How to hedge extreme risk of natural gas in multivariate semiparametric value-at-risk portfolio?

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Abstract: *The COVID-19 pandemic and the war in Ukraine have caused huge price changes in the natural gas market. This paper tries to minimise the extreme risk of natural gas, making two six-asset portfolios, where gas is combined with five developed and emerging European stock indices. We observe extreme risk from the aspect of classical parametric Value-at-Risk measure, but we also propose a new approach and optimise portfolios with semiparametric VaR as a target. Estimating the equicorrelation of the two portfolios, we determine that the emerging indices portfolio has a much lower level of integration, which is good for portfolio construction. Additionally, we divide the full sample into the pre-crisis and crisis periods to assess how portfolios look in the two intrinsically different subsamples. According to the results, both portfolios with the developed and emerging stock indices minimise extreme risk very well, but the latter portfolio is better. In the pre-crisis period, this advantage amounts to around 6% in the min-VaR portfolio and 3.5% in the min-mVaR portfolio. However, in the crisis period, the third and fourth moments come to the fore, meaning that hedging results increase significantly in favour of the emerging indices portfolios. In other words, the min-VaR and min-mVaR results of the emerging indices portfolio are better in amounts of more than 14% and 17%, respectively, vis-à-vis portfolios with the developed stock indices. We recommend using the semiparametric VaR metric because it is far more accurate and unbiased compared to the classical VaR since it considers all the key features of portfolio distribution.*

Keywords: *Extreme risk of gas, minimum VaR and mVaR portfolio optimisation, DECO-DCC-GJR-GARCH model.*

JEL clasification: *C30, G11, Q02.*

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Introduction

Natural gas has a pivotal role in the global energy market because it is a clean and environmentally friendly high-quality energy source. The importance of natural gas stems from the fact that it is used for various purposes – residential, industrial, electric power production, petrochemical plants, production of fertilisers, and as vehicle fuel (Bilgili et al., 2011; Brandão et al., 2016; Festic & Repina, 2009; Ródenas et al., 2020). However, a major problem for all natural gas users is the very volatile nature of gas prices (Daskalaki & Skiadopoulos, 2016). The price of natural gas is a function of global supply and demand, where various factors shape these forces. According to the U.S. Energy Information Administration (EIA, 2022), three major supply-side factors are: the amount of natural gas production, the level of natural gas in storage, and volumes of natural gas imports and exports.

On the other hand, the demand side is affected by variations in winter and summer weather, level of economic growth, availability, and prices of other fuels. On top of that, the world has been struck recently by two major crisis events – the COVID-19 pandemic and the war in Ukraine. These developments significantly disrupted global commodity markets, where the natural gas market is not an exception. The left plot in Fig. 1 clearly shows that natural gas prices started to rise in 2021, when the pandemic broke out, while the prices skyrocketed when Russia invaded Ukraine in February 2022. These happenings produced extensive turbulence in the natural gas market, which is well depicted in the daily returns of natural gas price (see right plot in Fig. 1). High oscillations in natural gas prices create a lot of risk for all agents who work with natural gas (producers, traders, investors, consumers), which requires action to protect against this risk. However, in spite of the fact that natural gas has become a very important daily necessity, the literature on the risk management of natural gas is very limited, according to Ghoddusi and Emamzadehfard (2017), so further research is needed. This is where we find a motive to do this research.

According to the above, this paper tries to hedge spot natural gas in a multivariate portfolio, combining gas with stock indices. In this process, we want to investigate this topic comprehensively, observing the research from several angles. In particular, firstly, we want to see which auxiliary assets are better to be found in a portfolio with gas. Assuming the case of a European agent who works with gas, we make two portfolios, which combine natural gas with five stock indices from the largest developed and emerging European markets. Following stock markets of Western European countries (WEC) are considered – Germany, France, Great Britain, Italy, and Spain, while the Polish, Czech, Hungarian, Slovakian, and Romanian stock markets are in the group of emerging Central and Eastern European countries (CEEC). We intentionally select the two groups of stock markets – more developed and less developed, because more developed stock markets have higher trading volumes, which reflects the higher volatility (Nishimura, 2016; Tissaoui et al., 2021). From this point, we can hypothesise that emerging stock indices might have an advantage in hedging because they are less integrated and, thus, less correlated. This is important because the level of mutual correlation is one of the primary factors for efficient portfolio optimisation.

To avoid arbitrariness in the mutual correlation appraisal, we estimate the dynamic conditional equicorrelation (DECO) model of Engle and Kelly (2012), which serves as a preliminary result. This model is a form of Engle's (2002)

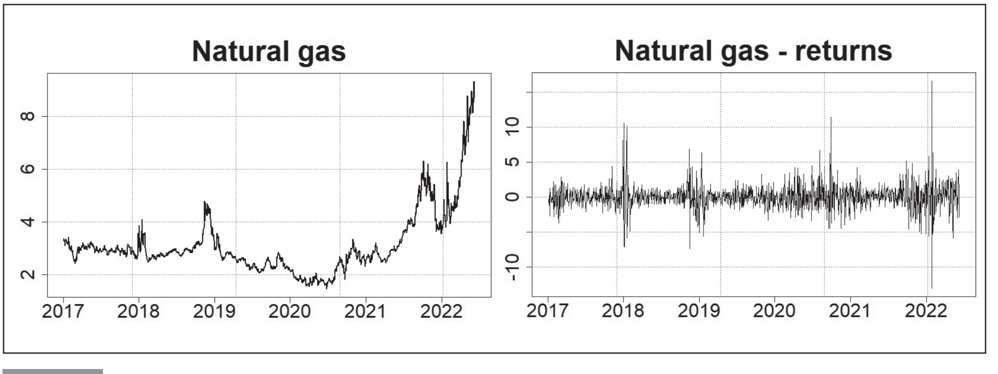

Fig. 1: Empirical dynamics of natural gas price and its returns

Source: own (based on data from the stooq.com website)

dynamic conditional correlation (DCC) model, developed to overcome computational and presentation difficulties of high-dimension data in the DCC model. In other words, the DECO-DCC model estimates dynamic correlations between all pairs of assets, but all these correlations are equal, which is called equicorrelation. This is an elegant way to understand the level of interconnectedness between the assets in a portfolio, which can be utilised to indicate which portfolio is a better hedge of natural gas. Besides, since we cover the period of the pandemic and the war in Ukraine, in which natural gas prices soared, equicorrelation can show whether the connection between the assets is stronger in the crisis vis-à-vis the pre-crisis period. Due to its low time consumption in the computational process, various researchers used the DECO model (e.g., Cui et al., 2021; Demiralay et al., 2019; Demiralay & Golitsis, 2021).

