Master Thesis U.S.E.[1]

# Stock Markets, Oil, and Bitcoin during the Russian-Ukrainian War

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## Abstract

This research examines the effect of the public interest in the Russian-Ukrainian war on the returns of the stock market indices, as well as on the oil and Bitcoin price returns. The stock market indices considered for the research are AEX, S&P/BMV, NIKKEI225, S&P 500, FTSE100, S&P/ASX 200, CAC40, and JSE, while the public interest is proxied by the Google Trends data. Our first research question is whether crude oil is a good hedging instrument at the time of Russian-Ukrainian war. Secondly, we investigate if Bitcoin has any hedging capabilities during the war. Thirdly, we search for the stock market indices to hedge the risk during the war against Ukraine. The research is conducted using panel data and time series methodologies. Panel data analysis indicates the diminishing positive effect over the analysed periods of the war. Time series results show both positive and negative associations between Google Trends queries of a certain location and its corresponding asset/index, thereby no definite inference can be drawn on which of the separately analysed assets may serve as an uncompromised safe-haven asset during the Russian-Ukrainian war. As an additional contribution, this research paves the way for future analyses and improvements to approaches in the field.



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# 1. Introduction

On the 24th of February, 2022 Russia started a full-scale invasion of Ukraine. Now it is known as the biggest military attack that Europe has faced since World War 2, certainly causing a major worldwide shock (Iddon, 2022). Thus, we are witnessing increased economic uncertainties and risk in the markets (Bunn et al, 2022). Immediately after the outbreak of the full-scale war, there was a drop in the price value of the majority of global stock indices, but at the same time a rapid rise in some commodities' prices (Fiszeder and Małecka, 2022). There has been also a fall in the prices of cryptocurrencies since investors excluded riskier assets during times of uncertainty (Wilson and Howcroft, 2022). Despite the general negative effect of the war on the global stock markets, there is still a possibility that markets could adapt to the protracted wars (Ritholtz, 2024). Therefore, this research aims to examine the effect of the public interest in the Russian-Ukrainian war on the stock market performance, as well as on the oil and Bitcoin prices. The stock market indices considered for the research are AEX, S&P/BMV, NIKKEI225, S&P 500, FTSE100, S&P/ASX 200, CAC40, and JSE indices, while the public interest is proxied by the Google Trends data. This paper approaches the research questions by considering different war periods separately, as well as the entire war period, to identify the dynamics and direction of the relationship between selected stock market indices, oil, and Bitcoin prices (later all to be referred to as assets, for convenience) and the public interest in the Russian-Ukrainian war.

Before going deeper into the research process itself, it is crucially important to identify possible investors' incentives to use this paper for improving the investment approach. Since investors' main goal is profit maximization (BlackRock, n.d.), the chosen relatively broad scope of analyzed assets is expected to reveal certain assets or general market indicators that tend to show stronger performance during times of uncertainty caused by the above-mentioned conflict. For instance, there are claims that the war in Ukraine induced the rise in oil prices (World Economic Forum, 2022). The research intends to examine the presence of such correlation during different war phases and identify other promising investment possibilities over the Russian-Ukrainian war period within other analyzed assets.

Secondly, investors are always trying to minimize their investment risk (Meagher, 2024). Consequently, the results obtained from the empirical part might serve as an alternative source of information during portfolio restructuring in times of higher market uncertainty as a result of the Russian-Ukrainian war. Some studies, such as Yousaf et al. (2022) recommend relocating funds from specific regions based on the adverse correlation between an asset price and war, as it should reduce the investment risk. Considering the fact that further escalation of the conflict is also possible, which is likely to drag the investment returns down in case the assets in possession are negatively correlated with the war development (public interest), the identification of an inverse relationship is highly relevant for investors (Frederick, 2023).

Thirdly, certain investors are interested in the long-term perspective in terms of constructing their investment portfolios (BlackRock, n.d.). For this reason, our research analyzes longer periods of war, compared to previous studies, to capture the dynamics and general tendencies of returns on each asset. It is important to mention that this effect also can differ over wartime as a consequence of a human psychological factor (How the Stock Market during War Shapes Your Investments, 2024). For instance, uncertainty and anxiety may prevail over the market sentiment during the early stages of war resulting in massive selling, which can cause sharp decreases in asset prices (D'Souza, 2023). At the same time, protracted conflicts are pushing investors to adaption to the new market reality leading to the relative stabilization of market behavior (How the Stock Market during War Shapes Your Investments, 2024). Therefore, this study may be of greater use for long-term investors.

Based on the analysis of the investors' intentions, we have identified the main questions of the research. Firstly, is crude oil a good hedging instrument at the time of Russian-Ukrainian war? Secondly, does Bitcoin have any hedging capabilities during the war? And lastly, are there any stock indices to hedge the risk during the war against Ukraine?

To address the needs of the investors, this paper builds a literature gap based on the three areas of existing theoretical background. The first area is in relation to the cryptocurrencies examination and their price reaction to the war in Ukraine. On the one hand, according to Jankovic (2024), the breakout of the Russian-Ukrainian war had no influence on the cryptocurrency market. On the other hand, there are claims that Bitcoin cannot be considered a safe-haven asset during turbulent times (Diaconasu et al., 2022). Our research contributes to the literature by providing empirical support identifying the influence of the war against Ukraine on Bitcoin prices.

The second area is regarding the studies analyzing the impact of the ongoing war in Ukraine on the major stock market indices. Authors in this research field present the results of the negative influence of the analyzed war on the global stock markets (Boungou & Yatie, 2022), while their analysis is also supported by other articles focusing on the specific region. For instance, Ahmed et al. (2022) identify the negative impact on the STOXX Europe 600 index, while den Dekker (2023) determines the negative influence on the US stock market and others. Alternatively, Yousaf et al. (2023) suggest investors consider the relocation of invested funds to North and Latin America during the period of the Russian-Ukrainian war based on the research results. Our paper aims to settle the debate and empirically identify the correlation between the prices of major stock indices of different geographical locations and the Russian-Ukrainian war with the help of panel data and time series methodology.

The third area of literature is the analysis of commodity prices and their reaction to the Russian-Ukrainian war, with an emphasis on crude oil. Some studies claim that one can consider oil as a safe-haven asset during the ongoing war (Zhang et al., 2023; Diaconacu et al., 2022). On the contrary, Shaik et al. (2023) use the wavelet coherence transformation and wavelet power spectrum empirical approach to conclude that among different types of assets, including oil, only gold remains to be a safe-haven asset during the turbulent events of the Russian-Ukrainian war. Therefore, this research pursues the intention to answer the question of whether oil can be considered a risk-offsetting asset during Russia's war in Ukraine by analyzing the oil price data.

