, and copula function and cross margining netting method. Findings are summarized in the final conclusion.

1.1 Literature review

Literature references might be divided into fields respecting the article contents as cross margining, eventually margins netting, correlation coefficient an its pitfalls and copula function.


In Embrechts, McNeil, Straumann [2] pitfalls of correlation are summarized and described; and copula function are presented as an appropriate alternative. Schmidt [6] refers about pitfalls and describes correlation risk as the risk of loss in financial position occurring due to a difference between an anticipated correlation and realized correlation what occurs when the estimate of correlation was wrong or the correlation in the market changes. Papadimitriou, Sun, Yu [4] notified of the problem that correlation changes over time, which might cause the anomalies in financial modeling and introduced method of local correlation tracking in time series.

Theoretical definition of copulas is well known concept nowadays. As a reference and quoted literature we used London [3] or Schmidt [7].

1.2 Data characteristics

Trading with electricity futures contracts on PXE had started on 17.7.2007. List of traded contracts were extending to nowadays portfolio of products traded, which includes electricity futures with base load and peak load delivery day time mode, monthly futures with delivery start from the following month to five next months, quarters futures with delivery start from the following quarter to four next quarters and years futures for the tree following years. There are physical and financial settlement for all types of futures contracts. Czech, Slovakian and Hungarian electricity is an underlying commodity for futures contracts. Spot contracts are listed as well but only for Czech and Hungarian geographic area.

For the analysis of dependencies measures on PXE we have chosen most liquid/traded products – futures with Czech electricity, base load and peak load contracts (notation bl or pl as first two characters), monthly futures for three following months, quarterly futures for three following quarters and yearly futures for two following years (notation m, q or y as a last letter and 1, 2 or 3 as a last number). For example an abbreviation plq2 means peak load quarter futures of the second following quarter from reference day. Dataset of all 2009 trading days have been used, thus we dispose 206 observations of each examined contract.

Before we start with core analysis we look into characteristics of data used. We focus on characteristics which will probably influence the process of subsequent method selection. Firstly, we compute the daily returns of all contacts selected. Afterwards, we calculate skewnesses and kurtosis of 16 obtained series, which are presented in table below.
### 2. Correlation coefficient

Correlation coefficient (apprehend Pearson’s correlation) is frequently used in order to quantify the linear relationship between two or more variables. For two variables $X$ and $Y$ (in our case $X$ and $Y$ represent daily returns of electricity futures time series) correlation is defined as

\[
Corr(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var(X) \times Var(Y)}}
\]

Where

\[
Cov(X, Y) = E((X - E(X))(Y - E(Y)))
\]

Correlation coefficient vary between -1 and 1. If $Corr(X, Y) = 0$ we say that variables $X$ and $Y$ are without linear relation. If $Corr(X, Y) < 0$, it refers to a negative linear relation between $X$ and $Y$ and if $Corr(X, Y) > 0$, it refers to a positive linear relation between $X$ and $Y$. For constant $a,b$ $Corr(X+a,Y+b) = Corr(X,Y)$.

For constants $a,b$ and $c$ $Corr(a+bX,c+dY) = Corr(X,Y)$ if $bc>0$. If $bc<0$ the sign of correlation changes².

Cross correlations of examined PXE electricity futures data are positive without exception, what is sign of positive linear relation between what could be expected for different products with one underlying instrument but different maturities or delivery mode.

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² SCHMIDT, T.: Correlation and correlation risk. Forthcoming in Encyclopedia of Quantitative Finance, 2008. pages 1,2
Correlation matrix might be used in order to compute the portfolio effect, calculate VaR of portfolio, set up the hedging strategy or apply the cross margin netting on derivatives exchange platform. European Commodity Clearing (subsidiary of European Energy Exchange) uses statistically significant correlation in order to group margin classes to margin group and achieve partial elimination of margins requirements.

Despite the correlation popularity, there are a group of pitfalls which must be considered before we rely on this statistic measure. Generally known pitfalls (described for example by Embrechts, McNeil, Straumann [2] or by Schmidt [6]) are explained, as well as our data’s specific problems are described in following subsections.

2.1 Correlation is not equivalent of dependence

Consider $X \sim N(0,1)$ and $Y = X^2$. Then $\text{Corr}(X,Y)$ is very close to zero or zero for sample which is large enough. Generally, perfectly positively dependent variables do not necessarily have a correlation of 1; perfectly negatively dependent variables do not necessarily have a correlation -1; and finally, perfectly dependent variables might have a correlation even 0. Correlation is misleading when we face up to nonlinear relations.

2.2 Correlation is a scalar measure which does not describe dependence structure

Correlation, as a one number, can not describe whole dependence structure. Correlation for overall time series quantifies overall linear relation, but tells nothing about possible relation in case of extreme occurrence (tail dependence) etc.