The second and most important contribution of our paper comes from the aspect of risk assessment. As it is known, most of the existing papers minimise variance in a portfolio, but this naive risk measure may be biased because variance takes into account both positive and negative returns equally, while investors are interested only in negative returns. In order to address the risk that really matters for investors, we construct portfolios that minimise downside risk. The most famous downside risk metric is value-at-risk (VaR), which was introduced by J. P. Morgan Bank in 1994. VaR observes a specific quantile at the left tail of the standard normal distribution, which means that VaR gives reliable estimates only if the empirical distribution of a portfolio follows the Gaussian function (He et al., 2020; Snoussi & El-Aroui, 2012). In other words, VaR takes into account only the first two moments, while skewness and kurtosis remain neglected (Junior et al., 2022). This means that VaR can be a misleading risk measure, particularly in turbulent times when all markets record extreme price swings. Nevertheless, the construction of the minimum VaR multi-asset portfolio is a very complex task, so relatively few papers applied this methodology (e.g., Abuaf et al., 2018; Al Janabi et al., 2019; Gatfaoui, 2019; Hammoudeh et al., 2013).

In order to address the two-moment bias, which is a primary drawback of the classical VaR, this paper makes a leap in constructing a downside risk portfolio. In other words, we design a more complex multivariate portfolio that targets downside risk but takes into account all four moments of portfolio distribution. Portfolio optimisation, where all four moments are taken into account, is very complicated to perform, but risk assessment is more accurate and reliable compared to the measure of parametric VaR, so it is worth trying this procedure. The four-moment risk measure is known as semiparametric VaR or modified VaR (mVaR), and it was introduced by Favre and Galeano (2002). mVaR is based on the Cornish-Fisher expansion (Cornish & Fisher, 1938), which considers all four moments of an empirical distribution. Applying the mVaR portfolio optimisation procedure, we want to find an optimal structure of assets in the portfolios that minimises mVaR. It is relevant to consider mVaR in the portfolios that take into account more and less developed stock markets because less developed markets are less liquid and thus prone to outliers (Xu et al., 2019). In this regard, the value of kurtosis comes to the fore, which can be manifested in the size of the downside risk. To the best of our knowledge, no other paper has ever attempted to construct a multivariate portfolio with minimum mVaR. Generally speaking, mVaR penalises unfavourable characteristics of a distribution, such as negative skewness and high kurtosis, and rewards positive features, such as positive skewness and low kurtosis (e.g., Bredin et al., 2017; Chai & Zhou, 2018). If an empirical distribution has zero skewness and kurtosis of 3, then mVaR reduces to classical parametric VaR. It is even possible that mVaR has better results than classical VaR, which might happen if the distribution has low kurtosis and positive skewness.

Due to the fact that we cover both tranquil and crisis periods, we divide the full sample into two subsamples and rerun portfolio VaR and mVaR optimisation procedures. This is an additional aspect of the research, which can give a thorough picture of how the portfolios should look when different market conditions are in focus. The complexity of our research reflects in the fact that we construct the two portfolios with different auxiliary assets, two different downside risk measures and two distinctively different sub-periods. This extensive and methodical approach can provide a complete answer about how to hedge natural gas in the best possible way in the portfolio with the European stock indices.

In the existing literature, relatively few studies addressed the issue of natural gas financial risk management, in spite of the fact that natural gas price recorded significant price fluctuations in the past decade. For instance, Chiou-Wei et al. (2020) researched whether it is important to incorporate fundamental variables in estimating price returns and volatilities by studying the U.S. natural gas market. They explained spot and futures returns and volatilities based on market fundamental variables such as weather, gas underground storage, oil price and macroeconomic news. They reported that the optimal hedge ratio was not constant but fluctuated significantly during the sample period. They asserted that incorporating a time-varying hedge ratio has improved hedging effectiveness by a large percentage while applying market fundamental variables in the hedging process significantly improves the hedging effectiveness. Ghoddusi and Emamzadehfard (2017) used the U.S. natural gas market to test multiple features of hedging performances. First, they compared the hedging effectiveness of single futures contracts used for hedging six different physical price positions. Second, they examined the performance of hedging when one uses a futures contract with time-to-maturity beyond the hedging horizon. Finally, they quantified the effect of accounting for cointegration and time-varying volatility in calculating optimal hedge ratios. They found that using longer maturity contracts may improve the hedging effectiveness, but accounting for cointegration and time-varying prices has minimal effect on the hedge ratio and hedging effectiveness for almost all physical prices. The study by Ling et al. (2019) investigated the risk transmission and hedging strategies between the natural gas market and stock markets of America and China. They used a multivariate GARCH framework, combining regime switching with multivariate long memory and asymmetry GARCH. They found Granger causality from the natural gas market to the Chinese stock markets in the crisis regime. As for the optimal design of a natural gas-stock portfolio, they found that investors in stock markets should have more stocks than natural gas asset in order to reduce their portfolio risk. Živkov et al. (2022) constructed four minimum-variance multivariate portfolios, combining Brent oil, WTI oil, gasoline and natural gas with four precious metals. They imposed 30% and 70% constraints on energy share in portfolios in order to reflect the different situations of market participants. They found that the highest share in all the portfolios have gold, while only in the two cases some tiny percentage go to palladium, while silver and platinum do not have a share in portfolios whatsoever. They reported more risk reduction in 30% portfolios than in 70% portfolios, which means that investors who want to pursue a less risky energy-portfolio should include more gold in a portfolio.

Besides the introduction, the rest of the paper is constructed as follows. The second section explains used methodologies – the DECO-DCC-GARCH model and portfolio optimisation procedure. The third section describes the used dataset. The fourth section presents the results in three sub-sections – equicorrelation results, and portfolio construction in the pre-crisis and crisis periods. The last section gives concluding remarks.

1. Research methodologies

1.1 DECO-DCC-GARCH model

In order to provide a preliminary insight into which portfolio might be more efficient in terms of lower downside risk, we calculate two dynamic equicorrelations between the two sets of assets. Equicorrelations are estimated by the multivariate DCC-DECO model of Engle and Kelly (2012), which overcomes computational and presentation difficulties of high-dimension data, e.g., when a large number of instruments is combined in a single portfolio. Since equicorrelations are time-varying, we can see how strongly stock markets and gas are integrated during the pre-crisis and crisis periods. These results can indicate which portfolio potentially has lower downside risk because the level of correlation is a very important input in the portfolio optimisation procedure.