This paper seeks to answer these questions by using data of different asset prices and Google Trends query of "Ukraine war" utilizing a panel data and time series methodology. More specifically, the impact on assets' prices is tested using panel data on three separate periods: from the 24th of February to the 24th of November, 2022, then the same time period of 2023, and from the 24th of February to the 24th of May, 2024, - to identify the strength and direction of relationship over the time. Additionally, in order to investigate the individual asset's return reaction, we apply a time series methodology for the entire period of war. Our study relates to the literature on the analysis of the Russian-Ukrainian crisis's influence on the stock, commodity, and cryptocurrency markets, possessing a growing academic interest in it. This urge in research was particularly driven by the Russian full-scale invasion of Ukraine in 2022. This paper contributes to the literature in several ways. Primarily, this paper intends to settle the debate on which asset appears to be the most attractive to relocate the funds in during the ongoing war. Additionally, our study seeks to identify the riskiest investment considering the market situation. Lastly, the data set used in this research is larger compared to previous studies in this area, including the latest historical information providing the ability to analyze different phases of the war and identify the strength of assets' reaction in dynamics.

Regarding the main results, the panel data approach indicates the diminishing positive association between the global Google Trends query for "Ukraine war" and assets' returns, which is not consistent with one of our initial hypotheses. The time series approach provides the equivocal results for each asset, thereby, based on our analysis, no concrete inference can be drawn on the matter of which of the assets analyzed separately might serve as an uncompromised safe-haven asset during the Russian-Ukrainian war.

In order to fulfill the mentioned idea, the paper is structured in the following way. After the introduction, we dive into the literature review to understand what was already done in the field and to identify the appropriate methodology for the problem. Later, the necessary data is described and the empirical solution to the research questions is implemented. Afterward, we present the results and interpretations of the empirical section. The final part includes a discussion of possible future investigations of the research topic.

## 2. Literature review and Theoretical Framework

The world is still recovering from the recent reverberating COVID-19 pandemic, and at the same time, there are some local wars that somehow affect every country. Unfortunately, the war is not a new phenomenon, so obviously the link between the war and the stock market was examined multiple times trying to establish the correlation. One of such studies is conducted in the paper of Cortes et al (2022), who analyze the impact of major US conflicts, fought on the foreign territory, on the volatility of the US stock market during the period of 1870-2017. The authors indicate that increasing government spending, especially on the defence sector, reduces the volatility of the US stock market. However, the paper is missing sufficient evidence on the direction of changes in returns of the US stock market. The influence on the S&P 500 and Dow Jones Industrial Average index returns was revealed by Brune et al. (2015), with demonstrated results that the rising likelihood of military conflict decreases stock prices. Analysed data period included major wars since World War 2. In contrast, Schneider et al. (2006) identified occasionally positive reactions of stock market indices such as Dow Jones, FTSE, and CAC to major military conflicts in the period of 1990-2000. The difference between the results of studies makes it more complicated to identify the standardized outcome of any military conflict on the returns of one or another stock market. Indeed, there are empirical confirmations that every war has a unique global effect, while different countries experience different effects (Choudhry, 1997).

Considering the abovementioned, and the fact that the Russian-Ukrainian war is among the most recent and comprehensive military conflicts, taking place in the fragile global environment right after the outburst of the COVID-19 pandemic, it provides us with a unique opportunity to attempt to estimate the effect of this war on the stock markets of different countries, as well as on several assets simultaneously, in order to find risk-offsetting investment opportunities.

One of the first empirical studies of such impact during the early stages of the Russian-Ukrainian war applied a panel data methodology using daily data on index returns of 94 different countries and Wikipedia Trends. The academic relevance of Wikipedia Trends was examined by Moat et al (2013), providing evidence that historical data from online encyclopedia usage may serve as a proxy variable for the process of information gathering and market analysis by investors, with a noticeable increase in interest during the periods of concern. According to the results of Boungou & Yatie (2022), there is a negative effect on the global stock market, whereas the impact was a lot greater during the first 2 weeks of the Russian invasion compared to the following time, indicating the market adaptation. Additionally, the study demonstrates results on proximity indicating that countries located closer to the war area are the ones affected the most (Boungou & Yatie, 2022). However, Boungou & Yatie (2022) cover only the first weeks of the ongoing war in their analysis, therefore coverage of a longer period may provide a different outcome.

Some studies are also focused on a specific geographical location. For example, a similar to the methodology in the last paper was implied to assess the relationship between the stock returns of separate firms in ten European countries and in Russia, providing evidence of the most substantial negative stock returns on the stock market of Russia, due to its direct involvement in the war (Das et al., 2023). Ahmed et al. (2022) used daily stock prices of companies within the STOXX Europe 600 index to estimate the effect of the Russian illegal announcement of Donetsk and Luhansk regions on the European stock market prices, finding a negative effect. The findings of Das et al.

(2023) and Ahmed et al. (2022) do not mention the influence on other regions, except for the European one. Therefore, taking into consideration the examination of the European region, we delve into the evidence of other geographical locations, since the full-scale war has already been happening for more than 2 years (since 2022) and it is more likely that the effect is wider, probably spreading to other regions.

According to Joshi et al. (2023), the commencement of the full-scale Russian-Ukrainian conflict negatively affected 18 different stock markets in the Asia-Pacific region, the only exception being the Indonesian stock market. Supporting previous research, Yousaf et al. (2023) with the help of an event study reached the conclusion that investors should consider relocating their funds to Latin America, North America, the Middle East, and African regions during the ongoing war against Ukraine since Asia and Europe are significantly negatively influenced (Yousaf et al., 2023). However, there is also evidence of financial losses on the stock markets of African countries, due to the Russian-Ukrainian war (Oyadeyi et al., 2024), and slightly delayed, but substantially negative effect on the U.S. stock market using the Willshire 5000 index – a substitution for S&P 500 index with a correlation coefficient of 0.986 - as a dependent variable (den Dekker, 2023). The identification of conflicting results in the literature increases the need for additional verification with the usage of the larger data sample.

Another scope of studies is focused on the identification of the impact of proximity to the geographical location of war. To identify the existence of the linkage between the analyzed war and the stock market, Chiţu et al. (2022) conducted research with a Vicinity variable on the ongoing Russian-Ukrainian war. Before the war, the proximity to Kyiv did not influence the movements in the global stock markets in the cross-country variation. Meanwhile, after the Russian invasion around 20% of the cross-country variations were explained by the distance to Kyiv (from the sample of 80 countries) (Chiţu et al., 2022). However, this study is focused on the short-term effect, therefore the impact could evolve over time. There is another empirical evidence of the war proximity effect with the research of Zhejiang University presenting it. The focus of the study is an analysis of the abnormal returns/cumulative abnormal returns of firms after the Russian invasion in order to define which of the 86 countries suffered the most in terms of the effect on its stock market, and on the contrary, who was able to buffer the negative influence. After the inclusion of the "Distance" variable, the results show that companies located further from Kyiv are more immune to the ongoing war (Sun & Zhang, 2023). Another paper also identifies the "proximity penalty", emphasizing that the disaster risk and risk of military escalation are higher in countries closer to the conflict, resulting in the declining trend of their stock markets (Federle & Sehn, 2022). Although, it is important to highlight the fact that the papers which analyse the proximity impact may possibly lack the inclusion of an additional control variable of investor sentiment to obtain deeper insights into the market reaction.

