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The Link between Asset Value and Fear Sentiment during Covid-19 Pandemic

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Covid-19 Pandemisi Boyunca Varlık Değeri ve Korku Hissiyatı Arasındaki Bağlantı

Abstract

This article explores the role of global financial instruments as hedging or safe-haven assets in the Covid-19 pandemic crisis, which has weakened the global economy, by linking it to the investor's fear sentiment perspective. Correspondingly, it analyses the effects of shocks in the VIX index, which represents the global investor's fear sentiment, on shocks in some investment assets during the ongoing pandemic. Eight major financial instruments from different asset classes are tested along with the VIX index to achieve this goal. The analysis covers a 156-week time series and assays the variables from symmetric and intertemporal perspectives. The findings show that the most robust asset is the American Dollar fiat currency, followed partly by the Euro and gold. BTC also has been safe for a short time.

Keywords : Covid-19 Pandemic, Fear Sentiment, Financial Assets, Safe-Haven, Portfolio Selection, the Rolling Window Estimation.

JEL Classification Codes : G01, G11, G15, G17.

Öz

Bu makale, küresel ekonomiyi zayıflatan Covid-19 pandemi krizinde riskten korunma veya güvenli liman varlıkları olarak küresel finansal araçların rolünü yatırımcının korku hissiyatı perspektifiyle ilişkilendirerek araştırmaktadır. Buna bağlı olarak, küresel yatırımcının korku hissiyatını temsil eden VIX endeksindeki şokların, devam eden pandemi sırasında bazı yatırım varlıklarındaki şoklar üzerindeki etkilerini analiz etmektedir. Bu amaca ulaşmak için farklı varlık sınıflarından sekiz ana finansal araç, VIX endeksi ile birlikte test edilmektedir. Analiz, 156 haftalık bir zaman serisini kapsamakta ve değişkenleri simetrik ve zamanlar arası perspektiflerden tahlil etmektedir. Bulgular, en sağlam varlığın Amerikan Doları itibari para birimi olduğunu, ardından kısmen Euro ve altının geldiğini göstermektedir. BTC'nin ise kısa süreliğine sağlam durduğu söylenebilir.

Anahtar Sözcükler : Covid-19 Pandemisi, Korku Hissiyatı, Finansal Varlıklar, Güvenli Liman, Portföy Seçimi, Hareketli Pencere Tahmini.

1. Introduction

The Covid-19 outbreak deeply shook the global financial system and caused great market chaos. The needs of investors who face unprecedented risks in the markets have augmented day by day, and at the same time, they have struggled to find a safe haven.

Considering that the pandemic is a combination of economic, political, and social troubles influencing the whole world, its cost differs significantly from other financial crises. Despite felicific news originating from vaccine studies' achievement and increased vaccination rate reflected on the markets positively, the future is still uncertain because of mutations of the virus. That is why it is promptly requisite to reassess the safe-haven role of certain types of financial assets.

Avoiding investor loss represents a greater sensitivity than seeking protection against investor losses in the face of extraordinary situations or crises. Simultaneously, this concept has been tested in experimental environments (Tversky & Kahneman, 1991). On the opposite side, avoiding a loss in the face of a market turmoil causes changes in optimum portfolio selection. It pushes investors to seek safe-haven investments from among various financial instruments. The concept of a safe-haven investment is motivated by hedging, and investors are more concerned with avoiding losses than possible gains (Hwang & Satchell, 2010).

In the face of unpredictable and unexpected events such as the stock market crash of 1987, investors withdrew their investments from risky assets and transferred them to secure assets. From this point of view, the ongoing Covid-19 pandemic is a pertinent case to query investors' pursuit of hedging tools. The literature has some evidence that gold, the US Treasury bills and bonds, and fiat currencies such as the US dollar and Swiss francs serve as safe havens throughout market turmoil (Baur & Lucey, 2010; Fleming et al., 1998; Grisse & Nitschka, 2015; Kaul & Sapp, 2006).

This paper aims to investigate and detect the time-varying impacts of the fear sentiment on major financial instruments during the Covid-19 outbreak. Thus, it will be possible to determine which financial instruments investors prefer and avoid. Furthermore, by reporting the outputs of a causality analysis that considers the period as a whole, the difference in the time-varying causality test will be better emphasised.

In this study, the intertemporal capital asset pricing model (ICAPM) revealed by Merton (1973) is applied to explore the interaction between major financial assets and VIX. While using this model, the basic assumption within the scope of the study is that VIX is a variable that measures systemic risk. In other words, the model focuses on knowledgeable traders who predict the trend of VIX-based financial asset prices through risk-return dynamics. As Merton (1973) remarks, ICAPM is based on consumer-investor behaviour, and assumptions must be intertemporal to be reasonable. The intertemporal nature of the model allows for capturing effects that would not appear in a static model.