In order to recognise an asymmetric effect, we use the GJR-GARCH model in the univariate specification. Equations (1–2) show the form of the mean and variance equations of the GJR-GARCH model.

$$y_t = C + \phi y_{t-1} + \varepsilon_t;\ \ \varepsilon_t \sim z_t\sqrt{\sigma_t^2} \tag{1}$$

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1};\quad I_{t-1} = \begin{cases} 1\ if\ \varepsilon_{t-1} < 0 \\ 0\ if\ \ \varepsilon_{t-1} > 0 \end{cases} \tag{2}$$

The mean equation has AR(1) form, which is enough lag-order to resolve the serial correlation problem in the selected time-series. C and c are constants in the mean and variance equations, respectively. y_t is 6 × 1 vector of stock indices and natural gas, while ε_t is 6 × 1 vector of error terms. Symbol z_t denotes independently and identically distributed process. In conditional variance equation, parameter β describes the persistence of volatility, while α measures ARCH effect. Parameter γ measures an asymmetric effect, i.e., if γ > 0, then negative shocks impact volatility more than positive shocks, and vice-versa. I_t is dummy variable.

In the DCC model, the positive definiteness of the variance-covariance matrix (H_t) is ensured:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{3}$$

where: $R_t = [\rho_{ij,t}]$ – the conditional correlation matrix; while the diagonal matrix of the conditional variances is given by $D_t = \mathrm{dig}(h_{1,t}, \ldots, h_{n,t})$. According to Engle (2002), the right-hand side of Equation (3) can be modelled directly by proposing the following dynamic correlation structure:

$$R_t = (Q_t^*)^{-1/2} Q_t (Q_t^*)^{-1/2} \tag{4}$$

$$Q_t^* = \mathrm{diag}(Q_t) \tag{5}$$

$$Q_t = [q_{ij,t}] = (1 - a - b)S + a u_{t-1} u'_{t-1} + b Q_{t-1} \tag{6}$$

where: $u_t = [u_{1,t}, \ldots, u_{n,t}]'$ is the standardised residuals, $u_{i,t} = \varepsilon_{i,t} / u_{i,t}$; $S = [s_{i,j}] = E[u_t\ u_t']$ is the $n \times n$ unconditional covariance matrix of u_t; a and b are non-negative scalars satisfying $a + b < 1$. The above-described model is called the DCC model. However, Aielli (2013) argued that the estimation of the covariance matrix Q_t in this way is inconsistent because $E[R_t] \neq E[Q_t]$. To fix this issue, he suggested the consistent DCC (cDCC) model for the correlation-driving process:

$$Q_t = (1 - a - b)S^* + a\left(Q_{t-1}^{*1/2}\, u_{t-1}\, u'_{t-1}\, Q_{t-1}^{*1/2}\right) + b Q_{t-1} \tag{7}$$

where: S^* – the unconditional covariance matrix of $Q_{t-1}^{*1/2}\, u_t$.

Engle and Kelly (2012) suggested that ρ_t can be modelled by using the cDCC process to obtain the conditional correlation matrix Q_t, and then taking the mean of its off-diagonal elements. This approach they called the dynamic equicorrelation (DECO) model, and the scalar equicorrelation is defined as:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}(J'_n R_t^{cDCC} J_n - n) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{8}$$

where: $q_{ij,t} = \rho_t^{DECO} + a_{DECO}\left(u_{i,t-1}\, u_{j,t-1} - \rho_t^{DECO}\right) + b_{DECO}(q_{ij,t} - \rho_t^{DECO})$, which is the (i,j)th element of the matrix Q_t from the cDCC model. Scalar equicorrelation is then used to estimate the conditional correlation matrix:

$$R_t = (1 - \rho_t) I_n + \rho_t J_n \tag{9}$$

where: J_n is $n \times n$ matrix of ones, and I_n is the n-dimensional identity matrix. This process allows a mutual co-movement level of a group of assets in a portfolio with a single time-varying correlation coefficient.

1.2 Portfolio optimisation with VaR and mVaR minimising goals

We construct downside risk-minimising portfolios with two different goals, VaR and mVaR, combining natural gas with the stock indices from developed and emerging European countries. The goal is to find an optimal combination of assets in the portfolios, where the portfolio optimisation procedure is a workhorse. This modus operandi was originally introduced by Markowitz (1952), who set minimum-variance as a target.

The starting point in making a downside risk portfolio is the construction of the minimum-variance portfolio, which can be achieved by solving Equation (10):

$$\min \sigma_p^2 = \min \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_i \sigma_j \rho_{i,j} \tag{10}$$

where: σ_p^2 is portfolio variance; σ_i^2 is variance of a particular asset i; w_i denotes calculated weight of an asset i in a portfolio; while $\rho_{i,j}$ is a correlation coefficient between the particular pair of assets (i and j). Necessary constraints in the every multivariate portfolio optimisation process is that sum of all weights is equal to one, while all individual weights are somewhere between zero and one.

$$\sum_{i=1}^{N} w_i = 1\,; \;\; 0 \leq w_i \leq 1 \tag{11}$$

Every portfolio with minimum variance has the corresponding mean value, which is the weighted average portfolio return (r_p), and it can be calculated as in Equation (12).

$$r_p = \sum_{i=1}^{n} w_i r_i \tag{12}$$

First (r_p) and second (σ_p) moments from Equations (12) and (10) are utilised to construct a minimum VaR portfolio (VaR_p), where $VaR_p = r_p + Z_\alpha \sigma_p$. Z_α is the left quantile of the normal standard distribution. Equation (13) shows how VaR portfolio can be calculated.

$$\min VaR_p(w), \sum_{i=1}^{n} w_i r_i \tag{13}$$

The optimisation process changes the weights of assets in a portfolio, with an aim to find the best combination of assets that minimises portfolio risk (e.g., Aboura et al., 2016; Chen et al., 2014; Vo et al., 2019).

However, a portfolio with minimum parametric VaR can be regarded as biased and misleading if the empirical distribution of a portfolio does not have the Gaussian characteristics. This assumption is very strict and highly unlikely, considering that we make a portfolio with daily stock indices and volatile energy commodity. The problem emerges because parametric VaR uses only the first two moments, while the third and fourth moments are disregarded. The minimum-VaR portfolio can be unbiased only if the skewness of a portfolio is near zero and kurtosis is around 3, which is an unrealistic scenario when daily time-series are in the question. In order to resolve possible bias of the min-VaR portfolio, we also calculate the min-mVaR portfolio, which overcomes this issue, because it takes into account all the four moments of empirical distribution. Accordingly, mVaR for a short position is defined as in Equation (14), whereas the minimum mVaR portfolio optimisation is given in Equation (15):

$$mVaR_\alpha = r_p + Z_{CF,\alpha}\, \sigma_p \tag{14}$$

$$\min mVaR_p(w), \sum_{i=1}^{n} w_i r_i \tag{15}$$

In Equation (14), $Z_{CF,\alpha}$ is the non-normal-distribution percentile adjusted for skewness and kurtosis according to the Cornish-Fisher expansion:

$$Z_{CF,\alpha} = Z_\alpha + \frac{1}{6}(Z_\alpha^2 - 1)\, S + \frac{1}{24}(Z_\alpha^3 - 3Z_\alpha)K - \\ - \frac{1}{36}(2Z_\alpha^3 - 5Z_\alpha)S^2 \tag{16}$$

where: S and K are measures of skewness and kurtosis of a portfolio.