2.3 Correlation is not invariant under general transformation

Correlation between $\log(X)$ and $\log(Y)$ is not same as correlation between $X$ and $Y$.

2.4 Correlation is very unstable

Correlation between two variables is usually very unstable and the value might changes dramatically when we add new observations as time flows. Final, the value strongly depends on analyst decision about length of series history which is taken into calculation. Example of correlation instability is illustrated on figures below, where correlation between blm1 and plm3 is calculated a.) from 100 observations for different time periods from the past, b.) for different number of historical observation starting at 100 last observations continuing to 206 last observation (the whole history of examined period 2009).

![Figure 1: Example of correlation instability. Source: Autor’s analysis, PXE data](image)

We can see that correlation vary from negative values to positive values which even exceeded 0.35.
In case that the instability of correlation is significant, we need to apply correlation tracking as proposed by Papadimitriou, Sun, Yu [4], or we can use some other method appropriate for correlation estimation.

### 2.5 More dependence structures lead to misleading correlation

For two periods \((t_0, t_m)\) and \((t_m, t_n)\) where \(t_0 < t_m < t_n\), we have two dependence structures. \(Y = X_j\) for the period \((t_0, t_m)\) and \(Y = X_k\) for period \((t_m, t_n)\), where \(j, k\) are positive constants. 

\[ \text{Corr}(X,Y)_{(t_0, t_m)} = 1 \quad \text{and} \quad \text{Corr}(X,Y)_{(t_m, t_n)} = 1 \quad \text{but} \quad \text{Corr}(X,Y)_{(t_0, t_n)} \neq 1. \]

Occurrence of specific economic event might change dependency structure, and adding new data to the initial data set (with initial dependency structure) might convey to misleading correlation results.

### 2.6 Others

Correlation coefficient is unsuitable for illiquid assets as a lot of PXE futures contracts are. Series of zero returns observations complemented with occasion non zero return observation might leads to unrealistic overvalued positive or negative correlation. Daily returns of plm3, plq3 and ply2, presented on figure below, are good example of inappropriate illiquid asset time series.

**Figure 2: Illiquid PXE data examples. Source: Author’s analysis, PXE data**

![Figure 2: Illiquid PXE data examples. Source: Author’s analysis, PXE data](image)

Another specific problem connected to the low contracts liquidity is manual prices adjustment which might be done by Trading Officer. Whenever the market is illiquid and prices do not seem to be fundamental (for exact principles see Trading Rules [9]), the Trading Officer adjusts the price of particular contract. It causes that periods with cluster of zero or very low daily returns might exist. Then price adjustment might be done and new period with “calm” returns comes.

Most of pitfalls described could be applied on Kendall’s Tau as well.

### 2.7 PXE data conclusion

After we appraise correlation coefficient in context of PXE futures data characteristics, we propose not to use this measure in order to margins requirements quantification. The copula function, which involves quantifying of multivariate distribution, can be used as a possible substitution. In the following section we introduce the basic theory of copula function and its special type multivariate Student’s T copula.
3. Copula function

Copula is a general method of formulating a multivariate distribution. In contrast with correlation coefficient, general types of dependences can be quantified. Definitions of copula in general and multivariate Student’s T copula, which is considered to be more appropriate for our time series characteristics (than correlation coefficient), are presented and quoted from London [3].

An n-dimensional copula is a function $C : [0,1]^n \rightarrow [0,1]$ that has the following properties:
1. $C(u)$ is increasing in each component $u_k$ with $k \in \{1, 2, \ldots, n\}$.
2. For every vector $u \in [0,1]^n$, $C(u) = 0$ if at least one coordinate of the vector $u$ is 0, and $C(u) = u_k$ if all the coordinates of $u$ are equal to 1 except $k$-th one.
3. For every $a, b \in [0,1]^n$, with $a \leq b$ given a hypercube $B = [a, b] = [a_1, b_1] \times [a_2, b_2] \times \ldots \times [a_n, b_n]$ whose vertices lie in the domain of $C$, its volume $V_C(B) \geq 0$.

Consequently, Sklar’s theorem express the basic idea of dependence modeling via copula functions, by stating that for any multivariate distribution function, the univariate marginals (the distribution functions in case of random variables) and the dependence structure can be separated, with the later completely described by a copula function. Sklar’s theorem is formulated as follow:

Let $G$ be an $n$-dimensional distribution function with margins $F_1, F_2, \ldots, F_n$. Then there exists an $n$-dimensional copula $C$ such that, for $x \in \mathbb{R}^n$, we have

$$ (3.1) \quad G(x_1, x_2, \ldots, x_n) = C(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) $$

Moreover, if $F_1, F_2, \ldots, F_n$ are continuous then $C$ is unique.

