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How to Reduce Extreme Risk of the U.S. Tourism Indices? - Minimum-CVaR Portfolio Approach

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Abstract

This paper combines two tourism indices from the U.S. with six auxiliary assets in a multivariate portfolio in order to minimize extreme risk of the indices. Extreme risk is measured by the conditional Value-at-Risk metric. We construct the two types of portfolios – one is the minimum-risk portfolio, and the other one has the 50% constraint on the tourism indices. Also, we determine the pre-COVID and COVID subsamples via the modified ICSS algorithm. The results indicate that the tourism indices are mostly removed from the minimum-risk portfolios because they are among the riskiest assets. Because of that, the tourism-dominated portfolios gain greater importance. Gold has the highest share as an auxiliary asset in the tourism-dominated portfolios because gold has relatively low risk, but more importantly, gold has very low pairwise correlation with the tourism indices. In the COVID period, the share of gold increases compared to the pre-COVID period, which means that the best hedging abilities of gold comes to the fore in a crisis. High risk of the tourism indices is reduced more than 40% in the tourism-dominated portfolios.

1. Introduction

In the last few years, tourism sector has become the main driver of growth and major source of employment in many countries, accounting for around 10% of global GDP (World Travel and Tourism Council, 2020). Salisu et al. (2021a) asserted that the tourism receipts in 2018 reached 1,451 billion U.S. dollars *vis-a-vis* 2 billion U.S. dollars in 1950, whereas international tourist arrivals increased from 25 million in 1950 to 1,401 million in 2018. Only in the U.S., travel exports rose 7.9% annually from 2003 to 2013. However, due to strong social interaction of this business, the industry is highly prone to downfall that can be caused by various factors, such as terrorism, natural disasters and infectious diseases (Bozkurt et al., 2021). The outbreak of the coronavirus pandemic in the late 2019 undoubtedly confirms the previous assertion. This highly infectious and deadly disease has compelled governments across the globe to impose drastic measures in order to curb the infection (Shang et al., 2021). In this regard, these actions have had devastating effect

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on the global economy, and particularly on the tourism sector, while all investors who prefer to invest in tourism indices have suffered tremendous losses (Pompurová et al., 2021).

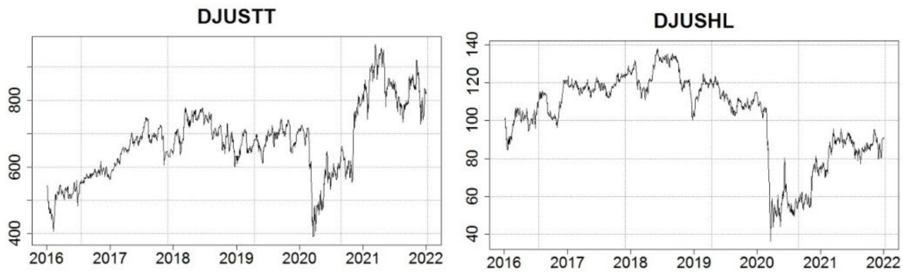
Fernandez et al. (2022) contended that the pandemic put up 75 million workers at immediate job risk, while travel and tourism GDP loss in 2020 goes up to US$ 2.1 trillion. Škare et al. (2021) claimed that the decrease in tourism activity is expected to be seven times greater than that resulting from the September 11 terrorist attack. Carter et al. (2022) stated that hotel occupancy during April 2020 was under 25%, compared to about 68% in April 2019, whereas the leisure and hospitality industry lost 7.7 million jobs in April 2020, in addition to 459,000 jobs lost in March 2020. Besides, Huynh et al. (2021) argued that all financial markets reacted to the outbreak of corona virus in greater or lesser extent by the end of February 2020 with considerable slumps and high volatilities. This happened because pandemic worsened the levels of uncertainty and investor confidence. For instance, in the first wave of the outbreak from February to April 2020, the stock indices in the U.S, U.K, and Australian markets recorded the most rapid fall (more than 20%), whereas tourism related indices are among the worst affected.

Although COVID19 pandemic has devastating effect on tourism industry, empirical studies on the impact of pandemic on the tourism sector are widely missing in the literature, according to Škare et al. (2021). One of the rare papers that addressed the impact of pandemic on tourism stocks was done by Sikiru and Salisu (in press). They researched how increased risk of Dow Jones travel and tourism (DJUSTT) index from NYSE can be hedged in the portfolio with gold. They covered five years sample, particularly addressing the COVID19 pandemic period. We use the paper of Sikiru and Salisu (in press) as a reference point for our research, with aim to upgrade it in several different ways, and this is where our motive comes from.

First difference from the aforementioned paper is that we broaden analysis, including yet another tourism related index from NYSE – the Dow Jones hotel and logging (DJUSHL) index. We consider DJUSHL because it is highly connected with the tourism sector, but encompasses different group of companies compared to DJUSTT index. However, both indices experienced severe downfall in the first quarter of 2020, as Figure 1 illustrates. This means that the presence of high risk is highly probable, and this paper tries to find a way to mitigate it. Also, adding one more index in the analysis, increases credibility of the overall results. In addition, these two indices have obvious idiosyncratic differences, in a sense that the DJUSTT index recovers faster than the DJUSHL index when the plunge happened in early 2020. In this regard, it would be interesting to see whether this difference has an effect on the value of extreme risk in the created portfolios, as well as on the structure of assets in these portfolios.

Second contribution of this paper is the fact that we construct two multivariate portfolios of seven assets. This is much more complex procedure than making a two-asset portfolio, which is the method of Sikiru and Salisu (in press). In particular, we construct the two minimum-risk portfolios, where the two U.S. tourism indices are regarded as primary asset in each portfolio. In other words, both tourism indices are combined with heterogeneous six auxiliary assets in the two separate portfolios. These instruments are Islamic DJI100X index, gold futures, corn futures, copper futures, 10Y U.S. bond and Bitcoin. All these auxiliary instruments behave intrinsically different, since they are all driven by different fundamental factors. This means that they probably have low correlation with the tourism indices, which is good for the diversification purposes. Besides, except Bitcoin, all the other assets have a reputation of low volatility instruments, which is an additional argument to include them in a portfolio (see e.g. Basher and Sadorsky, 2016; Spencer et al., 2018; Liu and Lee, 2022; Yang et al., 2022). In particular, DJI100X is considered in the portfolios because it observes Shariah complaint (Islamic) indices that bear relatively low risk. If firm wants to be included in an Islamic index, companies must not have account receivables above 45% of total assets and/or gross interest-bearing debt above 33% of total asset (see e.g. Mongi, 2019; Ali et al., 2021). These restrictions eventually reflect to lower risk of an Islamic index. Mentioned commodities (gold, corn and copper futures) are used in the portfolios because they all have specific supply and demand structures, which results in low correlation between themselves and all the other assets in the portfolios. Bonds depend on the changes in interest rate, level of inflation and monetary policy, while Bitcoin is subject to numerous global factors, and often to irrational and hasty trading. By all means, wide choice of low-correlated assets should produce low risk in the multivariate portfolios.

Figure 1 Empirical Dynamics of the Two U.S. Tourism Indices



Third difference *vis-à-vis* the paper of Sikiru and Salisu (in press) is related to the measurement of risk in the portfolios. These authors measured risk in the two-asset portfolio with a common variance. However, variance can be biased because it gives equal weight to positive and negative returns, while investors only want to know about negative returns. Therefore, a minimum-variance portfolio can lead to wrong conclusions and erroneous investment decisions. This potentially serious drawback of the minimum variance metric is circumvented by the introduction of Value-at-Risk (VaR) in 1994 by J.P. Morgan. VaR calculates how much an asset or a portfolio can lose within a given time period, assuming the pre-specified probability level (see e.g. Chen et al., 2015; Altun et al., 2017). Targeting minimum VaR in a multivariate portfolio is very complex and elaborate procedure, and relatively few papers constructed this type of portfolio (see e.g. Hammoudeh et al., 2013; Abuaf et al., 2018; Al Janabi et al., 2019). However, VaR cannot measure the mean loss, conditional upon the fact that VaR has been exceeded, which could lead to risk underestimation. In this regard, instead of VaR, we use conditional VaR (CVaR) of Rockafellar and Uryasev (2000), which is a better downside risk approximation than VaR. CVaR measures an average expected loss rather than a range of potential losses, as VaR calculates. We want to focus on extreme risk, so probability at which

CVaR is calculated is 99%, which indicates average loss in the worst 1% of returns (see Živkov et al., 2021). Assuming that tourism indices might be excluded from the minimum CVaR portfolio due to their high downside risk, besides the minimum CVaR portfolio, we also construct the portfolio with the constraint on tourism indices of 50%[1]. At the end, we provide a visual insight of the results, illustrating the efficient CVaR frontier lines, which present spatial position of all portfolios and assets.