Nevertheless, academic attention and the findings claim that the geographical location contributes significantly to the strength of impact. For this reason, it is possible to formulate the following hypotheses.

**Hypothesis 1:** Stock markets further from the geographical location of the Russian-Ukrainian war may serve as a safe-haven investment during the ongoing war.

Even though hypothesis 1 was tested in studies before, it was decided to retest it for the next two reasons. Firstly, empirical results may evolve and alter over time, therefore we are going to test if the geographical location implies noticeable relevance in dynamics to understand whether it remains stable over the different war periods. Secondly, the results of previous studies need to be checked on the latest historical data with the inclusion of the Google Trends variable, representing the market sentiment, to confirm their reliability and robustness. Nevertheless, it is expected that the outcome will be coherent with the results of previous studies in the context of the strength of influence on stock markets rising with the proximity to the geographical location of the Russian-Ukrainian war.

**Hypothesis 2:** there is a negative correlation between the analyzed assets and the Russian-Ukrainian war, but the impact decreases over every next period of the ongoing war.

Even though the Russian invasion of Ukraine in 2022 got a lot of academical attention at the beginning, there is a lack of academic studies with the latest historical data, therefore there is a need to test market behavior in dynamics to identify the trend of the ongoing war influence. We expect to see a decreasing negative impact on markets over the periods of the war, assuming that protracted military conflicts force investors to adapt their actions to new realities, taking more rational decisions resulting in relative stabilization of the market (How the Stock Market during War Shapes Your Investments, 2024).

Additionally, testing of Hypothesis 1 and Hypothesis 2 assists as a foundation to answer one of the main research questions: are there any stock indices to hedge the risk during the war against Ukraine?

Many articles emphasize the importance of investigating different financial assets during the turbulent time (Będowska-Sojka et al., 2022; Leigh et al., 2003). The identification of patterns might partially offset the uncertainties and create profitable investment opportunities. The analysis by the wavelet coherence transformation and wavelet power spectrum was employed by Shaik et al. (2023) to identify the movements in gold, oil, and stock returns during COVID-19 and Russian-Ukrainian war, summarizing that gold remains a safe-haven asset for the turmoil times. Another paper claims that for the countries importing crude oil the directly proportional correlation between the capital markets and the crude oil prices increased substantially after the beginning of the full-scale conflict (Huang et al., 2023). Additionally, some articles claim that investments in crude oil were risk-offsetting in the early stages after the Russian invasion (Diaconacu et al., 2022). However, previous studies examine the relationship between the ongoing military conflict and oil prices only during the early phases of the Russian full-scale invasion, therefore there is a need to research this link in further dynamics. The increasing importance of the Hypothesis 3 testing is also explained by the recent decline in oil prices with the simultaneously increasing intensity of the Russian war, due to their offensive operations on the front line since the end of April, 2024 (Financial Times, 2024; Kimball, 2024). At the same time, the importance of incorporation of crude oil prices variable into regression is also supported by the global leading positions of Russia as its exporter (Statista, 2024).

**Hypothesis 3:** Crude oil prices are positively correlated with the increasing concern about the Russian-Ukrainian war.

Even though such correlation has been already tested by previous researchers, the existence of contradictory results in the analyzed literature creates the need to retest Hypothesis 3 with the most recent data. Due to the increase in oil prices in recent years, we expect to find a positive correlation between oil price returns and the increasing concern about the Russian-Ukrainian war. This hypothesis should help to answer one of the research questions of whether crude oil is a good hedging instrument during the time of the Russian-Ukrainian war.

Along with the popularity of traditional assets, the world is now witnessing a booming trend in the FinTech market, specifically the rise in cryptocurrency trading and investment. Therefore, the idea of cryptocurrency investments as an instrument for portfolio diversification is becoming widely used among investors (Lapin, 2022). The possibility of offsetting risk with the help of cryptocurrencies in the context of recent events was also revealed in several studies. From one perspective, some findings claim that it is possible to obtain a hedging possibility from the combination of gold and Bitcoin during the war against Ukraine (Oosterlinck et al., 2023). The comparison of volatility during the ongoing war between the traditional and FinTech markets (meaning specific cryptocurrencies in this case) provides evidence of relative stability and investment attractiveness of the latter (Hasan et al., 2023). Such a pattern can be explained by the decrease in investors' confidence in conventional stocks during times of geopolitical uncertainty. However, other studies suggest that the breakout of the conflict between Russia and Ukraine had a negative and pronounced impact on the trading volumes of Bitcoin causing a decrease in its value (Appiah-Otoo, 2023). Nevertheless, the Bitcoin price reached its peak price in March 2024 after the rally from the beginning of the year (Investing.com, n.d.). Therefore, the opportunities of investing in Bitcoin during the Russian-Ukrainian war period should be reviewed to understand its real correlation.

**Hypothesis 4:** Bitcoin can serve as a safe-haven asset during the Russian-Ukrainian war.

Although such relationship has been already examined by previous researchers, the presence of contradictory results in the literature emphasizes the need for further investigation. Thus, it is necessary to reevaluate Hypothesis 4, incorporating the latest accessible data to obtain clearer insights. We expect to obtain results consistent with previous findings stating that Bitcoin has certain properties to be called a safe-haven asset during the Russian-Ukrainian war (Oosterlinck et al., 2023; Hasan et al., 2023; Jankovich, 2024). Additionally, this hypothesis aims to answer one of the research questions of whether Bitcoin has any hedging capabilities during the war.

All in all, the evidence of significant outcomes on markets is undoubtful due to a full-scale Russian invasion of Ukraine. The academic discussion on this topic was raised all over the world almost immediately. We have seen a variety of different methodologies for the investigation of it including panel data, event studies using the Fama–French five-factor model, wavelet coherence transformation, wavelet power spectrum, and others. There are researches examining the cryptocurrencies along with traditional assets such as common stocks, gold, and oil being investigated as well. However, some findings are controversial and should be reexamined. Therefore, for the purpose of this research, we test the identified hypotheses.

# 3. Empirical Strategy

## 3.1. Data

This section discusses the data used in the empirical analysis and its sources, along with the methodology applied for the investigation.