This research contributes to literature related to the globally crucial financial market instruments. First, this current article examines the price dynamics of main financial instruments under extreme threats for the entire world and explores their hedging and safe-haven properties. Absorbing the interplay between financial instruments and fear sentiment can give investors both portfolio management and risk management clues to deal with economic downside risks. It can also provide them with a spacious set of information. Second, fear sentiment greatly influences investment choices. Hence, it is a driving factor of volatility in asset prices, especially during economic downturns. Some previous studies have used the measurement of fear sentiment with dummy or proxy variables, but they always do not accurately reflect fear sentiment in finance theory. Therefore, the VIX was chosen to serve as a panic indicator in the financial market and confirm the ability of global financial assets to hedge against downside risks. VIX commonly supports the literature suggesting an acceptable indicator for investor behaviour that cannot be measured against various risks. Third and last, earlier studies ignore the time-varying of model parameters, which show the inconstant relationship between financial assets and VIX. This study also retests their interaction with rolling window regression by performing a bootstrapping approach.

Moreover, a causality test focuses on the intertemporal change of causality relationships between variables. Thus, whether financial assets act as a hedge in the face of fear sentiment will be based on the ICAPM, which shows a theoretically positive relationship between variables. If the fear index has a rising trend, the betas of safe-haven assets will be logically positive, but others will be negative.

The organisation of this study is as follows. Section 2 briefly mentions ICAPM and its equation within the scope of this study. A literature review of the research question is presented in Section 3. Section 4 describes the dataset, and Section 5 the methodology. The empirical results of the time-varying causality analysis between asset price data and VIX are discussed in Section 6. In the last section, there are results explanations.

2. Intertemporal Capital Asset Pricing Model

The basic logic of ICAPM is that long-term investors should be concerned with the level of their wealth over time and the intertemporal returns they earn from their wealth. ICAPM is a more rational model since investment opportunities change over time and are an idea closer to reality. Naturally, relative risk-averse, long-term, and conservative investors seek to hold on to intertemporal hedges, which are assets that perform better when investment opportunities worsen (Campbell et al., 2018: 207).

The common point of studies on ICAPM is the assumption that factor betas or risk prices change over time. In the practical implementation of the ICAPM, this study uses the VIX, a predictor of the market risk premium, a determinant of risk aversion, and a countercyclical variable. The analysis assumes that times of rising VIX are economically distressed because positive shocks in VIX generally lead to adverse shocks in wealth. Hence the ICAPM tested in this paper is as follows (Su et al., 2022):

$$E_{t-1}(R_t) = R^f + \mu(VIX_t) - \gamma\mu(VIX_t)R_{t-1} \quad (1)$$

“R^f”: It is asset price when the value of VIX is 0.

“$\gamma\mu(VIX_t)R_{t-1}$”: It highlights the behaviour of its traders that will affect the volatility of any financial asset market.

“$\mu(VIX_t)$”: It is “$1 - \gamma R_{t-1}$” and it is a positive value since $\gamma R_{t-1} < 1$.

In brief, it is necessary to prove that VIX has positively impacted the asset for an asset to be considered a safe haven.

3. A Brief Review of the Related Literature

In times of market turmoil, it has been a common research topic to determine the ability of financial assets to protect investors’ wealth in adverse economic conditions. It is worth re-evaluation of them in each new market turmoil. The Covid-19 infection is a case study that should be considered by finance and economics researchers. Although it covers about two years, a significant amount of research has been done, and it continues to be done, especially looking into its effect on financial assets.

Chen et al. (2020) explore the impact of a proxy variable of the fear sentiment arising from Covid-19 on Bitcoin price dynamics. They use search queries on Google about Covid-19 as a proxy variable. Findings prove that Bitcoin is not a safe haven during the pandemic. Conlon and McGee (2020) assay the frequently declared safe-haven features for Bitcoin during the Covid-19 outbreak, and the findings attest that Bitcoin does not move as a safe haven. Kristoufek (2020) emphasises that Bitcoin has no potential to be a safe haven in the Covid-19 outbreak and chaos in the financial markets. Simultaneously, Conlon et al. (2020) defend that Bitcoin and Ethereum are not safe havens for many international stock markets. As this study finds, their inclusion in the portfolio increases the downside risk of portfolio return throughout the Covid-19 turmoil. Raheem (2021) emphasises that Bitcoin’s being safe-haven hypothesis cannot be accepted with the Covid-19 announcement and that it has lost its safe-haven properties in this period. By contrast, Mariana et al. (2021) find that although Bitcoin and Ethereum exhibit high volatility, they are short-term safe havens for stock markets during the pandemic.