Following the paper of Sikiru and Salisu (in press), we also want to see whether the level of downside risk and portfolio structure vary when the two different subsamples are taken into account – 1) relatively tranquil pre-COVID subsample and 2) very volatile COVID subsample. However, unlike aforementioned authors, we avoid arbitrariness in dividing the full sample. To this end, we use the modified Iterative Cumulative Sum of Squares (ICSS) algorithm of Sansó et al. (2004) to detect exact break dates of the two tourism-related indices. These break dates serve to determine exact subsamples, i.e. with the highest (lowest) risk. After subsamples determination, we rerun the minimum-CVaR portfolio optimization procedure, taking into account the samples with the lowest and highest risk. In this way, we can see how structure of assets in the portfolio looks like and what is the minimum-CVaR measure in both portfolios when the two diametrically different samples are under scrutiny.

To the best of our knowledge, this is the first paper that investigates thoroughly the construction of the multivariate minimum-CVaR tourism-related portfolios. In this process, we use a wide range of auxiliary assets and the elaborate portfolio optimization procedure, which have never been done before.

Besides introduction, the rest of the paper is structured as follows. Second section provides overview of the existing literature. Third section explains used methodologies – construction of the minimum-CVaR portfolios and the way how subsamples are determined *via* the ICSS algorithm. Fourth section introduces dataset. Fifth section presents the results of the full sample, while sixth section is reserved for the results of the subsamples. Sixth section briefly discusses the results, while the last section concludes.

2. Literature Review

This section introduces the papers that researched the impact and effects of COVID-19 pandemic on tourism industry. However, these papers are generally scarce because pandemic broke out relatively recently. For instance, Pham et al. (2021) examined the short-run economic impacts of the pandemic on the inbound tourism industry in Australia. They asserted that the pandemic affects Australian tourism directly with a decline in output and employment. They reported that immediate decline of Australian inbound tourism industry is between A$39-A$42 billion, while direct job losses goes around 152,000 in tourism, extending to between 423,000 and 456,000 across many industries along the tourism value chain. Santos and Moreira (2021) researched the Portuguese case. They stated that the COVID-19

[1] This constraint is set up totaly arbitrary and should reflect position of an investor who prefer to invest in tourism index.

pandemic had serious effect on the national tourism system, although government measures have been implemented to mitigate the impacts. Their results showed that tourist accommodation had a slight recovery after the first phase of the pandemic, mainly in more consolidated destinations: Algarve and Madeira. On the other hand, the low-density territories with peri-urban and rural features, such as Alentejo and Central Portugal, suffered less severe impact on tourism demand, which means that domestic tourism was able to mitigate some negative effects. Carter et al. (2022) investigated the stock market performance of the U.S. travel-related firms (airlines, restaurants, and hotels) in response to the COVID-19 pandemic, covering the period from the second half of February to the latter portion of March 2020. They found that larger firms with greater cash reserves and higher market-to-book ratios experienced fewer negative returns, while firms with greater leverage were penalized more. Also, cash reserves were particularly important for hotels, according to their results.

The paper of Fernandez et al. (2022) tries to identify the most vulnerable countries and the variables that explain their vulnerability. They asserted that vulnerability is determined by combination of several characteristics: low competitiveness, high incidence of COVID-19 and high weight of tourism in its economy. Referring to these criteria, they identified the 13 most vulnerable countries, namely: Panama, Georgia, Bahrain, Morocco, Montenegro, Albania, Mexico, Dominican Republic, Jordan, Tunisia, Cape Verde, Honduras, and Lebanon. They concluded that the most effective action in the short term for these countries would be to control the incidence of the pandemic and improve tourism competitiveness, since diversification policies would take longer to be effective. Salisu et al. (2021a) researched the return and volatility transmission between the health and tourism stocks in the U.S., covering the sample between January 2018 and July 2020. They analysed full sample, pre-COVID and COVID periods, in order to emphasize the impact of the pandemic outbreak. They found significant negative bidirectional return spillover between the health and tourism sectors, especially during the COVID period. They also reported hedging effectiveness of health stocks for risks associated with tourism stocks, particularly during the pandemic period. They found significant improvement of risk-adjusted returns in diversified asset portfolio that includes health together with tourism stocks. Sikiru and Salisu (in press) evaluated the returns and volatility spillover transmission between gold and DJUSTT stock index as well as the hedging effectiveness of the former against the latter. They account for the relevance of the COVID-19 outbreak by portioning the data samples into the pre-COVID, COVID and full samples. They reported significant bidirectional return spillovers between the gold asset returns and DJUSTT stock returns. Also, they found that the hedging effectiveness of gold against the risks of the DJUSTT stocks is particularly more noticeable in the COVID period. In other words, a diversified asset portfolio that includes gold alongside the DJUSTT stocks may improve the risk-adjusted return performance.

3. Research Methodologies

3.1 CVaR-Based Portfolio Optimization

This paper constructs the minimum-CVaR multivariate portfolios, combining tourism-related indices with a wide spectrum of the low-correlated assets. The starting point in this process is the portfolio optimization procedure, originally introduced by Markowitz (1952) in the Modern portfolio theory. However, instead of variance, we target the minimum extreme risk of a portfolio, which is depicted by the conditional Value-at-Risk measure. As it is known, this theory discerns two types of portfolios – efficient and inefficient. Efficient portfolios are those where rising returns are followed by rising risk. This is acceptable option from the investor's point of view, while the only question is how much of risk investor is willing to accept. Inefficient portfolios are those where rising risk is followed by lower returns, which is bad choice for every investor. Generally speaking, portfolio optimization changes weights of assets in a portfolio with aim to find the best combination of weights that fulfils specific goal (see e.g. Armeanu and Balu, 2008; You and Daigler, 2013). The classical Markowitz portfolio optimization procedure takes into account variance of every asset in a portfolio and their pairwise correlations, while the minimum-CVaR procedure considers CVaR instead of variance.

However, regardless of whether the minimum variance or CVaR portfolio is calculated, several constraints need to be set up. First and foremost, sum of all weights in a multivariate portfolio needs to be equal to one, while all individual weights are somewhere in between zero and one.

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

where w_i denotes calculated weight of asset *i* in a portfolio.

Every portfolio with minimum risk has corresponding mean value, which is weighted average portfolio return (r_p), and it is calculated as in equation (2).

$$r_p = \sum_{i=1}^{n} w_i r_i \tag{2}$$

This paper observes extreme risk of a portfolio, and that is calculated *via* the parametric CVaR measure. CVaR is actually an integral of VaR. Therefore, parametric VaR for short position is calculated as in equation (3), while the expression for the CVaR calculation is given in equation (4).

$$VaR_\alpha = \hat{\mu} + Z_\alpha \hat{\sigma} \tag{3}$$

$$CVaR_\alpha = -\frac{1}{\alpha}\int_0^\alpha VaR(x)dx \tag{4}$$

where $\hat{\mu}$ and $\hat{\sigma}$ in equation (3) refer to the estimated mean and standard deviation of a particular portfolio, respectively. Z_α is the left quantile of the normal standard distribution, where α is calculated under 99% probability, which indicates to extreme risk.