Calculating both VaR and mVaR portfolios, we can see whether the difference between these two portfolios is significant, which would indicate that the third and fourth moments play an essential role. As an additional measure of the risk-minimising performance between the two portfolios, we calculate hedge effectiveness indices (HEI) in the following way:

$$HEI_{RM} = \frac{RM_{unhedged} - RM_{hedged}}{RM_{unhedged}} \times 100 \tag{17}$$

where: *RM* – particular risk measure of a portfolio, i.e., VaR or mVaR. Subscript *unhedged* refers to the investment only in natural gas, whereas the label *hedged* indicates the investment in the portfolios with the WEC and CEEC stock indices. As much as HEI index is closer to 100, the better hedge effectiveness is, and vice-versa.

2. Dataset description

This paper combines five daily WEC and CEEC indices with spot natural gas in a multivariate portfolio with an aim to hedge the extreme risk of natural gas. We select the following stock indices from the developed Western European countries – DAX (Germany), CAC (France), FTSE250 (Great Britain), FTSE-MIB (Italy) and IBEX35 (Spain), while WIG (Poland), P.X. (the Czech Republic), BUX (Hungary), SAX (Slovakia) and BET (Romania) are the indices from the Central and Eastern European countries. All the time-series are retrieved from the stooq.com website and transformed into log-returns (r_{it}) according to the expression $r_{i,t} = 100 \times \log(P_{i,t} / P_{i,t-1})$, where P_i is the price of a particular asset. The time-span ranges from January 2017 to June 2022 and both groups of stock indices are separately synchronised with natural gas. Due to the unavailability of some daily observations of the SAX index, the synchronised time series of CEEC have 1,091 observations vis-à-vis 1,311 observations of the WEC indices. Our sample covers the period before the COVID-19 crisis and the war in Ukraine, which we call the pre-crisis period, while the rest of the sample is referred to as the crisis period. Separating pre-crisis and crisis period, we have an opportunity to determine how the structure of portfolios looks like when the two distinctively different sub-periods are observed. In addition, we can stipulate which types of indices are better to combine with natural gas in a certain sub-period, and also, we can see how much extreme risk of a portfolio is higher in the crisis period compared to extreme risk in the pre-crisis period. We take January 1, 2020 as a breaking point between the pre-crisis and crisis periods.

Tab. 1 contains descriptive statistics of the full sample time-series, i.e., the first four moments, Jarque-Bera test of normality, Ljung-Box tests for level and squared residuals and Dickey-Fuller GLS unit root test. As can be seen, all mean values are very close to zero, while all standard deviations are relatively high. This means that the second moment will have a significantly more important role in the portfolio optimisation process than the first moment. This is particularly true for the VaR portfolios because variance is crucial in calculating parametric VaR. According to Tab. 1, natural gas has much higher volatility than all stock indices, which means that using stock indices as auxiliary assets in a portfolio is suitable for natural gas hedging. On the other hand, this also means that gas will probably have a relatively low share in the portfolios.

All stock indices have negative skewness, which means that more returns are placed to the left of the mean. For natural gas applies the opposite because gas has positive skewness. All the assets have very high kurtosis values, which means that all assets recorded extreme values in the observed sample.

Tab. 1: Descriptive statistics of the selected assets

	Mean	St. dev.	Skew.	Kurt.	JB	LB(Q)	LB(Q²)	DF-GLS
Natural gas	0.031	1.727	0.814	16.623	10,283.0	0.000	0.000	−38.579
Panel A: WEC stock indices								
DAX	0.005	0.554	−0.739	18.486	13,219.2	0.000	0.000	−37.056
CAC	0.007	0.540	−1.109	18.983	14,223.2	0.000	0.000	−36.498
FTSE250	0.003	0.479	−0.751	16.454	10,011.6	0.000	0.000	−12.550
FTSE-MIB	0.005	0.608	−2.263	32.693	49,281.4	0.000	0.000	−23.181
IBEX35	−0.004	0.554	−1.386	23.578	23,550.0	0.000	0.000	−12.259
Panel B: CEEC stock indices								
WIG	−0.003	0.565	−1.599	21.614	16,215.3	0.005	0.000	−16.071
PX	0.014	0.437	−1.308	17.968	10,495.6	0.000	0.000	−5.542
BUX	0.007	0.617	−1.661	16.991	9,400.6	0.000	0.000	−15.496
SAX	0.002	0.435	−0.199	12.620	4,214.0	0.065	0.000	−2.871
BET	0.010	0.491	−2.178	26.151	25,227.6	0.000	0.000	−5.940

Note: J.B. – value of Jarque-Bera coefficients of normality; L.B.(Q) and L.B.(Q2) tests – *p*-values of Ljung-Box Q-statistics of level and squared returns of 10 lags. Assuming only constant, 1% and 5% critical values for DF-GLS test with 10 lags are −2.566 and −1.941, respectively.

Source: own (based on data from the stooq.com website)

As a matter of fact, all the indices, except SAX, have higher kurtosis than gas, which indicates that the presence of outliers are more frequent in the stock markets than in the gas market. The third and fourth moments have a role only in the mVaR portfolio construction, which means that assets with negative skewness and high kurtosis, e.g., FTSE-MIB, will probably have a very low share in the mVaR portfolio. Besides, it should be noticed that values of the second moment do not coincide with kurtosis values, which implies that the structure of VaR and mVaR portfolios will probably differ significantly.

Due to high skewness and kurtosis values, all the assets do not follow Gaussian distribution, which is confirmed by the Jarque-Bera test. In addition, all the assets report problem with autocorrelation and heteroscedasticity, which can be resolved by the DECO-GJR-GARCH model. At the end, the last column in Tab. 1 shows that all time-series are stationary, which is a necessary precondition for the DECO modelling.

3. Research results

3.1 Equicorrelation estimation

This subsection presents the results of the estimated equicorrelations, which serve as an indication of whether portfolio with WEC or CEEC indices have better hedging results. We hypothesise that a portfolio with the CEEC indices probably has lower equicorrelation than the WEC counterpart because less developed stock markets are less integrated, which favours the CEEC indices as a better hedging tool. Calculating time-varying equicorrelations reveals the level of integration in both the pre-crisis and crisis period, which is important since we make portfolios in these distinctive time-periods. In order to save space, we do not present the parameters of the DECO models but they can be obtained on request.