### 3.1.1. Dataset for panel data

The time frame of the analysis covers three separate periods during the war: from the 24th of February to the 24th of November, 2022, then the same time period of 2023, and from the 24th of February to the 24th of May, 2024. The periods are not continuous since Google Trends allow export of daily data up to 8 months. According to Huang et al. (2023), to ensure the comparability of different periods we take the same periods of the year (except for 2024 due to this research being in process on June 2024) with the maximum period length possible to be exported from the Google Trends website. Utilizing the panel data, we investigate the impact of the Russian-Ukrainian war on different assets, with the start of the full-scale invasion being February 24, 2022. In the empirical analysis we consider several major stock markets, along with cryptocurrency and commodity markets, particularly including the price returns of the following assets: oil, Bitcoin, and AEX, S&P/BMV, NIKKEI225, S&P 500, FTSE100, S&P/ASX 200, CAC40 and JSE indices. Additionally, the different time periods of the war are compared to identify the tendency of the influence over time.

According to Preis et al. (2013), societal activity on the Internet may influence financial market movements, specifically, it was identified that there is a rise in Google Trends volume of keywords associated with financial markets before the market downturn. This result implies that people tend to collect and analyse information about the market state during periods of concern (Preis et al., 2013). The paper of Boungou and Yatié (2022) operates with Wikipedia Trends as a metric for the evaluation of public concern for the investigation of the stock market response. In our research, we use Google Trends, where the number of queries is indexed from 0-100, with 100 being the maximum search volume for the selected time and region (Google Trends, n.d). It provides broader coverage as a result of its vaster popularity while gathering data all over the globe. Additionally, Google Trends counts every search query, while Wikipedia Trends includes views and edits only of a single Wikipedia page (Moat et al., 2013).

For these reasons, we implement Google Trends query for "Ukraine war" as a proxy of public concern and awareness about the Russian-Ukrainian war development. For instance, the picture above presents the huge spike in the global Google Trends query for "Ukraine war" connected with the beginning of the Russian full-scale invasion, the period presented on the graph – from the 15th of February, 2022 to the 15th of March, 2022 (Google Trends, n.d.).

**Figure 1**

*Global Google Trends query for "Ukraine war" at the beginning of the full-scale Russian invasion*


*Source: Google Trends website*

As for the dependent variable, the daily return of each of the stock indices is used. On the right side of the equation, we include the Google Trends query for the respective geographical location to assess the level of concern and uncertainty. Particularly, to investigate the reaction of the AEX index to the war as an independent variable, we use the Google Trends of "Ukraine war" search in the Netherlands, with the same logic applied to France for CAC40, in Japan for NIKKEI225, in Australia for S&P/ASX 200, in South Africa for JSE, in the U.S. for S&P 500, in Mexico for S&P/BMV and in the United Kingdom for FTSE100. For the analysis of Bitcoin and oil prices, we apply global Google Trends queries for "Ukraine war".

The daily data for the Google Trends queries is obtained from the Google Trends website, and the asset price data is collected from Investing.com (Google Trend, n.d; Investing, n.d).

### 3.1.2. Dataset for time series

To investigate the individual reaction of each asset return to the war against Ukraine we use the time series methodology. The daily data on Google Trends cannot be generated for a prolonged period, therefore the weekly data from the 20th of February, 2022 to the 19th of May, 2024 will be gathered for each variable. It is also necessary to emphasize that we use returns of prices instead of prices in levels, since returns standardize values, allowing for a proper comparison between different assets regardless of their original price levels, which should be necessarily considered for the individual analysis of assets and their comparison (Kothari and Zimmerman, 1995). The reasoning behind Google Trends usage was provided in the previous section.

The weekly data for the Google Trends searches is collected from the website trends.google.com, and the asset prices data (for stock market indices, oil, and Bitcoin) is collected from Investing.com (Google Trends, n.d; Investing, n.d).

## 3.2. Methodology

### 3.2.1. Panel data methodology

The study applies two types of methodologies in order to answer the research questions. Firstly, we use a panel data methodology. A similar regression methodology has been already applied by Boungo and Yatie (2022), who found a significantly negative effect on the global stock market returns during the first 2 weeks of the Russian invasion with a diminishing response afterwards. The contribution to the literature of this research includes analysis of the extended data period updated to the current time and incorporation of the cryptocurrency and commodity markets indicators, the relevance of which is demonstrated by Diaconaşu et al (2023) paper.

The panel data regression of Equation 1 presented below is based on the Boungo and Yatie (2022) methodology:

$$Asset_{L,d} = \beta_0 + \beta_1 War_{L,d} + \varepsilon_{L,d} \tag{1}$$

The dependent variable $Asset_{L,d}$ represents the market price returns of a certain asset (stock market indices, oil, and Bitcoin) of location L on day d. Consequently, independent variable $War_{L,d}$ stands for the Google Trends query in location L on day d. The error term is also included in the equation. The rationale of Google Trends usage is explained in the section above.

The panel data investigation requires undertaking some necessary steps to choose the estimation method. Therefore, for each data period we, first, apply pooled OLS and test for autocorrelation of the error term using the Breusch-Godfrey test. In case of a present autocorrelation, we re-estimate it with clustered standard errors. After, we apply the first-differences estimator, and conduct the autocorrelation test again to compare it with the fixed effects estimator, in order to establish which is preferable for each data set. Then, we use the fixed-effects estimator and random effects estimator (RE) and compare them with the help of the Hausman test (Appendix A). For each data period it was identified that the random effects estimator is more appropriate.

Boungo and Yatie (2022) used the fixed effects estimator, while our analysis reveals evidence of more sufficient usage of the random effects estimator for our datasets, which allows us to operate with a simplified model without fixed effects (day-specific effects and country-specific effects), since random effects estimator assumes that the unobserved effects are uncorrelated with the explanatory variables (Wooldridge, 2013).

### 3.2.2. Time series methodology

The approach is based on the article by Brune et al. (2014) for investigation of the stock market reaction to specific military conflicts. The equation we base our research on examines WW2. In the study, only the impact on the US stock market was analyzed with the help of a news proxy variable, which counts the quantity of articles in the New York Times magazine mentioning the keywords as ''war'' and ''Poland''. In our study we investigate the price returns of different assets (stock market indices, oil, and Bitcoin) during the Russian-Ukrainian conflict with the help of Google Trends query for "Ukraine war" as a proxy for the News variable. Therefore, following the approach of Brune et al. (2014), the equation is identified as:

$$Asset_{t-1} = \beta_0 + \beta_1 Asset_{t-2} + \beta_2 GoogleTrend_{t-1} + \beta_3 GoogleTrend_t + \beta_4 GoogleTrend_{t+1} + \varepsilon_t \tag{2}$$

The proxy for the News variable was changed due to the habits of modern society, since people use the Internet as a main resource of information, contrary to the times after WW2 when the main news source were newspapers (Massimiano & Trench, 2021). Thus, the substitution of this variable by Google Trends is done to include the most relevant estimator for the investigation of market reaction to the war in Ukraine based on the Boungou and Yatié (2022) methodology.