The minimum-CVaR optimization is written as in expression (5).

$$\min CVaR_p(w), \qquad \sum_{i=1}^{n} w_i r_i \tag{5}$$

Besides construction of the minimum-CVaR seven-asset portfolios, we also want to examine how multivariate portfolio would look like if weight constraints are imposed on the tourism-related indices (TRI). We hypothesize situation in which investor holds minimum 50% in tourism asset, while the remaining 50% goes to the other six assets. We consider this scenario because the share of the tourism-related index in the portfolio might be zero. This is realistic assumption because tourism indices bear a lot of extreme risk due to the COVID crisis. Imposed restriction on TRIs and the other assets in a portfolio is given as in expressions (6) and (7):

$$w_{TRI} \geq 0.5; \tag{6}$$

$$0 \leq w_i \leq 0.5; \quad i = 1,2, \dots, 6 \tag{7}$$

Calculating the hedge effectiveness index of CVaR, we quantitatively estimate how much extreme risk reduction is achieved by the construction of the minimum-CVaR portfolio. The HEI_{CVaR} risk measure is calculated in the following way:

$$HEI_{CVaR} = \frac{CVaR_{unhedged} - CVaR_{hedged}}{CVaR_{unhedged}} \tag{8}$$

Subscript $unhedged$ refers to the investment only in the tourism-related index, whereas the label $hedged$ indicates to the investment in the minimum-CVaR portfolio. As much as HEI index is closer to 1, the better hedging effectiveness is, and *vice-versa*.

In order to be see how the constructed minimum CVaR portfolios perform from the return-to-risk aspect, we follow Živkov et al. (2022) and calculate the three risk adjusted ratios – Sharpe, Sortino and modified Sharpe ratio. Sharpe ratio is a classical return-to-risk ratio of Sharpe (1966), which observes excess returns in relation to common standard deviation (σ), see equation (9).

$$Sharpe\ ratio = \frac{R - R_f}{\sigma} \tag{9}$$

where R is average log-return of a CVaR portfolio, R_f is risk-free rate, and σ is standard deviation of a portfolio. Yields of 3M treasury bills denote risk-free rate (R_f).

Sharpe ratio puts standard deviation in denominator, which could bias this indicator because standard deviation gives equal weight to positive and negative returns. For this reason, we calculate the two more indicators – Sortino and modified Sharpe ratio, which take into account only negative returns. In other words, Sortino ratio of Sortino and Price (1994) puts in denominator downside deviation (σ_D), while modified Sharpe ratio of Gregoriou and Gueyie (2003) observes absolute value of downside risk. These ratios are calculated as in equations (10) and (11), respectively.

$$Sortino\ ratio = \frac{R - R_f}{\sigma_D} \tag{10}$$

$$modified\ Sharpe\ ratio = \frac{R_p - R_f}{|mCVaR|} \tag{11}$$

3.2 Structural Breaks Detection with the ICSS Algorithm

We want be accurate as much as possible in the process of splitting the full sample into the subsamples. In that effort, we apply complex method of the structural break detection, known as the modified Iterative Cumulative Sum of Squares (ICSS) algorithm of Sans´o et al. (2004). Original version of the ICSS algorithm was developed by Inclan and Tiao (1994), but Sans´o et al. (2004) showed that original ICSS procedure can be significantly oversized due to the presence of heavy-tails (see Segnon et al., 2020). Therefore, Sansó et al. (2004) developed modified ICSS, which explicitly considers the fourth moment properties of the time-series. The break detection algorithm of Sansó et al. (2004) is based on the non-parametric Inclan and Tiao adjustment (AIT), which is specified as follows:

$$AIT = \sup_{k} \left| T^{-0.5} G_k \right| \tag{12}$$

where,

$$G_k = \hat{\lambda}^{-0.5}\left[C_k - (k/T)C_T\right]; \hat{\lambda} = \hat{\gamma}_0 + 2\sum_{l=1}^{m}\left[1 - l(m+1)^{-1}\right]\hat{\gamma}_l; \hat{\gamma}_l = T^{-1}\sum_{t=l+1}^{T}(\tau_t^2 - \hat{\sigma}^2)(\tau_{t-1}^2 - \hat{\sigma}^2)$$
$$\hat{\sigma}^2 = T^{-1}C_T;$$

According to the procedure of Newey and West (1994), we set the lag truncation parameter $m = 0.75T^{1/3}$.

4. Dataset Description

The multivariate seven-asset portfolio construction is conducted by using daily data of the two U.S. tourism indices – DJUSTT[2] and DJUSHL[3] from NYSE, and the six other auxiliary assets – DJI100X index, gold futures, corn futures, copper futures, 10Y U.S. bond and Bitcoin. Every tourism index is combined with the six auxiliary assets in the minimum-CVaR portfolio. Data-span covers the six years period, from January 2016 to December 2021. The tourism indices are collected from the *investing.com* website, while the auxiliary assets are obtained from the *stooq.com* website. Prices of all the assets are expressed in USD. Gold futures are in the USD per troy ounce, corn futures are expressed in the U.S. cents per bushel, while copper futures are in the U.S. cents per pound. All time-series are transformed into log-returns (r_i) according to the expression: $r_i = 100 \times log(P_{i,t}/P_{i,t-1})$, where P_i is the price of a particular asset. All log-returns of the selected assets are synchronized according to the existing observations, which implies exclusion of those observations that not appear in all the time-series. Table 1 presents the full sample descriptive statistics of all the time-series, along with the CVaR measures. CVaR is also added in Table 1 because we make the portfolios with minimum CVaR, in which the portfolio optimization takes into account CVaR, rather than variance. Knowing CVaR of the every asset, can give us a clue which asset might have higher (lower) share in the two portfolios with the minimum-CVaR goal.

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[2] Some of the companies listed in this index are: Expedia, Tripadvisor, Avis, Booking.
[3] Some of the companies listed in this index are: Host Hotels Resorts, Sunstone Hotel Investors, Diamondrock Hospitality, Apple Hospitality REIT.

Table 1 Descriptive Statistics of The Tourism-Related Indices

		Mean	*St. dev.*	*Skew.*	*Kurt.*	*JB*	*CVaR*
Primary assets	*DJUSTT*	0.028	1.995	-0.497	13.339	6782.7	-5.290
	DJUSHL	-0.008	2.396	-0.070	28.344	40388.2	-6.396
Auxiliary assets	*DJI100X*	0.040	0.878	-0.936	13.765	7497.4	-2.299
	Gold	-0.101	1.194	-1.992	13.115	7421.5	-3.282
	Corn	0.028	1.576	-1.229	18.716	15887.7	-4.172
	Copper	0.068	1.248	-0.188	4.798	211.9	-3.257
	Bond	0.016	3.342	1.144	27.695	38621.5	-8.887
	Bitcoin	0.226	4.381	-0.903	15.181	9522.1	-11.446

Notes: JB stands for the value of the Jarque-Bera coefficients of normality.

According to Table 1, all the assets have positive mean, except gold and the DJUSHL index. This means that prices of gold and DJUSHL fall on average in the full sample, while all the other assets record rise. On the other hand, gold is the second-best asset in terms of standard deviation, while the Islamic index is the first one. The riskiest assets are bitcoin and bond, whereas the two tourism-related indices follow. All the assets except bond has negative skewness, while all the assets except copper have exceptionally high kurtosis. However, third and fourth moments cannot be accounted in a measure of extreme risk because parametric CVaR uses only the first two moments. This is the reason why the Islamic index, copper and gold have the lowest conditional Value-at-Risk. Gold has slightly higher CVaR than copper, although gold has lower standard deviation. However, gold has negative mean, which increases negative value of the parametric CVaR. Low CVaR values of DJI100X, copper and gold means that these assets are good candidates to be found in the minimum-CVaR portfolios. High values of the third and fourth moments transfer to the high values of the Jarque-Berra coefficient, which indicates that the assets do not follow normal distribution.