3.1 Multivariate Student’s T Copula

There are different families of copula functions. T copulas belong to the elliptical family and are used very often in the process of financial returns dependencies structures modeling. Definition of Multivariate Student’s T copula is:

Let $R$ be a symmetric, positive definite matrix with $\text{diag}(R) = 1$ and let $T_{R,v}$ be the standardized multivariate Student’s t distribution with correlation matrix $R$ and $v$ degrees of freedom. Then the multivariate Student’s t copula is defined as

$$ (3.2) \quad C(u_1, u_2, \ldots, u_n; R, v) = T_{R,v}(t_1^{-1}(u_1), t_2^{-1}(u_2), \ldots, t_n^{-1}(u_n)) $$

Where $t_i^{-1}(u)$ denotes the inverse of the Student’s t cumulative distribution function. The associated Student’s t copula density is derived as

$$ (3.3) \quad C(u_1, u_2, \ldots, u_n; R, v) = \prod_{i=1}^{n} f_{\text{Student}}^{\text{Student}}(x_i) $$

$$ = |R|^{-\frac{v}{2}} \frac{\Gamma\left(\frac{v+n}{2}\right)}{\Gamma\left(\frac{v+1}{2}\right)} \left(\frac{\Gamma\left(\frac{v}{2}\right)}{\Gamma\left(\frac{v+1}{2}\right)}\right)^{\frac{n}{2}} \left(1 + \frac{\mathbf{u}^T R^{-1} \mathbf{u}}{v}\right)^{-\frac{v+n}{2}} \prod_{i=1}^{n} \left(1 + \frac{\mathbf{u}^T R^{-1} \mathbf{u}}{v}\right)^{-\frac{v+1}{2}} $$
After theory introduction, we can apply Student’s t copula on analyzed data.

### 3.2 Multivariate Student’s T Copula and application on analyzed data

As we anticipated in section 1.2, the strong autocorrelation has been detected by autocorrelation function, almost in case all analyzed time series. Before we start with copula function calibration, we need to obtain independent time series. Accordingly, we use General AutoRegressive Conditional Heteroskedasticity (model). As an eligible model we choose GJR-GARCH model derived by Glosten, Jagannathan and Runkle (1993) (Štěrba [8]), which is able to incorporate asymmetric effects of a positive and negative shocks. We would remain characteristics of analyzed time series as low liquidity and manual prices adjustments. Thus, we separate autoregressive variance and model residuals. Standardized residuals (model residuals divided by sigmas obtained) are supposed to be without autocorrelation.

Though model selection, we were not able to obtain residuals which are uncorrelated for all selected time series analyzed. Mainly series which contains a lot of zero returns observation where problematic. Therefore we decided to reduce set of data analyzed to eight most active contracts involving m1, m2, q1 and y1 series for base load and for peak load. Those standardized residuals were without autocorrelation (only one exception was blq1 contracts which were still with marks of slight autocorrelation, but we decided to keep this contract in examined dataset especially for its importance) and we can continue with Student’s T Copula fitting. An example of autocorrelation function for blm1 contract returns and for standardized residuals after GJR-GARCH model application is shown in Figure 3, below.

In some cases of autocorrelation reducing problem, X-12-ARIMA seasonal adjustment might helps.

Having standardized residuals (from the variance model used before), we can fit the multivariate Student’s t copula function using maximum likelihood approach. According
section 3.1 we obtain correlation matrix $R$ and $v$, which represents degrees of freedom. Degrees of freedom $v = 17.3528$ and $R$ for reduced dataset is presented in table below.

\[
\begin{array}{cccccccc}
  & blm1 & Blm2 & blq1 & bly1 & plm1 & plm2 & plq1 & ply1 \\
 blm1 & 1.00 & 0.78 & 0.73 & 0.41 & 0.83 & 0.69 & 0.59 & 0.41 \\
 blm2 & 0.78 & 1.00 & 0.73 & 0.44 & 0.68 & 0.73 & 0.66 & 0.44 \\
 blq1 & 0.73 & 0.73 & 1.00 & 0.60 & 0.71 & 0.74 & 0.71 & 0.51 \\
 bly1 & 0.41 & 0.44 & 0.60 & 1.00 & 0.39 & 0.41 & 0.55 & 0.70 \\
 plm1 & 0.83 & 0.68 & 0.71 & 0.39 & 1.00 & 0.71 & 0.65 & 0.40 \\
 plm2 & 0.69 & 0.73 & 0.74 & 0.41 & 0.71 & 1.00 & 0.71 & 0.43 \\
 plq1 & 0.59 & 0.66 & 0.71 & 0.55 & 0.65 & 0.71 & 1.00 & 0.55 \\
 ply1 & 0.41 & 0.44 & 0.51 & 0.70 & 0.40 & 0.43 & 0.55 & 1.00 \\
\end{array}
\]

Table 2: Correlation matrix $R$. source: Author’s analysis, PXE data

After fitting the copula function, we can simulate a set of random numbers that follows dependency structure of original series of standardized residuals. Afterwards, we reintroduce autocorrelation and heteroskedasticity by simulation of previously calibrated GJR-GARCH model.