Fig. 2 shows the estimated dynamic equicorrelations with the two groups of assets. Beneath both plots are the average values of equicorrelations, where it can be seen that ρ_t^{DECO} in the left plot is three time higher than the right plot counterpart. This clearly indicates that our initial hypothesis that the WEC indices are more integrated was right, and this finding will probably have an effect on the construction of the minimum VaR and mVaR portfolios. This is because the covariance matrix between the assets in a portfolio is one of the key elements in the portfolio construction process. In addition, we also calculate ρ_t^{DECO} values in the two subsamples, where it can be seen that equicorrelation in the crisis period is higher than in pre-crisis, which applies to both portfolios. Higher equicorrelation between the WEC indices is expected since developed stock markets are more coherent, and this is particularly true in crisis periods (Tiwari et al., 2022).

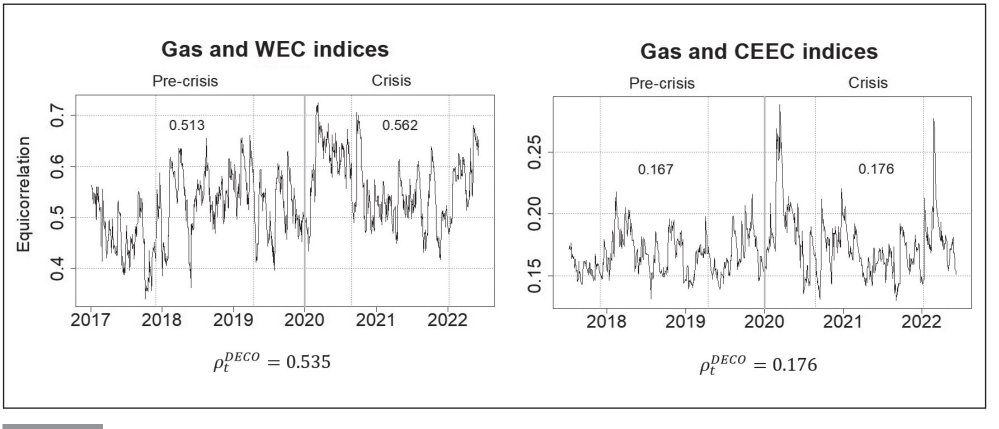

Fig. 2: Estimated equicorrelations of two portfolios with different stock indices

Note: X-axis on the right plot in Fig. 2 is shorter because the sample with CEEC indices has 220 observations less than the sample with WEC indices due to data synchronisation.

Source: own (based on data from the stooq.com website)

Tab. 2: Calculated VaR and mVaR values of the assets in the two portfolios

	Portfolio with WEC indices					Portfolio with CEEC indices			
	Pre-crisis		Crisis			Pre-crisis		Crisis	
	VaR	mVaR	VaR	mVaR		VaR	mVaR	VaR	mVaR
N. gas	−3.401	−6.318	−4.567	−8.801	**N. gas**	−3.451	−5.908	−4.471	−9.458
DAX	−0.858	−1.057	−1.659	−3.815	**WIG**	−0.877	−0.968	−1.634	−4.187
CAC	−0.798	−1.050	−1.640	−3.725	**PX**	−0.586	−0.719	−1.287	−2.801
FTSE250	−0.685	−0.893	−1.477	−2.972	**BUX**	−0.919	−0.995	−1.803	−3.858
FTSE-MIB	−0.998	−1.178	−1.788	−5.948	**SAX**	−0.952	−1.700	−1.063	−2.185
IBEX35	−0.837	−0.946	−1.700	−4.414	**BET**	−0.951	−4.200	−1.282	−3.218

Source: own (based on data from the stooq.com website)

On the other hand, the difference between CEEC equicorrelation in the two subsamples is relatively low.

The level of correlation between the assets is a significant input in constructing a portfolio. However, an even more important factor that determines the share of every asset in a portfolio is its level of risk. In this regard, we present calculated downside risk values (VaR and mVaR) of every asset in Tab. 2, taking into account both subsamples. These findings can help us to explain the portfolio optimisation results in the next two subsections. Tab. 3 shows that natural gas has significantly higher downside risk compared to all the stock indices. Also, all the mVaR values are higher than the VaR counterparts, which indicates that the third and fourth moments are important in calculating downside risk. Besides, it can be seen that all the VaR and mVaR numbers in the crisis period are much higher than their pre-crisis peers, which gives us a good reason to divide the full sample into the two subsamples.

3.2 Portfolio optimisation in the pre-crisis period

This subsection presents the results of the calculated portfolios in the pre-crisis period, where the minimisation of the two downside risk metrics is set as the target goal. Tab. 3 contains optimal shares of assets in the VaR and mVaR portfolios when natural gas is combined with both WEC and CEEC indices. We offer a logical explanation for each share-number in Tab. 3, and Tabs. 2 and 4 help us in this regard because the mutual correlation between

Tab. 3: Calculated shares of assets in the VaR and mVaR portfolios in the pre-crisis period

	Portfolios with WEC indices (%)			Portfolios with CEEC indices (%)	
	VaR	mVaR		VaR	mVaR
Natural gas	3	5	**Natural gas**	1	2
DAX	0	0	**WIG**	7	2
CAC	6	4	**P.X.**	48	56
FTSE250	69	48	**BUX**	7	14
FTSE-MIB	0	0	**SAX**	24	23
IBEX35	22	43	**BET**	13	3
Σ	100	100	**Σ**	100	100

Source: own (based on data from the stooq.com website)

the assets in a portfolio and the risk level of every asset are the two main factors that determine the share of assets in a portfolio. We have calculated equicorrelations between all the assets in the two portfolios, but they represent a joint level of correlation between all the assets in the portfolio. As such, they can be used as indicators but cannot help explain the particular share in a portfolio. This is the reason why we present pairwise correlations between all the assets in Tab. 4.

According to Tab. 4, natural gas has a very low share in all four portfolios. This is primarily because natural gas has a very high downside risk, as it is indicated in Tab. 2. Considering the very high downside risk levels of natural gas, a priory assumption could be that the gas share is zero. However, the reason why natural gas has a positive share in the portfolios is very low pairwise correlations between gas and both WEC and CEEC indices. According to Tab. 4, the average Pearson correlation between gas and WEC indices is 0.077, whereas between gas and CEEC indices is even lower, amounting to only 0.034.