Table 2 Pairwise Correlations between the Assets in the Full Sample

	DJUSTT	*DJUSHL*	*DJI100X*	*Gold*	*Corn*	*Copper*	*Bond*	*Bitcoin*
DJI100X	0.473	0.376	1.000	–	–	–	–	–
Gold	0.021	0.023	0.006	1.000	–	–	–	–
Corn	0.081	0.077	0.085	-0.019	1.000	–	–	–
Copper	0.257	0.229	0.348	-0.017	0.122	1.000	–	–
Bond	0.265	0.234	0.159	-0.104	0.056	0.158	1.000	–
Bitcoin	0.142	0.153	0.140	0.036	0.071	0.102	0.061	1.000

The second important factor in the portfolio optimization process is the mutual correlations of the assets, which is presented concisely in Table 2. The Islamic index has the highest correlation with the tourism indices because all the stock indices include companies, which are subject to the common global factors, such as the COVID pandemic, in greater or lesser extent. Gold has the lowest correlation with the tourism indices, while correlation with the other auxiliary assets is either negative or very low. This makes gold a very welcomed asset in a portfolio. Corn has very low correlation with the tourism indices and with the other auxiliary assets, which is a good characteristic of corn. Copper has somewhat higher correlation with the stock indices, and the same applies for bond. Bitcoin has relatively low correlation with all the assets, but it is the riskiest asset, which poses a problem for Bitcoin to have more significant share in the portfolios.

The next section presents the results of the calculated minimum-CVaR portfolios, which will dispel any doubts about the structure of the portfolios.

5. Empirical Results

5.1 Full Sample Analysis

This subsection presents the results of the constructed portfolios in the full sample. For every tourism index, we calculate the minimum-CVaR portfolio (hereafter MCVaRP) and portfolio with the share constraint of 50% on the tourism indices (hereafter tourism-dominated portfolio – TDP). Table 3 contains the shares of all the assets in the minimum-CVaR portfolio and TDP, while Figure 2 illustrates relative positions of the two portfolios and all the assets *via* the CVaR efficient frontier line. According to Table 3, the minimum-CVaR portfolios with the two tourism indices have the same composition in terms of shares. This is the case because the tourism indices are excluded from both MCVaRPs, i.e. they have zero share. Bitcoin also has zero share in both MCVaRPs, so the two minimum CVaR portfolios are actually composed of the five assets. Regarding the tourism indices, the reason for such results lies in the fact that these assets have very high downside risk (see Table 1), and also, they have relatively high correlations with the other assets in the portfolios (see Table 2). The Islamic index has the lowest downside risk, according to Table 1, and this is the reason why it has the highest shares in MCVaRPs, amounting 43%. This result is well in line with numerous papers that found good risk performance of the Islamic indices (see e.g. Hassan et al., 2019; Goldil et al., 2022).

On the other hand, gold has relatively high downside risk, but it has the second-highest share in MCVaRPs with the value of 29%. The reason for such good result of gold lies in the very low correlations between gold and the other assets in the portfolios. Corn and copper futures have the same share of 13%, although corn has higher CVaR risk than copper. However, copper has higher pairwise correlations with the other assets, and this offsets its lower downside risk, so these two ends up with the same share in the minimum-CVaR portfolios. The share of 10Y bond is very small, amounting only 2%, because bond has the second worst downside risk (-7.775). Bitcoin has by far the highest downside risk (-9.962), and because of that it is removed from the portfolios, although it does not have high correlations with the other assets, whatsoever.

Results in Table 3 confirm our assumption that tourism indices might be excluded from MCVaRPs due to high downside risk. Therefore, we additionally create the two suboptimal portfolios, with minimum 50% share of a tourism index in the portfolio. These portfolios should reflect position of an investor who prefer to invest in the tourism indices. Table 3 contains share-composition of these portfolios. According to the results, the shares of the assets in these two suboptimal TDPs are much different compared to MCVaRPs.

Table 3 Portfolio Composition in the Full Sample

	Portfolio with DJUSTT		*Portfolio with DJUSHL*	
	MCVaRP	***TDP***	***MCVaRP***	***TDP***
TRI	0%	50%	0%	50%
DJI100X	43%	0%	43%	3%
Gold	29%	30%	29%	30%
Corn	13%	13%	13%	12%
Copper	13%	7%	13%	5%
Bond	2%	0%	2%	0%
Bitcoin	0%	0%	0%	0%
Σ	100%	100%	100%	100%

In particular, the share of Bitcoin remains zero, the share of bond is also reduced to zero, which is not surprising since both assets have very high downside risk. However, somewhat unexpected is significant share reduction to 0% and 3% of the Islamic index in TDPs with DJUSTT and DJUSHL, respectively. The only logical explanation for such significant reduction of DJI100X in the suboptimal portfolios is the fact that the Islamic index has relatively high mutual correlation with both tourism indices. In other words, although the Islamic index has the lowest downside risk, its share in TDPs is significantly lower than in MCVaRP because level of correlation with DJUSTT and DJUSHL indices amounts 47.3% and 37.6%, respectively. In these conditions, gold emerges as the best auxiliary asset with the share of 30% in both suboptimal portfolios. This happens because gold has the lowest correlation with the tourism indices, which goes around 2%. These results are very much in line with the paper of Sikiri and Salisu (in press) who asserted that gold serves as a very strong hedge and safe haven for travel & tourism stocks. Besides, many other studies reported excellent hedging properties of gold in combination with stocks (see e.g. Beckmann, 2015; Beckmann, 2019; Abuzayed et al., 2022). Corn retains its share compared to MCVaRP, whereas copper shares reduced to 7% and 5%, probably because copper is the only commodity with the relatively high correlation with the tourism indices, more than 20%.

Table 4 contains the downside risk properties and the calculated hedge effectiveness indices of the tourism indices and TDPs. The CVaR results of the minimum CVaR portfolios are not presented in Table 4 because both TRIs are removed from MCVaRPs, which means that hedging is effectively not happening in MCVaRPs. However, Table 4 contains both parametric and historical CVaR and HEI_{CVaR} values. Theoretically speaking, portfolio distribution must have Gaussian properties, in order to use parametric CVaR in a reasonable way, but all the returns are not normally distributed (see Table 1). Therefore, parametric CVaR will be misleading and especially underestimating the tails. In this regard, Table 4 contains historical values next to parametric ones, which shows how much the parametric values are lower compared to the historical values. It can be seen that parametric values significantly underestimate downside risk, but HEI results are relatively equable between parametric and historical values because historical values of both TRIs and TDPs proportionally increase.

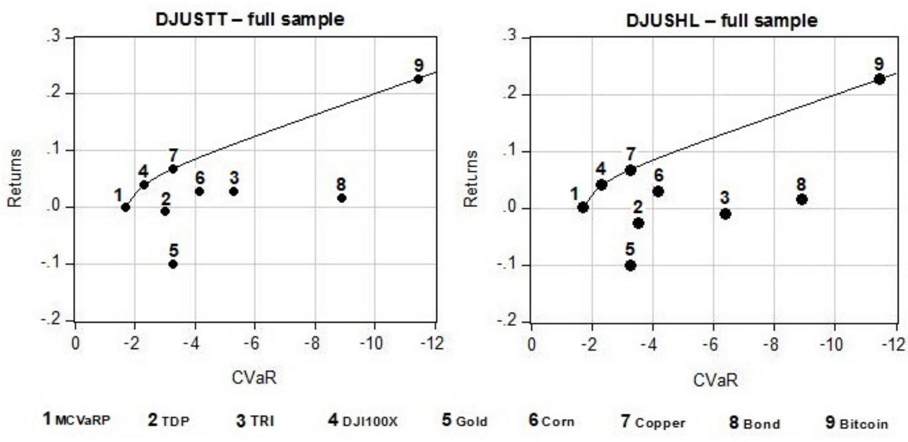
Table 4 Downside Risks and HEI Values of TRIs and TDPs in the Full Sample

	DJUSTT	*TDP$_{(DJUSTT)}$*	*DJUSHL*	*TDP$_{(DJUSHL)}$*
CVaR – parametric	-5.290	-3.008	-6.396	-3.520
HEI$_{CVaR}$ – parametric	–	0.431	–	0.450
CVaR – historical	-9.419	-5.167	-10.986	-5.586
HEI$_{CVaR}$ – historical	–	0.451	–	0.470

According to Table 4, TDP with DJUSTT has the downside risk of -3.008, while TDP with DJUSHL has the extreme risk of -3.520. Extreme risk reduction in TDP with DJUSTT is 43.1%, and 45.0% with DJUSHL compared to the sole investments in the tourism indices. However, although these numbers might seem small, for some investors in the tourism indices this could be acceptable. This can be concluded from the fact that the downside risk of both TDPs is relatively low, compared to the downside risk of all the individual assets. In other words, only the DJI100X index has lower downside risk *vis-à-vis* TDP$_{(DJUSTT)}$, while in the case of TDP$_{(DJUSHL)}$, this applies only for the Islamic index and gold.