Described procedure might be applied in order to derivatives evaluation, preparing the hedging strategy, value at risk calculation or finally to quantify cross margining netting potentiality, not only for energy data.

4. Copula application and cross margining netting method

In this part, we use described method from the previous section for cross margining netting quantification. To do so, we use the last prices observed in our dataset. Last prices for examined contracts from 31.12.2009 are shown in the Table 3.

\[
\begin{array}{cccccccc}
  & 31.12.2010 & blm1 & blm2 & blq1 & bly1 & plm1 & plm2 & plq1 & ply1 \\
 Contract price EUR/MWh & 42.25 & 39.75 & 38.50 & 41.00 & 58.00 & 53.00 & 52.50 & 71.90 \\
\end{array}
\]

Table 3: Prices of analysed contracts from 31.12.2009, source: PXE data

Few premises have to by made for our cross margining quantification. Confidence level is 99 % and holding period is one day. Margins, for particular contract and as well as bilateral margins, are presented as a margin in EUR per 1 MWh. Minimal contracts hours amount is not considered. Margins are calculated for reciprocal contracts pairs.

We calculate reciprocal margins as follow:

1. Absolute sum is the method which is currently used by PXE. Margins for both contracts are summed up regardless of the fact whether we sum up margins for two long positions or whether one of the position considered is short and one long. Margins for particular contracts are calculated as given quantile of simulated returns and they are presented in Table 4. Margins for bilateral positions (sum of single margins requirements) are presented in Table 5, row Absolute sum.

\[
\begin{array}{ccccccccc}
  blm1 & blm2 & blq1 & bly1 & plm1 & plm2 & plq1 & ply1 \\
  1.56 & 1.69 & 1.87 & 1.04 & 2.86 & 1.91 & 1.95 & 2.88 \\
\end{array}
\]

Table 4: Particular margins requirements,. source: Autor’s analysis, PXE data

2. Portfolio effect is quantified with the presumption that we keep two long positions of each contracts pairs of analyzed dataset. We calculate returns in EUR from simulated returns
and last observed prices. First, we sum up returns in EUR for both contracts for particular portfolios. 99 % quantile is then calculated from portfolio returns. Margins for bilateral positions are presented in Table 5, row Portfolio effect.

3. Netting effect is quantified with the premise that we keep one short and one long position for each contract pair of analyzed dataset. All other procedures are same as for portfolio effect quantification. Margins for bilateral positions are presented in Table 5, row After netting.

<table>
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<th>Margining</th>
<th>blm1</th>
<th>blm2</th>
<th>blq1</th>
<th>bly1</th>
<th>plm1</th>
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Table 5: Bilateral margins requirements. source: Author’s analysis, PXE data

It is obvious that margin requirements reduction is feasible after we incorporate reciprocal dependency structures to margin requirements calculation. Margin saving expressed as percentage to absolute margin sum is in some cases very different but in some cases similar, compared to correlation coefficient. As an example of different result we can point up pair blm1 and plm1. Correlation over 0.8 is in strong contrast with margin save under 55 %, given by copula approach application.

5. Conclusion

There is doubt that correlation coefficient is very popular and frequently used statistic however theory and practical experience (also financial crisis experiences) summarize a list of dangerous pitfalls. The copula function is presented as an acceptable alternative. We applied copula function on a PXE electricity futures time series dataset, which has to be reduced to only more liquid contracts, in order to apply GJR-GARCH model, but in general, we can consider the whole approach as applicable. Results presented as margin requirement netting savings differs from correlation coefficient, but in some case might be very similar.

Applied methods should be suitable for other financial or commodity assets as well.
Reference


Summary

Maržové požadavky, odvozené z otevřených derivátových / futures pozic účastníků burzovního obchodování, jsou základním prvkem risk managementu derivátových burz. Předpokládajíc, že jsou jednotlivé maržové požadavky stanovené správně, čelíme další otázce a to: Jak sečíst maržové požadavky plynoucí z otevřených pozic více kontraktů tak, abychom získali teoreticky správný celkový maržový požadavek konkrétního účastníka obchodování? V případě, že máme evidenci o možných závislostech napříč portfoliem kontraktů, můžeme aplikovat netting jednotlivých maržových požadavků. Tento článek zkoumá možnosti kvantifikace závislosti / vztahů na futures trhu PXE, kde doposud žádný netting maržových požadavků aplikován nebyl. Hlavní část článku tvoří pojednání o problémech Pearsonova korelačního koeficientu a využití tzv. copula funkce je prezentováno jako alternativní řešení.