Brune et al. (2014) use the lag of the explanatory variable, relative to the dependent one, which accounts for the delay between the stock market pricing of an event and the physical publication of a newspaper. Additionally, the incorporation of a one-period lag of the News variable is needed to consider the time required for the printing and distribution of the newspaper. However, it is essential to emphasize for the correct interpretation later the differences between the News variable from the paper mentioned and Google Trends: while the author accounts for the time needed for the newspaper dissemination, we need to take into account the time taken for the interest of the majority of the public to be raised. Therefore, the focus of our research is neither the media coverage nor the increase in military action intensity directly, but the public concern about the Russian-Ukrainian war. However, as it was discussed before by Preis et al. (2013), people tend to collect more information during times of concern and uncertainty, to which investor behavior is highly sensitive. Therefore, based on the methodologies abovementioned we investigate whether there is a certain delay between the public interest of a certain region about the war against Ukraine (using Google Trends) and the price return of an asset in the respective region.

Our dependent variable is lagged by one period, aligning with the reasoning of Brune et al. (2014), to account for the delay between the stock market pricing an event and the public reaction resulting in the "Ukraine war" Google search. On the right side of the equation, we implement four independent variables.

The first independent variable is $Asset_{t-2}$. The incorporation of the previous asset's price return in relation to the dependent variable accounts for the past influences capturing the fact that asset prices do not adjust immediately to the new information and may show autocorrelation, consequently $Asset_{t-2}$ variable improves the accuracy and the explanatory power of the regression employing the historical data that may predict future trend (Lewellen, 2022).

It was decided to implement the lagged structure of the model from Brune et al, (2014) paper into our empirical analysis to capture the dynamic effect. The rationale of the lagged structure of the model to capture the dynamic effect and analyze the correlation with different periods is also highlighted in several other researches (Cutler et al., 1987; Keele and Kelly, 2006).

Variable $GoogleTrend_{t-1}$ is included to investigate the public interest or concern about the Russian-Ukrainian war of a certain region in the previous period and its impact on the corresponding asset's return in the previous period (Brune et al., 2014).

Variables $GoogleTrend_{t}$ and $GoogleTrend_{t+1}$ are incorporated to examine the possible effect of an expected public interest or concern about the Russian-Ukrainian war of a certain region of the current and the next period and its impact on the corresponding asset's return in the previous period (Brune et al., 2014). Including $GoogleTrend_{t+1}$ in the equation might provide additional insight on whether such assumed anticipatory effect is present for the longer time period.

We also include the error term, $\varepsilon_t$. It is essential to highlight that even though we have a lagged dependent variable, the error term of the current period should be used to correct for the unpredictable aspects affecting the dependent variable, while also ensuring the completeness of the model and its statistical validity based on how error term functions within the time series study (Keele and Kelly, 2006).

## 3.3. Summary statistics

### 3.3.1. Panel data

Appendix B presents the summary statistics of the panel data analysis for the three different periods, specified before. The indicators include the minimum, maximum, median, and standard deviation values. Descriptive statistics show that the mean of the variable *Date* increases across periods, representing the chronological progression of data collection, but the data samples do not follow each other immediately (have an interruption period), since Google Trends do not allow for downloading longer periods with daily frequency. The summary statistics of the first period represent a slightly negative mean for the *Price* variable, signaling a general negative price return on the asset during this period, whereas the second and third periods display positive mean returns, which could be interpreted as the average appreciation of the assets' value. Standard deviation of the *Price* variable indicates the highest volatility during the first period. The second period exhibits a decrease, after which the turbulence again slightly increased in the third period, however, was far from reaching the previous level.

The data also depicts noticeable shifts in minimum and maximum values of the *Price* variable across periods. The first one has the most extensive range, representing more extreme fluctuations in returns, after which we observe a decreasing tendency in the fluctuations of the following periods. Overall, the summary statistics of the *Price* variable prove that there is a need to check the Hypothesis 2 since there could be the decrease in the reaction to the war against Ukraine over every next period. As for the *Google Trends* variable, it could not be compared across periods, since Google Trends computes every period at a certain scale of 0-100. The indicator values of each period represent the popularity of a query term relative to the highest point at this specific time period. The last presented variable *Region_id* depicts that the same sample of assets was analyzed for each period.

### 3.3.2. Time series

Appendix C reports the summary statistics of the time series analysis for the returns of 10 different stock market indices and assets: AEX, SP500, FTSE100, CAC40, JSE, SPASX200, NIKKEI225, SPBMV, Bitcoin, Oil, and Google Trends of the corresponding regions. The analysis used includes the minimum, maximum, median, and standard deviation values.

The first thing that catches the eye is the positive mean value of each analyzed variable's return, which suggests that there was an overall positive price return from assets over the analyzed period. On the one hand, Bitcoin returns have the highest mean value of 0.0078677, indicating the most considerable average increase in price return compared to other analysed assets, and possibly being the best investment during the considered war. On the other hand, the *Oil* variable possesses the smallest mean score of 0.0001722, reflecting the smallest increase in price return. At the same time, both mentioned assets' returns were the most volatile during the Russian-Ukrainian war based on the values of standard deviation. For that reason, this econometrical analysis aims to detect which asset could be considered as a safe haven during the turbulent time of the ongoing war. Consequently, we test Hypotheses 3 and 4.

The region with the highest mean of Google Trends score for the query "Ukraine war" is the Netherlands with a mean value of 22.45763. Thus, we might suggest that the AEX index was influenced the most among analyzed ones due to the highest interest. At first glance, the effect also may be bigger in France than in South Africa, for instance, which corresponds to the literature findings and Hypothesis 1, regarding that the strength of influence on stock markets rises with the proximity to the geographical location of the war. The tendency can be also traced among other *Google Trends* variables, since countries of the European region, such as France, the Netherlands, and the United Kingdom possess higher mean values of Google Trends than countries that are farther away from the geographical location of the war, such as Japan, South Africa, Mexico, the USA. Although, Google Trends values of Australia stand out of the general trend having a mean value of 18.16102, which is even higher than in the United Kingdom. Therefore, there is a need to test the Hypothesis 1 in order to examine whether the effect of the ongoing war is dependent on the distance to it.

# 4. Empirical Results and Interpretation

## 4.1. Regression results of Panel data

In this section, we present the panel data analysis results on the effect of the Russian-Ukrainian war on the selected assets: Bitcoin and Oil, and indexes AEX, SP500, FTSE100, CAC40, JSE, SPASX200, NIKKEI225, SPBMV. In the Panel data, we used regular but not continuous periods due to the specifics of Google Trends data being indexed which does not allow usage of daily frequency for the longer periods, not making them continuous in our case. Therefore, in order to obtain a more comprehensive result, 3 separate periods for 3 different years were used. Additionally, the whole time period from the start of the full-scale war was considered later in the context of time series analysis. The results are presented in the table below.