Dutta et al. (2020) claim that gold is a safe haven for global crude oil markets during ongoing cases of patients and deaths. Ji et al. (2020) appraise investors’ search for safe haven among various financial assets such as stock market index, cryptocurrency, commodity, and fiat currency throughout the Covid-19 pandemic. Findings underpin that gold and soybean commodity futures remain durable as safe-haven assets. Kinateder et al. (2021) analyse which of the world’s dominant financial asset classes are safe havens during the pandemic and identify that gold, US, UK, and German government bonds are secure for investors. Dividing the pandemic dates into two phases, Akhtaruzzaman et al. (2021) argue that gold serves as a safe-haven asset for exchanges during the initial phase of the pandemic (between

12/31/2019 and 03/16/2020). However, it loses its safe-haven role in the second phase (between 03/17/2020 and 03/24/2020).

On the contrary, Mensi et al. (2020) note that gold and oil markets are inefficient, especially during the pandemic. Disli et al. (2021) argue that gold, crude oil, and Bitcoin did not exhibit safe-haven properties during the pandemic. Chemkha et al. (2021) defend that gold is a weak safe haven and that Bitcoin cannot be a safe haven due to its volatility. Similarly, Cheema et al. (2020) remark that gold and silver failed to maintain investors’ wealth. According to them, the US Treasuries and Swiss Francs are key safe havens during Covid-19.

Aslam et al. (2020) show that the Canadian Dollar and Swiss Francs exhibited the highest efficiency during the outbreak. AlAli (2020) analyses the validity of the hypothesis of whether Swiss Francs, gold, and Bitcoin will behave as safe-haven assets in the course of Covid-19. Whereas Swiss Francs and gold have positive returns in line with their characteristics of safe-haven assets, Bitcoin does not.

Yarovaya et al. (2020) compare stock indices, precious metals, 10-year government bonds, and cryptocurrencies during the Covid-19 outbreak. They claim that gold and stock indices have a powerful average return potential, although returns have declined. Additionally, 10-year bond yields have minor decreases, but the highest loss is in cryptocurrencies. Further, Brunnermeier et al. (2020) recommend the US Treasury bills as a globally safe asset in crisis times. Liu et al. (2020) create a fear index for the Covid-19 pandemic. They explore the fear sentiment’s influence on the risk of collapse for the Shanghai Stock Exchange. They conclude that the Chinese stock market’s failure risk increases as confirmed deaths augment. Papadamou et al. (2020) examine the impact of a coronavirus search index presented by Google Trends on thirteen leading stock market volatilities. The findings indicate that the Covid-19 outbreak is higher risk-averse, especially in European stock markets. Also, Baker et al. (2020) assert that the US stock market reacted much stronger to Covid-19 than in previous market turmoil. As a counterclaim, Salisu et al. (2020) advocate that commodity returns increase as fear sentiment increases, and the commodity market offers better safe-haven instruments than the stock market at the same time. Rubbaniy et al. (2021) explore the safe-haven properties of environmental, social, and governance (ESG) stocks during the pandemic. Accordingly, it is concluded that the ESG indices do not have safe-haven properties, depending on the proxy variables representing the pandemic.

In summary, the effect of fear sentiment on the financial asset classes is unclear, and there is a research question of whether they can be a safe haven in the pandemic. Further study of the impact of VIX on financial asset classes will evidence whether they can be considered a safe haven asset in fear sentiment. Based on this research, investors can decide by looking at the beta sign which assets to hold to avoid wealth losses caused by the high VIX. Thus, they can achieve the purpose of hedging asset risk.

4. Data Set and Descriptive Statistics

The study analyses a 156-week time series that includes critical moments, such as when China reported a mysterious respiratory disease to WHO and when WHO declared a pandemic. The relevant period covers three years, from January 7, 2019, to December 27, 2021.

The Chicago Board Options Exchange (CBOE) Volatility Index or VIX is an index that measures the degree of fear in the markets as a measure of systematic risk. It is designed to estimate the 30-day expected volatility of the US stock market, derived from the real-time, mid-high prices of the S&P 500 Index call and put options. Most succinctly, it detects the anticipated volatility of the stock market focused on the relationship between option prices and market volatility (CBOE, 2021). It also represents the fear sentiment in this study.

Theoretically, it can reach any value from zero to positive infinity, but not negative. A high VIX Index means that expectations are negative and future risk projections are high. The generally accepted rule for the limit of the VIX is that if its value is 12 and below, the market is in a low volatility period. Above 20, the market is in an abnormally high volatility period. If it goes above 30, the markets are excessively volatile.