Looking at the WEC portfolio with VaR as a goal, the highest share has FTSE250 in the amount of 69%, which is due to two reasons. First, it has the lowest VaR (−0.685), and second, it has the lowest average Pearson correlation with other assets (0.596). The second highest share in the VaR portfolio has the Spanish IBEX35 index, with 22%. IBEX35 has the fourth lowest VaR (−0.837), which is not a good trait of this index, but it has the lowest correlation with FTSE250 (0.638), which has the highest share in the portfolio. Due to this fact, IBEX35 has a relatively high share in the min-VaR portfolio in spite of its relatively high VaR. French CAC has 6% share, although it has the second-lowest VaR (−0.798). The explanation probably lies in the fact that CAC has a higher correlation with FTSE250 (0.752) than IBEX35 has with FTSE250 (0.638). DAX and FTSE-MIB indices have zero share in the VaR portfolio because DAX has the third highest VaR and relatively high correlation with FTSE250 (0.724) and IBEX35 (0.772). FTSE-MIB has by far the highest VaR (−0.998), and this is the primary reason why it has 0%.

In the mVaR portfolio, the structure of assets changes significantly. In other words, the share of FTSE250 decreases to 48%, while the share of IBEX35 increases to 43%. The reason lies in the fact that the downside risk difference between the second and first asset is 0.152 in the VaR portfolio, while in the mVaR portfolio, this difference is only 0.053. The gas level slightly increases

Tab. 4: Pairwise Pearson correlation coefficients between the assets in the pre-crisis period

		N. gas	DAX	CAC	FTSE250	FTSE-MIB	IBEX35	Average ρ
WEC indices	Natural gas	1	0.063	0.089	0.138	0.054	0.043	0.077
	DAX	0.063	1	0.895	0.724	0.769	0.772	0.645
	CAC	0.089	0.895	1	0.752	0.783	0.797	0.663
	FTSE250	0.138	0.724	0.752	1	0.595	0.638	0.569
	FTSE-MIB	0.054	0.769	0.783	0.595	1	0.798	0.600
	IBEX35	0.043	0.772	0.797	0.638	0.798	1	0.610
		N. gas	WIG	PX	BUX	SAX	BET	Average ρ
CEEC indices	Natural gas	1	0.076	0.015	0.041	0.048	−0.009	0.034
	WIG	0.076	1	0.435	0.492	0.044	0.166	0.243
	PX	0.015	0.435	1	0.379	−0.008	0.292	0.223
	BUX	0.041	0.492	0.379	1	0.038	0.142	0.218
	SAX	0.048	0.044	−0.008	0.038	1	0.026	0.030
	BET	−0.009	0.166	0.292	0.142	0.026	1	0.123

Source: own (based on data from the stooq.com website)

to 5%, while CAC slightly decreases to 4%, probably because gas has positive skewness, while CAC has relatively high negative skewness, and these factors most likely contribute to the changes of the mVaR-portfolio structure.

As for the portfolios with the CEEC indices, in the VaR portfolio, the highest share has P.X. with 48%, while SAX and BET follow with 24% and 13%, respectively. P.X. has the lowest VaR (−0.586), and this is the reason why it has the highest share. On the other hand, SAX has the second highest VaR (−0.952) but it has a very low average correlation with all the other assets in the portfolio (0.030), which puts SAX in second place in the VaR portfolio. As in the case of SAX, BET also has a very high VaR (−0.951) but it has a very low average correlation (0.123), which is enough for 13% of BET in the VaR portfolio. Both WIG and BUX have 7% in the portfolio because they have a relatively high correlation with P.X., 0.435 and 0.379, respectively.

In the mVaR portfolio, the structure changes in favour of P.X., which has 56%, while SAX has a slightly lower share of 23%. The P.X. index has the lowest mVaR primarily because it has the lowest variance (Tab. 1). SAX retains the second position due to the lowest correlation with other assets. On the other hand, drastic changes happen to BET and BUX indices. BET records the highest drop, from 13% to 3%, probably because it has the highest kurtosis and the highest negative skewness (Tab. 1). On the other hand, BUX goes to third place, from 7% to 14%, because it has the second lowest third and fourth moments. Polish WIG descends from 7% to 2% due to the second-highest kurtosis and the second-highest negative skewness.

3.3 Portfolio optimisation in the crisis period

This subsection tries to answer how the structure of the portfolios changes when the crisis subsample is in focus. Tab. 5 contains the calculated shares of assets in the portfolios, while Tab. 6 shows pairwise correlations, which are used in explaining the results in Tab. 5. Even at first glance, it is obvious that the structure of the portfolios significantly differs in the crisis period compared to the pre-crisis, which legitimises separate investigation of these two distinctively different subsamples.

Looking at the VaR portfolio with the WEC indices, only the three assets find their place in the portfolio. The shares of FTSE250 and gas increase to 76% and 7% from 69% and 3%, respectively, while IBEX35 falls to 17% from 22%. CAC is excluded from the VaR portfolio in the crisis period. The explanation of the findings is similar as in the previous section. FTSE250 has the lowest VaR (−1.477), and this is why it has the highest share. Although IBEX35 has the second largest share of 17%, it actually has the third highest VaR (−1.700), but IBEX35 has a relatively low correlation with FTSE250 (0.802), and this explains the relatively high share of the Spanish index in the portfolio. Natural gas has a very high VaR in the crisis period (−4.567), but it has a relatively high share of 7% because

Tab. 5: Calculated shares of assets in VaR and mVaR portfolios in the crisis period

	Portfolios with WEC indices (%)			Portfolios with CEEC indices (%)	
	VaR	mVaR		VaR	mVaR
Natural gas	7	18	**Natural gas**	3	10
DAX	0	0	**WIG**	5	4
CAC	0	0	**P.X.**	20	0
FTSE250	76	82	**BUX**	0	0
FTSE-MIB	0	0	**SAX**	53	59
IBEX35	17	0	**BET**	19	27
Σ	100	100	**Σ**	100	100

Source: own (based on data from the stooq.com website)

gas has a very low pairwise correlation with FTSE250 (0.100) and IBEX35 (0.077).

On the other hand, in the mVaR portfolio, only FTSE250, with 82% and gas, with 18%, have a share, while all the other assets have no share. The rationale for these results lies in the fact that FTSE250 has the lowest mVaR (−2.972) due to the relatively low kurtosis and negative skewness (Tab. 1). Gas fills up the rest of the portfolio with 18% because gas has a relatively low correlation with the British index.

As for the portfolios with CEEC indices, the situation changes significantly vis-à-vis the pre-crisis portfolios. In particular, P.X. falls to 20% from 48% in the pre-crisis period, while SAX jumps to 53% from 24%. BET has 19% compared to 13% in pre-crisis, WIG drops slightly to 5% from 7%, while gas slightly rises to 3% from 1%. Hungarian BUX has zero share in the VaR portfolio in the crisis period. SAX has the highest share because its VaR is the lowest (−1.063). P.X. takes second place with 20% because it has the third lowest VaR (−1.287). Comparing the situation between SAX and P.X. indices, it can be concluded that the volatility of P.X. increased more than the volatility of the SAX index in crisis, and this is why they changed their places in the VaR portfolio in crisis. BET increases to 19% because it has the second-lowest VaR (−1.282) and a negative correlation with the most dominant SAX (−0.028). WIG has the third highest VaR (−1.634), while BUX has the second highest VaR (−1.807), which explains why WIG has a very low share of 5%, whereas BUX has 0% share. Gas has 3% share in the portfolio only because gas has a very low pairwise correlation with the two assets with the highest share in the portfolio – SAX (−0.055) and P.X. (0.063).