**Table 2**

*Panel data results*

| Dependent variable: Returns of the selected assets | **First period** | **Second period** | **Third period** |
|---|---|---|---|
| Google Trends | 0.0000941**<br>(0.0000353) | 4.99e-06<br>(0.0000116) | 0.0000254*<br>(0.0000137) |
| Estimation method | Random Effect | Random Effect | Random Effect |
| Wald chi (1) | 7.11 | 0.18 | 3.44 |
| Number of observations | 2420 | 2420 | 890 |
| R-squared overall | 0.0029 | 0.0001 | 0.0039 |

*Note*. Standard deviations are reported in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

As for the results for the first period (24th of February, 2022 - 24th of October, 2022), a positive correlation was identified, specifically where one point increase in Google Trends with the query "Ukraine war" is associated with an increase in asset returns by 0.0000941, keeping all else constant. The indicator Wald chi suggests that our model for the first period is overall statistically significant.

In the second period (24th of February, 2023 - 24th of October, 2023) the coefficient 4.99e-06 demonstrates a positive relationship, but this relationship is not statistically significant due to both t-statistic and Wald chi values.

In the third period (24th of February, 2024 - 24th of May, 2024) we can observe a declining positive relationship compared to the first one, contradicting Hypothesis 2. Particularly, one point increase in Google Trends with the query "Ukraine war" is associated with an increase in assets' returns by 0.0000254, keeping all else constant. Additionally, the indicator Wald chi suggests that our model for the third period is overall statistically significant.

The identified relationship is opposite to the findings of Boungo and Yatie (2022), who found a significantly negative effect on the global stock market returns during the first 2 weeks of the Russian invasion with diminishing negative responses afterwards.

The findings are also not consistent with the Hypothesis 2, since neither the negative relationship between Google Trends with query "Ukraine war" and analyzed assets, nor the decrease of this relationship is identified. On the contrary, the results indicate the diminishing positive effect when we compare first and third periods.

However, among all the important factors that should be highlighted in the panel data analysis are the low values of the R-squared indicator for each considered period, meaning that Google Trends query of "Ukraine war" explains a relatively small amount of the variation in the selected assets' returns.

## 4.2. Regression results of Time series

In order to account for the possibility that there might be individual effects on different assets (meaning stock market indices, oil, and Bitcoin) we conduct the time series analysis.

To decrease the possibility of obtaining biased results, several tests were conducted. Dickey-Fuller test was performed for each variable in each regression confirming that all variables are stationary. Additionally, the Breusch-Pagan test for heteroskedasticity and the Breusch-Godfrey test for autocorrelation were used for each regression to reject possible problems of heteroskedasticity and autocorrelation being present. The independent variables were also checked for multicollinearity problem. The testing procedure revealed the only issue of multicollinearity sporadically. Thus, regressions were adjusted, when necessary, by excluding irrelevant variables – the ones exceeding a certain threshold, according to the testing procedure of variance inflation factors (VIF). All the test results are presented in Appendix D. Therefore, the obtained results in Table 2 appear to be unbiased and can be considered for interpretation.

**Table 2**

*Time series results*

| | $Asset_{t-2}$ | $Google\ Trends_t$ | $Google\ Trends_{t-1}$ | $Google\ Trends_{t+1}$ | *F-test* |
|---|---|---|---|---|---|
| 1.$AEX_{t-1}$ | -0.0720826 | - | 0.0004924 | -0.0010011*** | 2.9 |
| | (0.0897883) | | (0.0003413) | (0.0003619) | |
| 2. $S\&P\ 500_{t-1}$ | -0.1145684 | - | 0.0011041* | -0.0025008*** | 2.95 |
| | (0.0943636) | | (0.0006118) | (0.0008999) | |
| 3. $NIKKEI225_{t-1}$ | -0.1268998 | - | 0.0007878* | -0.0009603* | 1.68 |
| | (0.0933125) | | (0.0004531) | (0.0005505) | |
| 4. $S\&PASX200_{t-1}$ | 0.0089262 | - | 0.0008554* | -0.0011827* | 1.19 |
| | (0.0951521) | | (0.0005158) | (0.000642) | |
| 5. $S\&P/BMV_{t-1}$ | 0.0964199 | 0.0012681** | -0.0006597 | -0.000689 | 1.34 |
| | (0.0948874) | (0.000607) | (0.000509) | (0.000579) | |
| 6. $JSE_{t-1}$ | -0.2054654** | - | -0.0003362 | - | 2.91 |
| | (0.0925312) | | (0.0002992) | | |
| 7. $FTSE100_{t-1}$ | -0.0025785 | - | 0.0010482*** | -0.0016215*** | 3.39 |
| | (0.0884691) | | (0.0003611) | (0.000536) | |
| 8. $CAC40_{t-1}$ | -0.0593356 | 0.0016594** | 0.0001286 | -0.0020344*** | 4.18 |
| | (0.0856615) | (0.0006522) | (0.0001286) | (0.0005129) | |
| 9. $Oil_{t-1}$ | -0.1643896* | - | - | -0.0002282 | 2.00 |
| | (0.0846566) | | | (0.0009966) | |
| 10. *Bitcoin* | 0.0547848 | -0.0108848** | 0.0078468** | - | 2.20 |
| | (0.0931937) | (0.0045245) | (00.0036621) | | |

*Note.* Standard deviations are reported in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The dependent variable *Bitcoin* is used in the current period to increase the explanatory power of regression since the regression with $Bitcoin_{t-1}$ does not provide statistically significant coefficient estimators.

Unfortunately, based on the results of the time series analysis we cannot specifically determine the individual assets' reactions, since the coefficients are somewhat contradictory, several of them are positive, and some are negative. Despite this, we still try to observe some effects that might be present.

First of all, it should be noted that the results are somewhat ambiguous, therefore we can not imply the causal effect being established – thus the term association is used further. Given the fact that the implications of the results are not straightforward, this interpretation is intended to emphasize the key findings, while highlighting the complexities and variations across different assets.

The obtained significant results of the models present a clear tendency that the lead of a corresponding Google Trends variable has a negative association with the dependent variables in the majority of regressions, while the lag of a corresponding Google Trends variable has a positive association with the dependent variables in the majority of regressions.

For instance, one unit increase in the Google Trends query for "Ukraine war" in the USA in the next period is associated with 0.0025008 units decrease of the S&P 500 return in the previous period, keeping all else constant. The same direction of association between the $GoogleTrend_{t+1}$ and assets' returns was found for such indices as AEX, NIKKEI225, S&P/ASX 200, FTSE100, and CAC40. The identified tendency in the obtained results may be explained by the next possible reasons. A higher "Ukraine war" query might be an indication of an increased public as well as investor awareness of developments in geopolitical tensions, which could have been already priced in the stock market in the previous period. Alternatively, a higher "Ukraine war" query might reflect rising concerns or uncertainties resulting in a possible anticipation of the negative impact on the stock market performance. These findings are also consistent with the study of Boungo and Yatie (2022) on the identification of a negative effect on global stock market returns.