In addition to an indicator of fear sentiment, a time series of eight main assets in the same period are included in the analysis. Financial instruments consist of a cryptocurrency, a stock market index, a government bond, three commodities, and two fiat currency indices. Table 1 below contains some information related to them and their descriptive statistics.

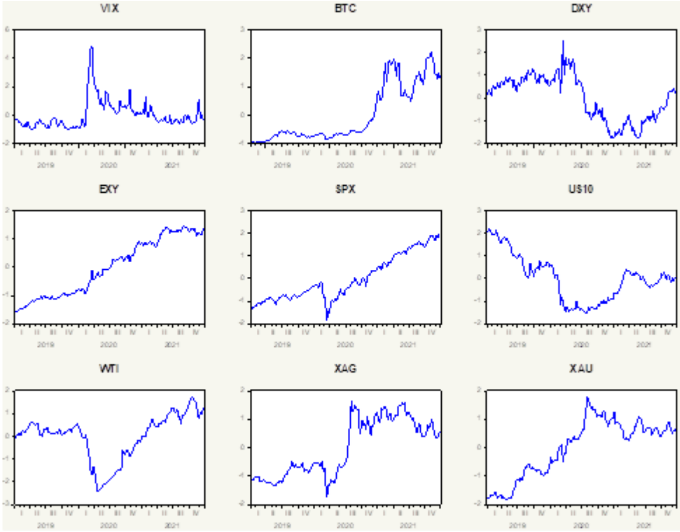
Table: 1
Variables Used in the Study

Variables	Abbreviation	Unit	Source	Mean	Median	SD
Fear Sentiment	VIX	%	Yahoo Finance	21.00	18.08	9.23
The US 10-Year Bond Yield	US10	%	Yahoo Finance	1.48	1.51	0.60
Bitcoin Price	BTC	$	Yahoo Finance	22253.04	10634.34	19310.30
The US Dollar Index	DXY	%	Yahoo Finance	95.25	96.10	3.01
Euro Index	EXY	%	Investing.com	102.20	102.11	6.62
Crude Oil WTI Futures Price	WTI	$	Yahoo Finance	52.46	56.11	18.27
Gold Spot Price	XAU	$	Yahoo Finance	1682.35	1753.86	216.58
Silver Spot Price	XAG	$	Yahoo Finance	20.65	18.59	4.59
Standard & Poor's 500 Index	SPX	$	Yahoo Finance	3478.66	3283.30	640.62

Since the units and numerically sizes of the variables are different in Table 1, the study continues with their standardised forms. Besides reducing the variables to a certain extent, the standardisation of variables does not cause any information loss. Figure 1 below displays variables' value movements in the relevant period.

Due to the pandemic announcement by WHO on March 11, it can be monitored on the VIX graph that the fear index increased. At the same time, this rise displays the fear sentiment of investors. The pandemic announcement's impact is quite visible on the graphs, with rapidly falling or rising values of some assets immediately after March 11, 2020.

Figure: 1
The Display of Variables' Standardized Forms on Graphs



5. Methodology

One of the previous approaches in developing the Granger (1969) causality test is the standard Wald test based on the asymptotic distribution theory. However, when the variables are stationary at different degrees or cointegrated, the traditional asymptotic approach is not convenient for testing causal impacts. Engle and Granger (1987) and Granger (1988) enounce solving this problem with the Vector Error Correction Model. Implementing the causality relationship of integrated or cointegrated variables in the VAR system brings a series of complex pre-test procedures. This proposal is a functional empirical practice. Still, it has severe difficulties, such as testing unit roots and cointegration analysis. Providentially, Toda and Yamamoto (1995) propose a proper VAR system procedure regardless of variables' integration order or the cointegration space's size. Even though the lack of a pre-test obstacle is the most crucial advantage of this test, this approach fails to fulfil standard assumptions, especially the error term's distribution (Wesseh Jr. & Zoumara, 2012: 521). Thus, Hacker and Hatemi-J (2006) propound a bootstrap technique that eliminates these problems in the literature concerning causality. Also, they declare that this methodology is appropriate for scrutinising market efficiency.

5.1. Hacker and Hatemi-J (2006) Causality Test

Toda and Yamamoto (1995) improve a causality test based on a standard asymptotic distribution regardless of the number of unit roots and the data's cointegration relationship. Moreover, the T-Y test offers analysis data without pre-test conditions. However, Hacker and Hatemi-J (2006: 1489) unravel that the chi-square performs poorly in the error term's asymptotic distribution when the T-Y causality test is practised for small sample sizes. For this reason, they recommend using a leveraged bootstrap distribution to reduce size deterioration. Bootstrapping is an approach to Monte Carlo simulation. They bring out a new symmetric causality test as a progression of the T-Y causality test.