The left and right plots in Figure 2 provide a good visual perspective of the spatial position of every asset and the portfolios. Both plots are almost identical, while the only differences are positions of TDPs (dot 2) and the two tourism indices (dot 3). In the case of the DJUSHL index, the dot 3 is slightly moved to the right because this index has higher downside risk compared to DJUSTT.

Figure 2 CVaR Efficient Frontier Lines in the Full Sample



Notes: MCVARP is minimum CVaR portfolio, TDP stands for tourism dominated portfolio, while TRI is tourism-related index.

In order to see how the two tourism-dominated portfolios perform from the return-to-risk aspect, we present Table 5 that contains calculated values of the three ratios. According to the results, TDP$_{(DJUSTT)}$ achieves higher returns per unit of risk, taking into account both ordinary risk and downside risk. This happens because TDP$_{(DJUSTT)}$ has lower risk (see table 4), but it also has higher returns compared to

$\text{TDP}_{(\text{DJUSHL})}$. Higher returns of $\text{TDP}_{(\text{DJUSTT})}$ *vis-à-vis* $\text{TDP}_{(\text{DJUSHL})}$ can be seen in the positions of the dots 2 in Figure 2.

Table 5 Return-To-Risk Ratios of the Two Tourism Dominated Portfolios in the Full Sample

	$\textit{TDP}_{(\textit{DJUSTT})}$	$\textit{TDP}_{(\textit{DJJUSHL})}$
Sharpe ratio	-0.0069	-0.0207
Sortino ratio	-0.0086	-0.0259
Modified Sharpe ratio	-0.0026	-0.0077

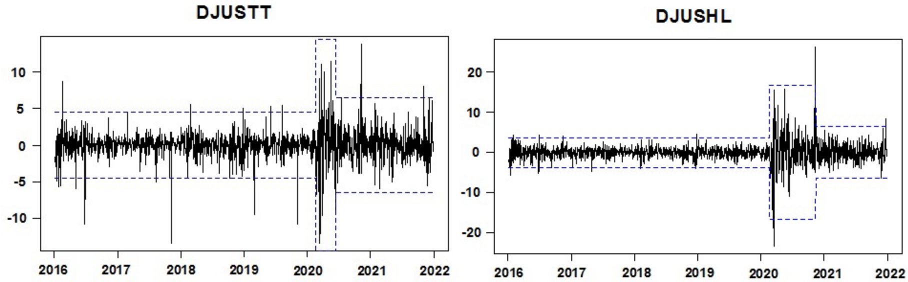
6. Complementary Analysis Via Subsamples

6.1 Structural Breaks Detection

This section examines how the composition of the assets in the portfolio diverges when the two diametrically different subsamples are analysed separately. In this process, it is important to properly determine the time-span of the subsamples. In order to be accurate as much as possible, we use the exact mathematical procedure, known as the modified ICSS algorithm, to detect structural breaks in the two tourism log-returns time-series. These structural breaks are then used to partition subsamples. Figure 3 presents graphically the detected structural breaks, while Table 6 shows exact dates when they occurred.

We find two structural breaks in both indices. According to Table 6, the first structural break took place at the same time in both tourism indices: February 21, 2020, which is linked with the beginning of the pandemic. On the other hand, the second structural break does not coincide between the indices, i.e. the second period lasted longer in the DJUSHL index for about five months. Also, DJUSHL is less risky in the pre-COVID period, whereas in the COVID period, this index is riskier. Besides, Figure 3 clearly shows that DJUSHL index has bigger outliers in the second subsample, which implies greater daily losses, i.e. greater downside risk. Level of riskiness in the third sub-period is almost identical. In order to make subsamples comparable, we set identical length of the crisis subsample, taking the longer subsample of the DJUSHL index as a benchmark. In other words, the crisis subsample stretches out from February 21, 2020 to November 13, 2020.

Figure 3 Detected Structural Breaks Via Modified ICSS Algorithm



Notes: Doted lines denote bands of ±3 standard deviations.

Table 6 Exact Break-Dates of the Two Tourism Indices

DJUSTT		***DJUSHL***	
Subsamples	***St. dev.***	***Subsamples***	***St. dev.***
1/1/2016 – 2/21/2020	1.511	1/1/2016 – 2/21/2020	1.235
2/22/2020 – 6/12/2020	4.842	2/22/2020 – 11/12/2020	5.590
6/13/2020 – 12/31/2021	2.149	11/13/2020 – 12/31/2021	2.150

In order to emphasize differences between the pre-COVID and COVID subsamples, we calculate minimum-CVaR portfolios only for the first and second subsamples because the second sample bears higher risk.

6.2 Pre-COVID Subsample Analysis

This subsection presents the calculated structure of both tourism-related portfolios in the lower volatility subsample, also distinguishing between MCVaRPs and TDPs. Table 7 shows the results of the shares in the portfolios, whereas Table 8 helps to explain the results. In other words, Table 8 contains the pairwise correlations between the assets as well as the CVaR values, and these two factors are crucial for the weight calculation in the minimum-CVaR portfolio.

According to Table 7, the shares of the DJUSTT and DJUSHL indices amount 0% and 8% in MCVaRPs, respectively. This is different comparted to the full sample where both tourism indices have no share. In other words, hedging is actually happening in the portfolio with DJUSHL in the pre-COVID period. On the other hand, DJUSTT is excluded from the minimum CVaR portfolio because it is riskier tourism index in the pre-COVID period, and also it has higher pairwise correlations with the other assets (see Table 8). DJI100X has notable change of the share in the pre-COVID sample relative to the full sample, which is particularly true for the MCVaRP with DJUSTT. In other words, the share of the Islamic index is 49% in the pre-COVID period *vis-à-vis* 43% in the full sample. This is because the portfolio optimization gives more weight to less risky DJI100X in the portfolio with DJUSTT.

Table 7 Portfolio Composition in the Pre-COVID Period

	Portfolio with DJUSTT		*Portfolio with DJUSHL*	
	MCVaRP	***TDP***	***MCVaRP***	***TDP***
TRI	0%	50%	8%	50%
DJI100X	49%	10%	44%	14%
Gold	21%	20%	21%	18%
Corn	14%	10%	13%	12%
Copper	11%	8%	10%	5%
Bond	4%	0%	3%	0%
Bitcoin	1%	2%	1%	1%
Σ	100%	100%	100%	100%

On the other hand, in the portfolio with DJUSHL, this percent is lower (44%) because more weight goes to less risky DJUSHL. The share of gold is a little bit smaller in both MCVaRPs in the pre-COVID period compared to the full sample, probably because gold has relatively high downside risk (-3.282) in the lower-volatility sample. The shares of corn and copper do not differ significantly between the pre-COVID period and the whole period because their levels of risk and pairwise correlations do not change significantly between the full sample and the first subsample. Bond has higher share in the pre-COVID MCVaRPs due to significantly lower downside risk in this period. On the other hand, Bitcoin has very low correlations with the other assets, which goes around zero, and this increases its share to 1% in MCVaRP.

As for the tourism-dominated portfolios, it can be seen that the share of the tourism indices increases mostly on the expense of the Islamic index because the tourism indices have the highest correlations with DJI100X. The share of the other assets in TDPs is also lower, but not as much as in the case of the Islamic index. However, the obvious difference in relation to the full sample is the fact that the share of the Islamic index increases from 0% to 10% in the portfolio with DJUSTT, and from 3% to 14% in the portfolio with DJUSHL. The reasons are the same as in the case of MCVaRP, i.e. the Islamic index has the lowest downside risk. On the other hand, gold has the highest share of the all auxiliary assets in TDPs, primarily because gold has very low correlation with the other assets. Bitcoin has even lower pairwise correlations than gold, but Bitcoin has the highest downside risk, so the share of Bitcoin is only 2% and 1% in TDPs.