In case of the variable $GoogleTrend_{t-1}$, for example, one point increase in the Google Trends query "Ukraine war" in the USA in the previous period is associated with an increase in the S&P 500 returns in the previous period by 0.001104 unit, keeping all else constant. The same direction of association between the $GoogleTrend_{t-1}$ and assets' returns was found for such indices as S&P/ASX 200, FTSE100, NIKKEI225l, and Bitcoin price return.

This kind of association suggests that the increased public concern about the war in Ukraine of a particular region positively affects the respective stock market performance, which might suggest that the more active developments in the Russian-Ukrainian war and higher public interest in it are positively perceived by investors, which may sound counterintuitive. Therefore, we may assume that there could be a lag in market reaction or even the other way around – the market prices were already corrected before the public interest had time to rise. These results are also opposite to the findings of Yousaf et al. (2023) that stock markets of Asia and Europe are negatively influenced stronger than other ones, as a result of Russian invasion of Ukraine. At the same time, results support the findings of Jankovic (2024) that Bitcoin possesses the properties of being a safe-haven asset during times of uncertainty.

To bring some clarity on this matter we proceed with the result interpretation of the $GoogleTrend_t$ variable, but it is essential to mention that the association found above needs future investigations, possibilities of which will be considered in the Discussion part.

Variable $GoogleTrend_t$ in most regressions is excluded due to the identification of the multicollinearity problem. A statistically significant association with $GoogleTrend_t$ variable is found only in the Mexican stock market index, in the French stock market index, and in the Bitcoin price. While higher Google Trends queries in Mexico and France in the current period appear to be positively associated with the respective stock market returns in the previous period, the higher global public interest in the war against Ukraine in the current period is negatively associated with the Bitcoin price return in the current period.

In case of Mexico, the positive coefficient, also with a reference to Hypothesis 2, might suggest that the higher Mexican public interest in the current period is positively associated with the Mexican stock market returns in the previous period as a result of the country being far from the geographical location of the war. This association is also consistent with findings that stock markets located further from the geographical location of the war should be considered by investors as a place to relocate their funds to during the ongoing war (Federle & Sehn, 2022; Sun and Zhang, 2023). However, French stock market returns are associated in a similar direction with a higher French public interest in the war in Ukraine, with the country being located much closer to the geographical location of the war than Mexico. Therefore, Hypothesis 2 cannot be proved nor rejected based on the obtained results.

The conducted investigation does not provide sufficient evidence to either accept or reject Hypothesis 3 about the positive correlation between crude oil prices and the increasing public concern. In case of oil, the variables $GoogleTrend_t$ and $GoogleTrend_{t-1}$ are excluded due to the multicollinearity problem, while the variable $GoogleTrend_{t+1}$ is not significant. Based only on these results we can assume that the global public interest in the Russian-Ukrainian war does not influence the oil price returns, which does not necessarily mean that there is no connection between this war and oil prices, implying that further investigations of oil returns might need to incorporate another proxy for the News variable.

As for Bitcoin, the investigation also does not make it possible to draw a definite conclusion about Hypothesis 4, since an increase in the Google Trends query "Ukraine war" in the current period is associated negatively with the Bitcoin returns of the current period, while an increase in the Google Trends query "Ukraine war" in the previous period is associated positively with the Bitcoin returns of the current period. This might indicate a possible negative direct association between the Bitcoin price returns and the higher global interest in the Russian-Ukrainian war in the same time period, with the one-period lagged positive effect on the Bitcoin returns.

For this reason, we can not state that Bitcoin presents safe-haven properties during the Russian-Ukrainian war turbulence time, referencing Hypothesis 4, mainly due to the opposite direction of association between the time periods. This relationship needs to be deeper examined further.

Based merely on the time series results we cannot derive the "net effect" of the Google Trends queries, since in most of the regressions we receive an outcome indicating the presence of an equivocal impact. In this case, it would be rational to reference our panel data results, where the overall positive correlation between the "Ukraine war" query and assets' returns was identified. Therefore, we may assume that the individual "net effect" might be positive as well, though we could not claim that unequivocally due to the limited properties of data, since the time periods and the data frequency used for panel data and time series analyses are not completely identical, constraining our approach from providing deeper insights on the possible relationships.

Considering the abovementioned, and given the results presented earlier, it is evident that further research in this field is more than necessary. Therefore, the last part of our research is dedicated to the discussion of possible future improvements.

# 5. Discussion

## 5.1. Limitations

This study is obviously not without its limits. Firstly, the variable that represents the public interest and concern about the Russian-Ukrainian war is Google Trends queries, which implies certain limits on the export of the data. The Google Trends data does not represent the exact numbers for any query on any topic. Instead, the data is indexed from 0-100, with 100 being the maximum search volume for the selected time and region (Google Trends, n.d). Additionally, the Google Trends website does not allow for the export of daily data for the time periods of more than 8 months, meaning that for the period longer than 8 months only weekly data can be exported. The mentioned properties of Google Trends make us introduce some adjustments to our econometrical methodology. For this reason, in panel data, we could not use periods following each other immediately, since longer time periods would mean the unavailability of daily frequency. Therefore, in our time series analysis we utilize weekly data to investigate the relationship between individual assets and public concern about the war of the corresponding region for the entire period of the full-scale Russian-Ukrainian war. Therefore, one of the possible improvements for future studies using panel data could be the use of the dataset with a continuous sample, while for the time series, the suggestion is to apply daily data. In addition, the ability to collect the actual number (absolute values, not indexed) of Google Trend queries has the potential to be more efficiently employed in future research. Alternatively, another proxy variable could be used for the public concern representation. However, such an option was not found in our research, but potentially could be available in the future.

Secondly, our analysis is mainly based on the studies of Brune et al. (2014) and Boungo and Yatie (2022), who investigate the relationship between news or Google Trends variables and stock markets, not controlling for any other possible macroeconomic determinants. At the same time, some papers emphasize the importance of macroeconomic indicators integration to capture their influence on the asset return (Cortes et al., 2022). Thus, future studies should consider such improvement.