There are some similarities between the H-H test and the T-Y test, and the H-H test does not care about the cointegration relationship and the degree of integration. On the other hand, the difference between the H-H and the T-Y test is that it obtains critical values using bootstrap when error terms do not have a normal distribution (Ozer & Kirca, 2018: 193-194).

The H-H symmetric causality test can be mathematically expressed as follows:

$$\begin{bmatrix} VIX_t \\ X_t \end{bmatrix} = \beta_0 + \beta_1 \begin{bmatrix} VIX_{t-1} \\ X_{t-1} \end{bmatrix} + \cdots + \beta_{p+d_{max}} \begin{bmatrix} VIX_{t-p+d_{max}} \\ X_{t-p+d_{max}} \end{bmatrix} + e_t \tag{2}$$

As examined equation with number 1, "p" represents the optimal lag number detected by the Vector Autoregressive (VAR) model, and d_{max} symbolises the maximum degree of integration between the two series. VIX refers to the proxy variable of fear sentiment, and X refers to all assets separately.

The optimal lag length is assigned by utilising a variety of information criteria. The Hannan-Quinn and Schwarz information criteria are some of them. Researchers can select the optimal lag length by pointing to the same lag. However, they sometimes do not beckon the same lag and choose different lag lengths optimally. Providing that a similar situation is encountered, Hatemi-J (2003) has introduced the Hatemi-J information criterion (HJC) to the literature to avoid this complexity. The HJC procedure can be formulated as follows:

$$HJC = ln(|\widehat{\Omega}| + j\left(\frac{n^2 lnT + 2n^2 ln(lnT)}{2T}\right), j = 0 \dots\dots, p \tag{3}$$

As glanced at an equation with the number 2, "Ω" typifies the variance-covariance matrix of error terms in the VAR model when predicting lag length, "n" is the number of the equation in the model, and "T" symbolises the number of observation (Deger & Pata, 2017: 38).

On the other side, the maximum degree of integration between variables is found by unit root tests. Structural breaks and trends in the series should be considered while applying the unit root test. Unit root tests with breaks also report more accurate results if structural breaks are observed in the series.

5.2. The Rolling Estimation and the Time-Varying Parameters

Four econometric approaches are generally used to predict the model if there are structural breaks in the period to be analysed. These are recursive estimation, rolling estimation, regime-switching, and time-varying parameters. According to Stock and Watson (1996) and Barnett et al. (2014), time-varying parameters and rolling estimation outperform other approaches. Similarly, Groenewold and Fraser (1999) found that a rolling estimate captures structural breaks better for time-varying beta applications (Inglesi-Lotz et al., 2014: 207).

In the Time-Varying Causality Test, the rolling window method is applied. For this, the researcher should decide on the sub-sample dimension. Firstly, the sub-sample dimension up to "n" is selected in the model. Then, it can analyse the data from the first observation to the nth observation with the Hacker and Hatemi-J (2006) Causality Test (Kamisli et al., 2017: 577).

The Hacker and Hatemi-J (2006) Causality Test is an approach that investigated the period as a whole. However, as Tang (2008) stated, causality relationships can switch over time with the effect of economic and political events (Ertekin & Kirca, 2017: 56). A political or an economic shock in the global economy influences many indicators related to financial markets, and the duration of this impact can vary with time. In this regard, a time-varying causality test focuses on the intertemporal change of causality relationships between variables. Further, this test provides information about the stability level of a continuous causality relationship between them (Bolukbas, 2019: 10). Hence, it is essential to use these methods to observe intertemporal changes.

In the study, the Time-Varying Causality Test and the Rolling Estimation Regression are implicated in obtaining different results from the traditional methods. Before beginning this test, some criteria must be selected, as stated above. Initially, analysts should choose the sub-sample dimension. The sub-sample dimension is meant for the number of windows. There is no precise technique for detecting it; however, not being able to decide on it correctly can sometimes induce erroneous results. Withal, selecting too large or too small a sub-sample makes it challenging to obtain beneficial effects. Thus, choosing the most optimal window number is necessary to balance the accuracy and representativeness (Acik et al., 2019: 7).

6. Empirical Results

When performing the H-H causality test, it is crucial to test the stationarity since the maximum degree of integration of the variables must be suffixed to the model. Supposing that it is known that a vulnerability such as a crisis or a phenomenal event is experienced within the period analysed in a study, choosing tests that consider breakpoints to perform the stationary of the series will allow more doubtless results. In parallel to this, the two-break LM unit root test developed by Lee and Strazicich (2003) checks whether the time series have a unit root or not. Perron (1989) states that the regression line estimated using sample data deviates from the regression line in case of a structural break. In this case, using a unit root test without a break will weaken the estimation. Similarly, Charemza and Deadman (1997) remark that despite fragility in time series, the unit root tests that do not consider a structural break give different results. For this reason, the Breakpoint Unit Root Test results are presented in the table below.