Table 8 Pairwise Correlations between the Assets and Values of CVaR in the Pre-COVID Period

	DJUSTT	***DJUSHL***	***DJI100X***	***Gold***	***Corn***	***Copper***	***Bond***	***Bitcoin***
DJI100X	0.402	0.335	1.000	–	–	–	–	–
Gold	0.014	-0.015	-0.001	1.000	–	–	–	–
Corn	0.087	0.012	0.067	-0.028	1.000	–	–	–
Copper	0.186	0.176	0.321	0.015	0.070	1.000	–	–
Bond	0.219	0.249	0.153	-0.047	0.039	0.236	1.000	–
Bitcoin	-0.007	0.022	-0.011	0.007	0.034	0.038	0.000	1.000
CVaR	-3.486	-2.869	-1.640	-2.925	-3.201	-2.531	-4.641	-9.600

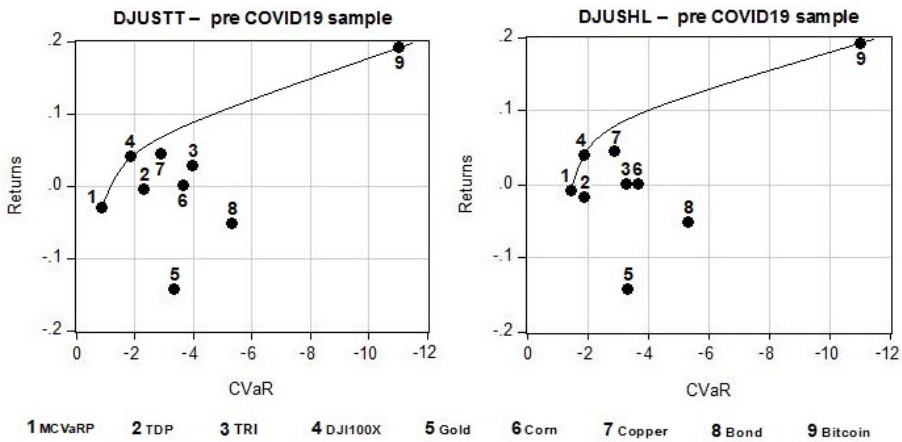
In order to be consistent with Table 4, Table 9 also contains the parametric and historical CVaR values of the created TDPs as well as the hedge effectiveness indices. Extreme risk is lower in the portfolios with the DJUSHL index because this index is less risky than DJUSTT in the pre-COVID period. This difference especially comes to the fore in the historical CVaR values. Being more risky means that $TDP_{(DJUSTT)}$ has better hedging results, according to the historical HEI_{CVaR}.

Table 9 Downside Risks and HEI Values of TRIs and TDPs in the Pre-COVID Sample

	DJUSTT	*$TDP_{(DJUSTT)}$*	*DJUSHL*	*$TDP_{(DJUSHL)}$*
CVaR – parametric	-3.998	-2.335	-3.287	-1.912
HEI_{CVaR} – parametric	—	0.416	—	0.418
CVaR – historical	-7.165	-3.746	-3.942	-2.397
HEI_{CVaR} – historical	—	0.477	—	0.392

Figure 4 illustrates relative position of all the assets and all the portfolios in the pre-COVID subsample. The only difference between the left and right plots is positions of dots 1, 2 and 3, while all other dots have the same positions because the pre-COVID sample has the same time-span regarding both tourism indices.

Figure 4 CVaR Efficient Frontier Line in the Pre-COVID Period



Notes: MCVARP is minimum CVaR portfolio, TDP stands for tourism dominated portfolio, while TRI is tourism-related index.

As in the full sample, $TDP_{(DJUSTT)}$ has better return-to-risk characteristics than $TDP_{(DJUSHL)}$, according to Table 10. Although $TDP_{(DJUSTT)}$ has higher risk, it also has higher returns (see positions of dot 2), and these higher returns compensate higher risk, resulting in better return-to-risk ratios.

Table 10 Return to Risk Ratios of the Two Tourism Dominated Portfolios in the Pre-COVID Sample

	$TDP_{(DJUSTT)}$	$TDP_{(DJJUSHL)}$
Sharpe ratio	-0.0048	-0.0246
Sortino ratio	-0.0058	-0.0356
Modified Sharpe ratio	-0.0018	-0.0092

6.3 COVID Subsample

This section presents the findings of the constructed portfolios in the volatile COVID subsample. Table 11 shows the calculated shares of the assets in MCVaRPs and TDPs, while Table 12 contains the pairwise correlations between the assets.

Similar to the full sample, the MCVaR portfolios do not contain tourism indices in the COVID subsample because these indices bear very high downside risk, -9.781 (DJUSTT) and -15.135 (DJUSHL), which is expected. This implies that the structure of both MCVaRPs is the same. However, in spite of the different CVaR values of TRIs, the structure of both TDPs is also the same. In other words, gold has 37%, corn has 13%, and the rest goes to TRIs. Corn actually has lower CVaR (-3.753) compared to gold (-3.976), but gold has higher share due to the significantly lower correlation with the tourism indices (see Table 12).

Table 11 Portfolio Composition in the COVID Period

	Portfolio with DJUSTT		*Portfolio with DJUSHL*	
	MCVaRP	***TDP***	***MCVaRP***	***TDP***
TRI	0%	50%	0%	50%
DJI100X	16%	0%	16%	0%
Gold	35%	37%	35%	37%
Corn	26%	13%	26%	13%
Copper	22%	0%	22%	0%
Bond	1%	0%	1%	0%
Bitcoin	0%	0%	0%	0%
Σ	100%	100%	100%	100%

Relatively high values of gold in both MCVaRP and TDP portfolios speaks in favour that gold is a good hedging instrument in the crisis period. This finding coincides with some papers, which also found a good hedging properties of gold in the combination with stocks during the COVID pandemic (Chemkha, 2021; Akhtaruzzaman et al., 2021; Salisu et al., 2021b)

Table 12 Pairwise Correlations between the Assets and Values of CVaR in the COVID Period

	DJUSTT	***DJUSHL***	***DJI100X***	***Gold***	***Corn***	***Copper***	***Bond***	***Bitcoin***
DJI100X	0.648	0.502	1	–	–	–	–	–
Gold	0.029	0.077	0.033	1	–	–	–	–
Corn	0.224	0.216	0.220	0.062	1	–	–	–
Copper	0.403	0.333	0.470	-0.050	0.249	1	–	–
Bond	0.338	0.220	0.189	-0.203	0.105	0.115	1	–
Bitcoin	0.397	0.350	0.454	0.164	0.189	0.134	0.176	1
CVaR	-9.781	-15.135	-3.966	-3.976	-3.753	-3.879	-19.508	-12.806

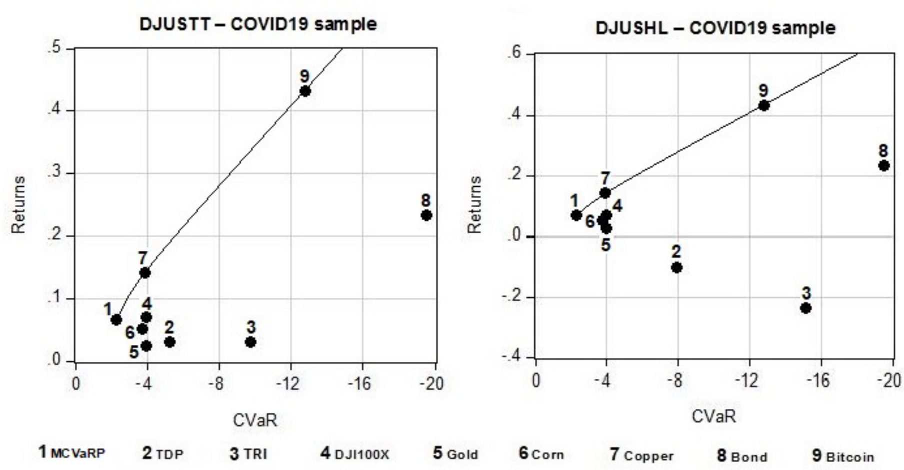
Table 13 contains the calculated parametric and historical CVaR values of the constructed TDPs as well as their corresponding HEI numbers. The downside risk values of the constructed portfolios are significantly higher than their counterparts in the pre-COVID sample, which is expected, since this section analyses the very risky COVID sample. The historical CVaR values are particularly high in the COVID sample, which means that parametric CVaR significantly underestimates CVaR in the COVID sample. Hedge effectiveness is higher in the case of the DJUSHL index, probably because this index is riskier in the COVID sample.