In the mVaR portfolio, SAX further increases its share to 59%, which is also the case with the BET index (27%). The gas increases to 10% from 2% because gas has the lowest correlations with the two dominant indices in the mVaR portfolio, SAX (–0.055) and BET (0.060). These enlargements in the mVaR portfolio are happening at the expense of the P.X. index, which reduces to 0%. BUX retain 0% in the mVaR portfolio because it has a relatively high mVaR (–3.858), while WIG increases 2%, from 2% to 4%, because WIG has the two lowest correlations with SAX (–0.050) and BET (0.558).

In order to analyse constructed portfolios, Tab. 7 shows the first four moments, VaR and mVaR values of the portfolios. As can be seen, all portfolios minimise their goals, which indicates that all the portfolio optimisations

Tab. 6: Pairwise Pearson correlation coefficients between the assets in the crisis period

		N. gas	DAX	CAC	FTSE250	FTSE-MIB	IBEX35	Average ρ
WEC indices	Natural gas	1	0.114	0.101	0.100	0.085	0.077	0.095
	DAX	0.114	1	0.953	0.849	0.911	0.869	0.739
	CAC	0.101	0.953	1	0.869	0.917	0.905	0.749
	FTSE250	0.100	0.849	0.869	1	0.782	0.802	0.680
	FTSE-MIB	0.085	0.911	0.917	0.782	1	0.900	0.719
	IBEX35	0.077	0.869	0.905	0.802	0.900	1	0.710
		N. gas	WIG	PX	BUX	SAX	BET	Average ρ
CEEC indices	Natural gas	1	0.082	0.063	0.076	−0.055	0.060	0.046
	WIG	0.082	1	0.583	0.636	−0.050	0.558	0.362
	PX	0.063	0.583	1	0.621	−0.044	0.624	0.369
	BUX	0.076	0.636	0.621	1	0.000	0.533	0.373
	SAX	−0.055	−0.050	−0.044	0.000	1	−0.028	−0.035
	BET	0.060	0.558	0.624	0.533	−0.028	1	0.350

Source: own (based on data from the stooq.com website)

Tab. 7: First four moments, VaR and mVaR of the created portfolios in the two sub-periods

	Portfolios with WEC indices		Portfolios with CEEC indices	
	min-VaR portfolio	min-mVaR portfolio	min-VaR portfolio	min-mVaR portfolio
Panel A. Pre-crisis period				
Mean	0.000	−0.001	0.006	0.008
Variance	0.082	0.086	0.041	0.043
Skewness	−0.197	−0.247	−0.588	−0.351
Kurtosis	2.098	1.401	1.770	0.884
VaR	−0.658	−0.678	−0.465	−0.476
mVaR	−0.836	−0.821	−0.610	−0.563
Panel B. Crisis period				
Mean	−0.001	0.011	0.005	0.015
Variance	0.375	0.434	0.107	0.135
Skewness	−0.852	−0.348	−1.494	0.160
Kurtosis	9.190	5.775	7.719	3.462
VaR	−1.426	−1.523	−0.755	−0.839
mVaR	−2.957	−2.551	−1.430	−1.089

Source: own (based on data from the stooq.com website)

are successfully conducted. In other words, all the portfolios with minimum VaR as a target has minimum VaR, while all the portfolios with minimum mVaR as a goal achieve this objective. It is interesting to note that all the mVaR portfolios have significantly lower kurtosis than their VaR counterparts, while in three out of four cases, the mVaR portfolios also have lower skewness. These results strongly indicate that the optimisation of the mVaR portfolio emphasises third and fourth moments, further strengthening the validity of the constructed mVaR portfolios. Tab. 7 allows directly comparing these portfolios' features and testing the hypothesis that the CEEC portfolios are better risk-minimisers than the WEC portfolios due to the lower integration of these indices.

Looking at the pre-crisis period (Panel A; Tab. 7), it can be seen that the CEEC portfolios have significantly lower both downside risks compared to the WEC portfolios, although downside risks of all the CEEC and WEC indices are relatively equal (Tab. 2). This means that the level of correlation between the assets in the two portfolios plays a key role in determining which portfolio is better. In particular, the minimum VaR in the CEEC portfolio is −0.465, while in the WEC portfolio, it is −0.658. On the other hand, the minimum mVaR in the CEEC portfolio is −0.563, while in the WEC counterpart, it is −0.821. These findings clearly show that better hedging of natural gas can be achieved with the CEEC indices, and Tab. 8 answers how much better. It can be seen that the CEEC portfolio is 6% better than the WEC portfolio in the pre-crisis period when the target is a common VaR metric. On the other hand, the CEEC portfolio is better for about 3.5% when more elaborate mVaR is observed.

As for the crisis period (Panel B; Tab. 7), the difference between the downside risks of the CEEC and WEC portfolios is more pronounced than in the pre-crisis period. In other words, the CEEC portfolio has −0.755 and −1.089 minimum VaR and mVaR values, respectively, while the WEC portfolio has VaR of −1.426 and mVaR of −2.551. These results very convincingly show that hedging gas with the CEEC indices is much better than with the WEC indices in turbulent periods. The reason probably lies in the much lower connectedness and integration of