Table: 2
The Results of the Breakpoint Unit Root Test*

Variables (ß)***	**Model A**		
	Test Statistic	**Critical Value****	**Breakpoint**
BTC	-2.466	-4.524	3/02/2020
Δ BTC	-11.093		0/18/2021
VIX	-3.962	-4.524	3/16/2020
ΔVIX	-12.820		11/29/2021
DXY	-2.641	-4.524	5/17/2021
ΔDXY	-16.893		8/03/2020
EXY	-2.843	-4.524	5/31/2021
ΔEXY	-16.465		12/20/2021
SPX	-4.252	-4.524	3/23/2020
ΔSPX	-13.555		3/02/2020
US10	-3.271	-4.524	4/06/2020
ΔUS10	-13.178		2/22/2021
WTI	-3.193	-4.524	4/20/2020
ΔWTI	-11.068		3/02/2020
XAG	-2.865	-4.524	4/19/2021
ΔXAG	-12.731		7/27/2020
XAU	-3.778	-4.524	8/10/2020
ΔXAU	-11.670		6/24/2019

According to Table 2, "Δ" refers to the first difference forms of variables. Also, the trend specification of the models is a trend and intercept, and they allow one structural break. It represents critical values at a 5% significance level, and the null hypothesis is explained as "H_0: "ß" has a unit root with a break."

As is clear from Table 2, all variables have a unit root in level. It is due to the absolute values of their test statistics being less than the fundamental values of critical statistics. Therefore, when their stationary is controlled at the first difference level, it is seen that all variables are stationary at this level. However, all variables include intercept and trend, as seen in Figure 1. Thus, test results are confident when determining the degree of integration.

The VAR model must choose the most appropriate lag length to carry out the H-H test. The procedure suggested by Hatemi-J (2003) can be employed at this point. This procedure indicates that the HJC can be consulted to decide the most appropriate lag length. The table below reports the lag lengths (k) detected by HJC, the degree of integration (d_{max}) between VIX and others, and the H-H test results.

As seen in Table 3, the WALD statistic values are higher than the critical statistics calculated by bootstrap Monte Carlo simulation at a 5% statistical significance level for null hypotheses with numbers 1, 2, and 3. In this case, the relevant null hypotheses are rejected. It is observed that there is causality from VIX to SPX, US10, and EXY. Conversely, there is no symmetric causality relationship between VIX to DXY, WTI, BTC, XAU, and XAG.

Table: 3
The Results of the H-H Symmetric Causality Test

Rank	Null Hypotheses	WALD Statistic	WALD Critical Value**	k*	d_{max}	$p+d_{max}$
1	VIX ⇏ SPX	13.172[a]	6.548	2	1	3
2	VIX ⇏ US10	11.776[a]	3.937	1	1	2
3	VIX ⇏ EXY	6.495[a]	6.203	2	1	3
4	VIX ⇏ XAU	1.929	3.956	1	1	2
5	VIX ⇏ XAG	0.764	3.990	1	1	2
6	VIX ⇏ WTI	0.176	3.991	1	1	2
7	VIX ⇏ BTC	0.121	3.801	1	1	2
8	VIX ⇏ DXY	0.055	3.969	1	1	2

*Notes: * Optimal lag length is determined by HJC. ** Critical values are calculated with 10000 bootstrap simulations. a. It represents statistical significance at a 95% confidence interval.*

When moving to intertemporal analyses, Figure 2 and Figure 3 show the causality relationship and the time-varying beta coefficients. Unlike the symmetric test, which considers the period as a whole, information about the time when the causal relationship occurred is presented here. The rolling window widths of 20-, 28- and 32-week are changed, respectively, and these outcomes are similar to the 30-week rolling window.

According to the results of the analysis, when focusing on the declaration of the pandemic and its environment (March 11, 2020), it is seen that the causality relationship increases; that is, the fear index affects the prices of the assets (see Figure 2 and 3 (left side)). Looking at the intertemporal beta coefficients around the same period in Figure 3 (right), it is seen that the betas of WTI, US10, and SPX assets are negative. This situation supports that the assets in question are far from safe havens. On the other hand, graphs showing the beta coefficient of assets in Figure 2 (right), XAU, DXY, and EXY have positive beta around the pandemic. This situation proves that they are safe-haven instruments and manage to maintain their value even in this turmoil. BTC and XAG with betas close to zero are not fully solid instruments that we would consider for the pandemic, and they are at least not as much as XAU, DXY, and EXY.