Table 13 Downside Risks and HEI Values of TRIs and TDPs in the COVID Sample

	DJUSTT	*$TDP_{(DJUSTT)}$*	*DJUSHL*	*$TDP_{(DJUSHL)}$*
CVaR – parametric	-9.781	-5.270	-15.135	-7.932
HEI_{CVaR} – parametric	–	0.461	–	0.475
CVaR – historical	-18.691	-10.305	-30.880	-16.340
HEI_{CVaR} – historical	–	0.449	–	0.469

Figure 5 presents relative position of all the assets and the created portfolios in the COVID sample. At the first glance, it is obvious that scale of the Y axis differ significantly between the left and right plots. This happens because $TDP_{(DJUSHL)}$ has negative returns (-0.102), which is also the case with DJUSHL (-0.234). This puts dots 2 and 3 below zero, which is not happening in the case of DJUSTT. Accordingly, these results have significant repercussions on the return-to-risk ratios.

Figure 5 CVaR Efficient Frontier Line in the pre-COVID Period



Notes: MCVARP is minimum CVaR portfolio, TDP stands for tourism dominated portfolio, while TRI is tourism-related index.

According to Table 14, the three ratios are positive in the case of $TDP_{(DJUSTT)}$, which means that this portfolio has significantly better return/risk results than the $TDP_{(DJJUSHL)}$ portfolio in the COVID sample. Comparing dot 2 between the two plots, this is obvious.

Table 14 Return-To-Risk Ratios of the Two Tourism Dominated Portfolios in the COVID Sample

	$TDP_{(DJUSTT)}$	$TDP_{(DJJUSHL)}$
Sharpe ratio	0.0156	-0.0349
Sortino ratio	0.0203	-0.0496
Modified Sharpe ratio	0.0059	-0.0130

7. Discussion of the Results

This section briefly discusses the results of the tourism-dominated portfolios in the full sample and the two subsamples. According to the results, extreme risk of the tourism indices is reduced over 40% in the tourism-dominated portfolios, where gold has dominant role, as an auxiliary asset, in these portfolios. This is particularly true in the COVID sample, where the risk of high losses is most pronounced. These results are in line with the paper of Sikiru and Salisu (in press), which reported that gold is the best hedging instrument for the DJUSTT index. However, these authors constructed much simpler portfolio of only two assets, while our portfolio consists of seven assets. Therefore, it is logical to ask whether and how much the seven-asset portfolio is better than the two-asset counterpart. In this regard, we additionally construct the two-asset tourism-dominated portfolio, where gold takes 50% share. These results are presented in Table 15, which shows CVaR values in the full sample and the two subsamples, taking into account that TDPs are constructed with all the assets and only with gold.

Table 15 The Values of CVaR in TDPs with All the Assets and with Gold Only

	Full sample		*Pre-COVID sample*		*COVID sample*	
	$TDP_{(DJUSTT)}$	$TDP_{(DJJUSHL)}$	$TDP_{(DJUSTT)}$	$TDP_{(DJJUSHL)}$	$TDP_{(DJUSTT)}$	$TDP_{(DJJUSHL)}$
TDP with all the assets	-3.008	-3.521	-2.335	-1.912	-5.270	-7.931
TDP with gold only	-3.163	-3.656	-2.642	-2.343	-5.324	-7.966

As can be seen, all the two-asset portfolios have higher CVaR risk than the seven-asset portfolios[4]. This means that more complicated portfolios give better results, where the difference is especially evident in the pre-COVID sample. This happens because the share of gold is the lowest in the pre-COVID period, which leaves more space to the other assets in the portfolio. On the other hand, gold has the highest share in the COVID portfolios, since gold is the best hedging instrument in crisis, and this is the reason why TDP with all assets have slightly better CVaR result than the portfolio with only gold. Better results of the seven-asset portfolios actually means that covariance matrix plays an important role in constructing the multivariate portfolios.

However, thinking from the aspect of efficiency and the ease of implementation, construction of seven-asset portfolio implies higher transaction cost, while hedging gains are slightly better, particularly in the crisis. Therefore, investors

[4] It should be underlined that the seven-asset TDP has never been actually constructed because some of the assets were excluded. In the best case, we made a six-asset portfolio.

will not make a mistake if they combine only gold with tourism index in TDP because it seems that gold does much of the work.

8. Conclusions

This paper constructs the multivariate minimum-CVaR portfolios, combining the two U.S. tourism indices (DJUSTT and DJUSHL) with the six auxiliary assets – DJI100X, futures of gold, corn and copper, the U.S. 10Y bond and Bitcoin. We gauge extreme risk *via* the conditional Value-at-Risk measure. In order to be more thorough in the analysis, we design the two types of portfolios – one that minimizes CVaR without constraints, and the other one that has 50% constraint on the tourism indices. Also, we conduct the analysis taking into account the two different subsamples – pre-COVID and COVID. These subsamples are accurately determined, using the modified ICSS algorithm.

Based on the results, we have several noteworthy findings to report. First, in the most MCVaRPs, the tourism indices are removed because they are among the riskiest assets. Because of that, we focus on the suboptimal tourism-dominated portfolios. According to the results, gold has the highest share as an auxiliary asset in the tourism-dominated portfolios. In particular, in the full sample, the share amounts 30%, in the pre-COVID sample, the share is somewhat lower, while in the COVID sample, the share is somewhat higher. This is because gold has relatively low risk, but more importantly, gold has very low pairwise correlation with the tourism indices, and this puts gold at the top of all the auxiliary assets. This also means that covariance matrix plays very important role in the CVaR portfolio optimization process. This assertion is also confirmed from the fact that the Islamic index is excluded from TDP, although it is the least risky asset. This happens because the Islamic index has very high correlation with the tourism indices, and this is why its share drops to 0% in TDPs.

As for the risk reduction of the tourism indices, the amount is above 40%, whereas DJUSTT has better return-to-risk performances than DJUSHL. It is important to say that CVaR is not an ideal risk measure because it underestimates risk. This is the case because CVaR takes into account only the first two moments, while the third and fourth moment remain neglected. The solution might be the usage of semiparametric CVaR, which takes into account all the four moments. This idea is left to future studies.

Results of this paper can show investors in the tourism indices and companies from the tourism industry how to make portfolios in order to reduce high risk of losses, because this sector is highly sensitive to various global happenings. The results are available for both the pre-COVID and COVID periods, i.e. the paper makes a clear distinction between tranquil and crisis periods.

REFERENCES

Abuaf N, Ayala T, Sinclair D (2018): Global Equity Investing: An Efficient Frontier Approach. *International finance*, 22(2):1-16.

Abuzayed B, Al-Fayoumi N, Bouri E (2022): Hedging UK Stock Portfolios with Gold and Oil: The Impact of Brexit. *Resources Policy*, 75:102434.

Akhtaruzzaman M, Boubaker S, Lucey BM, Sensoy A (2021): Is Gold a Hedge or a Safe-Haven Asset in the COVID–19 Crisis? *Economic Modelling*, 102:105588.

Al Janabi MAM, Ferrer R, Shahzad SJH (2019): Liquidity-Adjusted Value-at-Risk Optimization of a Multi-Asset Portfolio Using a Vine Copula Approach. *Physica A: Statistical Mechanics and Its Applications*, 536:122579.