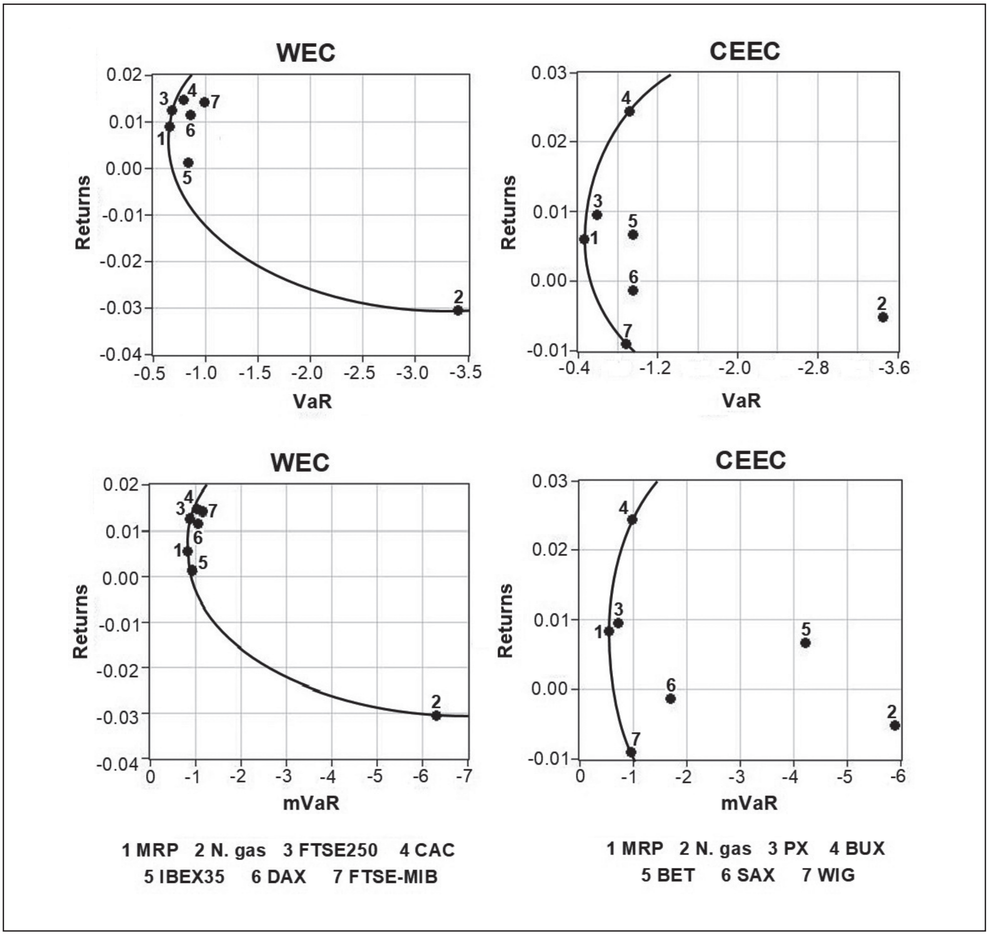

Fig. 3: Created efficient frontier lines of the VaR and mVaR portfolios in the pre-crisis period

Note: MRP – minimum risk portfolio, i.e., VaR or mVaR.

Source: own (based on data from the stooq.com website)

the CEEC indices vis-à-vis the WEC indices, illustrated in Fig. 2, which contributes to more efficient portfolio optimisation. Tab. 8 reveals via HEI values how much better the portfolio with the CEEC indices is. In particular, the VaR minimisation with the CEEC indices is more than 14% better than with the WEC indices, while in the case of mVaR, this amounts to more than 17%.

Fig. 3 presents the VaR and mVaR efficient frontier lines of the created portfolios in the pre-crisis period, as well as the spatial positions of all the assets in the portfolios. Efficient frontier lines in the crisis period can be obtained on request. Visual inspection of the created plots in Fig. 3 indicates that reducing the extreme risk of natural gas is very efficient in both WEC and CEEC portfolios because point 2 is significantly distanced from point 1. However, it is evident that portfolios with CEEC indices have the upper hand, particularly in the crisis period.

The high downside risk of gas implies its low share in the portfolios, which coincides very well with the papers of Ling et al. (2019) and Živkov et al. (2022). The former paper combined natural gas with stocks in a portfolio and

Tab. 8: Calculated hedge effectiveness indices

	Portfolios with WEC indices		Portfolios with CEEC indices	
	min-VaR portfolio	min-mVaR portfolio	min-VaR portfolio	min-mVaR portfolio
Panel A. Pre-crisis period				
HEI	80.654	87.008	86.526	90.472
Panel B. Crisis period				
HEI	68.781	71.017	83.104	88.483

Source: own (based on data from the stooq.com website)

reported that in the optimal natural gas-stock portfolio, investors should have more stocks than natural gas in order to reduce their portfolio risk, which is very similar to our findings. The latter paper combined gas with precious metals in a minimum-variance portfolio and also found a very low share of gas.

Conclusions

Due to recent global developments, such as the COVID-19 pandemic and the war in Ukraine, the natural gas market has recorded significant price turbulences, implying extreme risk. This paper tries to mitigate this risk by combining natural gas with the five developed and emerging European stock indices in multivariate portfolios. In order to address this task, we apply complex downside risk portfolio optimisation procedures. We observe downside risk in the form of a classical VaR metric and a more elaborate mVaR metric, which considers all four moments of portfolio distribution. In addition, we create these portfolios in the relatively calm pre-crisis period and very volatile crisis period. In this way, we gain the opportunity to make several comparisons of the portfolios – WEC vs CEEC, VaR vs mVaR and pre-crisis vs crisis.

Before portfolio construction, we estimate the two equicorrelations, serving as indicators of which portfolio might be more efficient – WEC or CEEC. The results indicate that the CEEC equicorrelation is significantly lower than the WEC counterpart, which gives a strong belief that the CEEC indices might be better auxiliary instruments in the portfolio with natural gas.

Observing the pre-crisis period, we find that British FTSE250 has the highest share in the VaR and mVaR portfolios, while in the CEEC portfolios, it is the Czech PX index. These two indices have the lowest VaR and mVaR in the pre-crisis period, which is why they have the highest share. In the crisis period, FTSE250 further increased its share in the portfolios, while in the CEEC portfolios, the situation changed in the sense that SAX now has a dominant role in the portfolios due to the lowest VaR and mVaR values.

Comparing the hedging results between the WEC and CEEC portfolios, we find that both portfolios have very good hedging characteristics. However, the portfolios with the CEEC indices are better, which confirms the hypothesis that assets with lower equicorrelation make more efficient portfolios. In the pre-crisis period, this advantage amounts to around 6% in MVaRP and 3.5% in MmVaRP. However, in the crisis period, the hedging characteristic increases significantly in favour of the CEEC portfolio, i.e., the risk-minimising difference is more than 14% in MVaRP and more than 17% in MmVaRP.

The results from this paper can offer a proposal to market participants who operate with natural gas on how to minimise its extreme risk. The results are even more valuable because we apply a very complex method of targeting semiparametric VaR, which is a novelty in constructing downside risk portfolio. We highly recommend this metric because it is far more accurate and unbiased compared to the classical VaR, since it takes into account all the key features of the portfolio distribution. However, one obvious unfavourable characteristic of the results is the fact that gas has a very low share in the portfolios, which could pose a problem for agents who hold large quantities of gas. This implies large investments in stock indices, which is highly impractical. Therefore, future studies could impose a share-constraint on gas (e.g., 50%) in order to see how these suboptimal portfolios look like and what their characteristics are. Also, future studies could consider making the mVaR portfolio with other auxiliary assets, which traditionally have a low risk, such as precious and industrial metals, agricultural commodities or bonds.

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