Figure: 2
The Results of the Time-Varying Causality Test and the Rolling Estimation Regression

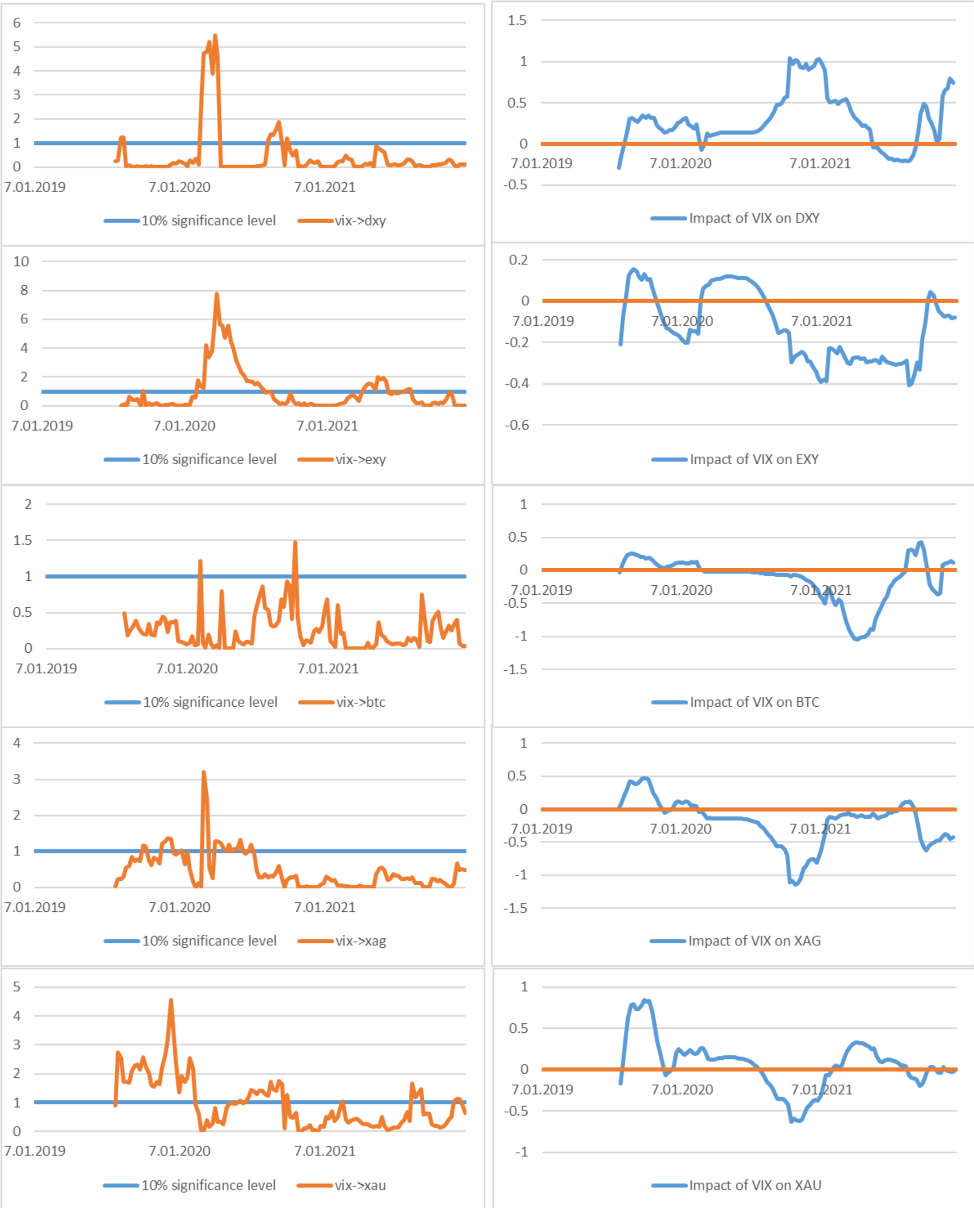
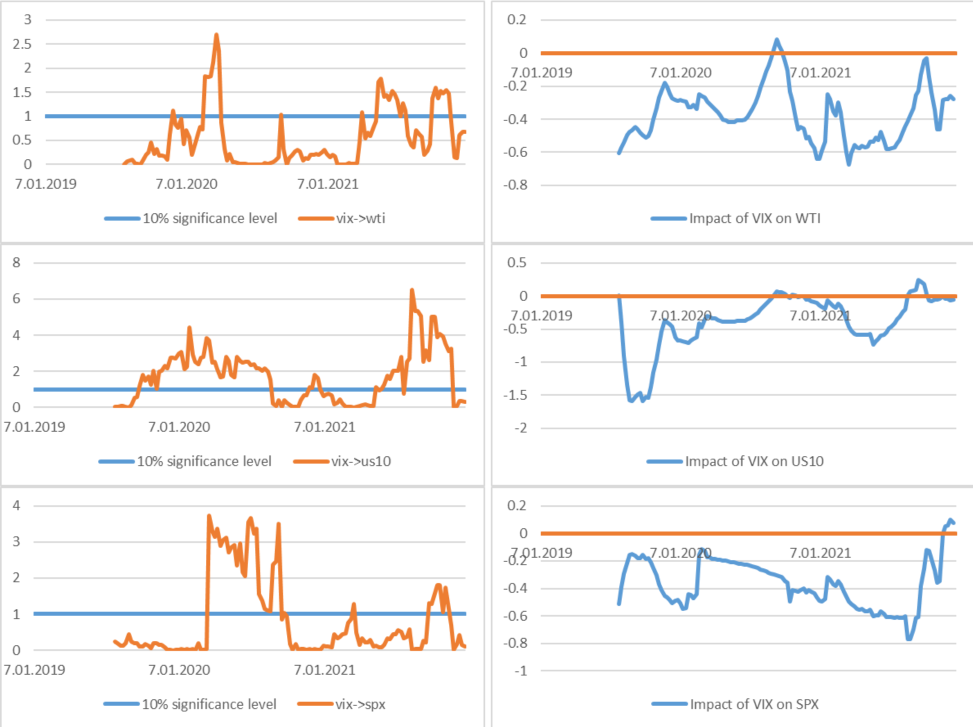