Ali F, Jiang Y, Sensoy A (2021): Downside Risk in Dow Jones Islamic Equity Indices: Precious Metals and Portfolio Diversification before and after the COVID-19 Bear Market. *Research in International Business and Finance*, 58: 101502.

Altun E, Alizadeh M, Ozel G, Tatlidil H, Maksayi N (2017): Forecasting Value-at-Risk with Two-Step Method: GARCH-Exponentiated Odd Log-Logistic Normal Model. *Romanian Journal of Economic Forecasting*, 20(4): 97-115.

Armeanu D, Balu FO (2008): Testing the Efficiency of Markowitz Model on Bucharest Stock Exchange. *Economic Computation and Economic Cybernetics Studies and Research*, 42 (1-2): 201-217.

Basher SA, Sadorsky P (2016): Hedging Emerging Market Stock Prices with Oil, Gold, VIX, and Bonds: A Comparison between DCC, ADCC and GO-GARCH. *Energy Economics*, 54, 235–247.

Beckmann J, Berger T, Czudaj R (2015): Does Gold Act as a Hedge or a Safe Haven for Stocks? A Smooth Transition Approach. *Economic Modelling*, 48: 16–24.

Beckmann J, Berger T, Czudaj R, Hoang T-H-V (2019): Tail Dependence between Gold and Sectorial Stocks in China: Perspectives for Portfolio Diversification. *Empirical Economics* 56: 1117–1144.

Bozkurt K, Armutçuoğlu Tekin H, Can Ergün Z (2021): An Investigation of Demand and Exchange Rate Shocks in the Tourism Sector. *Applied Economic Analysis*, 29(86), 171-188.

Carter D, Mazumder S, Simkins B, Sisneros E (2022): The Stock Price Reaction of the COVID-19 Pandemic on the Airline, Hotel, and Tourism Industries. *Finance Research Letters*, 44: 102047.

Chemkha R, BenSaïda A, Ghorbel A, Tayachi T (2021): Hedge and Safe Haven Properties during COVID-19: Evidence from Bitcoin and Gold. *The Quarterly Review of Economics and Finance*, 82: 71–85.

Chen S, Wilson WW, Larsen R, Dahl B (2015): Investing in Agriculture as an Asset Class. *Agribusiness*, 31(3): 353-371.

Fernandez JAS, Martínez JMG, Martín JMM (2022): An Analysis of the Competitiveness of the Tourism Industry in a Context of Economic Recovery Following the COVID19 Pandemic. *Technological Forecasting and Social Change*, 174: 121301.

Godil DI, Sarwat S, Khan MK, Ashraf MS, Sharif A, Ozturk I (2022): How the Price Dynamics of Energy Resources and Precious Metals Interact with Conventional and Islamic Stocks: Fresh Insight from Dynamic ARDL Approach. *Resources Policy*, 75: 102470.

Gregoriou GN, Gueyie J-P (2003): Risk-Adjusted Performance of Funds of Hedge Funds Using a Modified Sharpe Ratio. *Journal of Wealth Management*, 6(3): 77–83.

Hammoudeh S, Santos PA, Al-Hassa A (2013): Downside Risk Management and VaR-Based Optimal Portfolios for Precious Metals, Oil and Stocks. *North American Journal of Economics and Finance*, 25: 318– 334.

Hassan K, Hoque A, Gasbarro D (2019): Separating BRIC Using Islamic Stocks and Crude Oil: Dynamic Conditional Correlation and Volatility Spillover Analysis. *Energy Economics*, 80: 950–969.

Huynh N, Dao A, Nguyen D (2021): Openness, Economic Uncertainty, Government Responses, and International Financial Market Performance during the Coronavirus Pandemic. *Journal of Behavioral and Experimental Finance*, 31:100536.

Liu M., Lee C-C. (2022): Is Gold a Long-Run Hedge, Diversifier, or Safe Haven for Oil? Empirical Evidence Based on DCC-MIDAS. *Resources Policy*, 76:102703.

Markowitz H (1952): Portfolio Selection. *Journal of Finance*, 7(1):77-91.

Mongi A (2019): The Global Influence of Oil Futures-Prices on Dow Jones Islamic Stock Indexes: Do Energy-Volatility's Structural Breaks Matter? *International Journal of Emerging Markets*, 14(4):523-549.

Newey WK, West KD (1994): Automatic Lag Selection in Covariance Matrix Estimation. *Review of Economic Studies,* 61:631–654.

Pham TD, Dwyer L, Su J-J, Ngo T (2021): COVID-19 Impacts of Inbound Tourism on Australian Economy. *Annals of Tourism Research*, 88:103179.

Pompurová K, Šebová L, Šebo J, Valihorová M, Kaščáková A (2021): The State of Tour Operators in Slovakia before the COVID-19 Pandemic. *Ekonomický Časopis, 69*(9):975 – 993.

Rockafellar R T, Uryasev S (2000): Optimization of Conditional Value-at-Risk. *Journal of Risk*, 2(3):21–41.

Salisu AA, Akanni LO, Vo XV (2021a): Volatility Spillovers and Hedging Effectiveness between Health and Tourism Stocks: Empirical Evidence from the US. *International Review of Economics and Finance*, 74:150–159.

Salisu AA, Vo XV, Lucey B (2021b): Gold and US Sectoral Stocks During COVID-19 Pandemic. *Research in International Business and Finance*, 57:101424.

Sansó A, Aragó V, Carrion-i-Silvestre J (2004): Testing for Changes in the Unconditional Variance of Financial Time Series. *Revista de Economia Financiera*, 4:32–53.

Santos N, Moreira CO (2021): Uncertainty and Expectations in Portugal's Tourism Activities. Impacts of COVID-19. *Research in Globalization*, 3:100071.

Segnon M, Lau CK, Wilfling B, Gupta R (2022): Are Multifractal Processes Suited to Forecasting Electricity Price Volatility? Evidence from Australian Intraday Data. *Studies in Nonlinear Dynamics and Econometrics*, 26(1):73-98.

Sikiru AA, Salisu AA (in press): Hedging Against Risks Associated with Travel and Tourism Stocks during COVID-19 Pandemic: The Role of Gold. *International Journal of Finance and Economics*, DOI: 10.1002/ijfe.2513

Shang D, Yu C, Diao G (2021): Study on Impacts of COVID-19 Pandemic Recession Based on Monte Carlo Simulation. *Prague Economic Papers*, 30(6):724–747.

Sharpe WF (1966): Mutual Fund Performance. *Journal of Business*, 39(S1): 119–138.

Sortino FA, Price L N (1994): Performance Measurement in a Downside Risk Framework. *Journal of Investing*, 3(3):50–58.

Spencer S, Bredin D, Conlon T (2018): Energy and Agricultural Commodities Revealed through Hedging Characteristics: Evidence from Developing and Mature Markets. *Journal of Commodity Markets*, 9:1–20.

Škare M, Soriano DR, Porada-Rochon M (2021): Impact of COVID-19 on the Travel and Tourism Industry. *Technological Forecasting and Social Change*, 163:120469.

World Travel and Tourism Council (2020) Global Economic Impact and Trends, June file:///C:/Users/105893/Downloads/Global_Economic_Impact_&_Trends_2020.pdf.

You L., Daigler RT (2013): A Markowitz Optimization of Commodity Futures Portfolios. *Journal of Futures Markets*, 33(4):343-368.

Yang C, Wang X, Gao, W (2022): Is Bitcoin a Better Hedging and Safe-Haven Investment than Traditional Assets Against Currencies? Evidence from the Time-Frequency Domain Approach. *North American Journal of Economics and Finance*, 62:101747.

Živkov D, Balaban P, Kuzman B (2021). How to Combine Precious Metals with Corn in a risk-Minimizing Two-Asset Portfolio? *Agricultural Economics – Zemedelska Ekonomika*, 67(2):60-69.

Živkov D, Damnjanović J, Papić-Blagojević N (2022). How to Hedge Energy Commodities with Precious Metals in a Multivariate Markowitz Portfolio? *Finance a úvěr – Czech Journal of Economics and Finance*, 72(1):50-70.