Figure: 3
The Results of the Time-Varying Causality Test and the Rolling Estimation Regression



7. Discussion and Conclusion

The literature often states that BTC cannot be a hedging tool for investors (Chen et al., 2020; Conlon & McGee, 2020; Kristoufek, 2020; Conlon et al., 2020; AlAli, 2020; Raheem, 2021; Disli et al., 2021; Chemkha et al., 2021). But it is not fully supported by the findings of this study. No causal relationship between BTC and VIX could be determined symmetrically, but they had intertemporally. The pandemic’s statistical significance on Bitcoin price movements saw in only time-varying tests’ results. The study findings on BTC are similar to Mariana et al. (2021). With the pandemic announcement, it can be said that BTC has been solid for a short time.

Provided commodities are discussed, three commodities (crude oil, gold, and silver) appear unaffected by the fear sentiment regarding symmetrical causality. However, there seems to be an effect intertemporally around the pandemic announcement. In parallel with the peak of the pandemic’s fear sentiment, although the price war in oil started by Saudi Arabia and Russia on March 8, 2020, shook the financial markets even more deeply, major assets hitting rock bottom started to climb immediately following days. However, crude oil futures prices declined until trade relations between oil-producing countries began to normalise. On the other hand, gold and silver spot prices displayed similar price movements during the pandemic. According to findings, gold, frequently seen as a safe haven by investors in the literature, partially proved its strength in the face of fear during the pandemic here. The study findings on gold are similar to Akhtaruzzaman et al. (2021). Although gold remained intact around the pandemic, it seems to have a negative relationship with VIX for a while in the following periods. The weaker finding is valid for silver.

To summarise the commodities, it can be said that the XAG did not fully fulfil its characteristics of being a safe haven for the pandemic period, and the findings were not symmetrically detected. XAU is intertemporally better than XAG. But WTI is a complete failure.

Furthermore, the American stock index shows high recovery potential even in very high shock periods but does not reiterate its safe-haven characteristics. Although Yarovaya et al. (2020) state that the US bonds react less negatively to the shock and reach their highest 2020 value after the Covid-19 announcement, the study's finding concerning the US bond does not promote general literature. Investors see the US dollar index more successfully as a hedging tool during the pandemic among the financial assets within the study's scope. Even if the Euro index is flourishing around the pandemic, the beta coefficients become negative in the following periods, similar to gold.

To sum up, this study evaluates the price reactions of financial assets to fear sentiment for 156 weeks during the ongoing pandemic. Whether a total of eight financial assets from four different asset groups are safe havens for investors in the relevant period, the findings can help investors make more informed portfolio decisions to control downside risk in the face of extraordinary events. Investors will likely be sensitive to local news such as domestic infected cases, deaths, and worldwide news. Herewith, intelligible and well-timed communication about the Covid-19 outbreak will give the market a rough-and-ready forecast.

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