Finally, the model uses lagged variables, but the choice of certain lags might not fully capture the dynamics between search trends and assets' returns - what the results obtained in this paper explicitly showed. At the same time, some possible improvements on this matter could be considered in future studies. For instance, the implemented approach in this study may not capture the complexity of the investigated relationship in modern times, since the methodology of Brune et al. (2014) investigates the correlation between the news variable and the stock market in the context of the wars after WW2. Even though we applied Google Trends instead of the news variable to account for the differences in technological development, we use a similar dynamic (lagged) structure of the regression. One of the possible ways for improvement is a replacement of the lagged dependent variable for the lead one, in order to capture not the time required for the newspaper dissemination (Brune et al., 2014), but the time that has already passed after the publication of the news before the public interest was raised. Future studies should also investigate the relevance of the inclusion of additional lags or the exclusion of existing ones (previously used) due to the changes in the market reaction over time. In case the additional lag is implemented, one should consider other types of empirical tools – for instance, Vector Autoregressive Models, in order to get more precise estimates of the results since VAR can capture the dynamics of interactions between multiple time series variables with a flexible lag structure (Stock & Watson, 2001).

## 5.2. Implications

Even though the ambiguous results raise more questions for future research than they answer, the conducted research still significantly contributes to the existing academic literature in several ways. Firstly, our study presents the utilization of Google Trends data in financial econometrics analyzing both traditional and alternative asset returns during the Russian-Ukrainian war. This expands the growing literature base on this matter investigating the intersection of public interest and asset returns. Secondly, the statistically significant results serve as evidence that Google Trends data may be implemented as a proxy for market sentiment, however, the method used still requires developments. Additionally, the results of a study show how the public interest may influence market movements.

For this paper to be considered useful by investors looking for hedging opportunities in the context of the continuation of the Russian-Ukrainian war or during events similar to it, the methodological approach applied in this paper needs to be further improved by the researchers, providing the latter with the relevant material to work on. In turn, the ultimate result would potentially supply investors with desired insights on the hedging properties of certain assets during the Russian-Ukrainian war or similar events.

## 5.3. Conclusion

This study examines the effect of the public interest in the Russian-Ukrainian war on the stock market indices performance, as well as on the oil and Bitcoin prices. The stock market indices considered for the research are AEX, S&P/BMV, NIKKEI225, S&P 500, FTSE100, S&P/ASX 200, CAC40, and JSE indices, while the public interest is proxied by the Google Trends data. The research investigates 3 research questions, which are formulated based on the existing literature. Firstly, we investigate whether crude oil is a good hedging instrument at the time of Russian-Ukrainian war. Secondly, we examine if Bitcoin has any hedging capabilities during the war. Lastly, we search for the stock indices to hedge the risk during the war against Ukraine. The research is conducted using panel data and time series methodologies, implementing the approaches of Boungo and Yatie (2022) and Brune et al. (2014) respectively.

At first, we conduct the panel data analysis to test if there is a negative correlation between the analyzed indices/assets and the Russian-Ukrainian war, with a decrease in such relationship over every next period of the ongoing war. The results indicate the diminishing positive effect over the analysed periods, which is opposite to the initial hypothesis.

Secondly, we use a time series approach to examine the individual effects of the public interest of the Russian-Ukrainian war on different indices and assets. We obtain results implying both positive and negative associations between Google Trends queries of a certain location and its corresponding asset/index, thereby no definite inference can be drawn on which of the separately analyzed assets may serve as an uncompromised safe-haven asset during the Russian-Ukrainian war.

An important contribution is that this research paves the way for future analyses and improvements to approaches in the field. We make the early attempts to integrate Google Trends queries - as a proxy for the public interest in a certain topic - into the empirical methodology in order to examine the possible effect of a particular event on the stock market indices and several assets. By developing this approach further, future researchers might find themselves able to conduct a necessary analysis to provide investors with relevant and useful information.

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# 7. Appendices

## 7.1. Appendix A

### Panel data testing procedure

First period, Hausman Test

```
. hausman fixed, force

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed          .          Difference          S.E.
-------------+----------------------------------------------------------------
 googletrend |   .0001021     .0000941        7.97e-06        .0000118
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        0.46
                Prob>chi2 =      0.4989
```

Second period, Hausman Test

```
. hausman fixed, force

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed          .          Difference          S.E.
-------------+----------------------------------------------------------------
 googletrend |   .0000179     4.99e-06        .0000129        .0000175
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        0.54
                Prob>chi2 =      0.4624
```

Third period, Hausman Test

```
. hausman fixed, force

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed          .          Difference          S.E.
-------------+----------------------------------------------------------------
 googletrend |   .0000389     .0000254        .0000135        .0000202
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        0.45
                Prob>chi2 =      0.5030
```

## 7.2. Appendix B

# Summary Statistics for panel data

First period

| Variable | | Mean | Standard deviation | Min | Max | Observations |
|---|---|---|---|---|---|---|
| Date | overall | 22821 | 70.1619 | 22700 | 22942 | N =2430 |
| | between | | 0 | 22821 | 22821 | n =10 |
| | within | | 70.1619 | 22700 | 22942 | T=243 |
| Price | overall | -.0003666 | .0172639 | -.1562901 | .1459069 | N =2420 |
| | between | | .0006831 | -.0022218 | .0002157 | n =10 |
| | within | | .0172517 | -.1544348 | .1477622 | T=242 |
| Google Trends | overall | 9.924691 | 11.4451 | 0 | 100 | N =2430 |
| | between | | 3.271174 | 4.757202 | 15.25926 | n =10 |
| | within | | 11.01616 | -3.906584 | 105.1675 | T=243 |
| Region_id | overall | 5.5 | 2.872873 | 1 | 10 | N =2430 |
| | between | | 3.02765 | 1 | 10 | n =10 |
| | within | | 0 | 5.5 | 5.5 | T=243 |

Second period

| Variable | | Mean | Standard deviation | Min | Max | Observations |
|---|---|---|---|---|---|---|
| Date | overall | 23186 | 70.1619 | 23065 | 23307 | N=2430 |
| | between | | 0 | 23186 | 23186 | n=10 |
| | within | | 70.1619 | 23065 | 23307 | T=243 |
| Price | overall | .000179 | .0111033 | -.0727765 | .1019737 | N=2430 |
| | between | | .0006718 | -.0003371 | .0018243 | n=10 |
| | within | | .011085 | -.0744218 | .1003284 | T=242 |
| Google Trends | overall | 33.46708 | 19.50466 | 0 | 100 | N=2430 |
| | between | | 16.96617 | 1.82716 | 55.83539 | n=10 |
| | within | | 11.01178 | -.8950617 | 131.6399 | T=243 |
| Region_id | overall | 5.5 | 2.872873 | 1 | 10 | N=2430 |
| | between | | 3.02765 | 1 | 10 | n=10 |
| | within | | 0 | 5.5 | 5.5 | T=243 |

Third period

| Variable | | Mean | Standard deviation | Min | Max | Observations |
|---|---|---|---|---|---|---|
| Date | overall | 23474.5 | 25.9936 | 23430 | 23519 | N=90 |
| | between | | 0 | 23474.5 | 23474.5 | n=1 |
| | within | | 25.9936 | 23430 | 23519 | T=9 |
| Price | overall | .0006952 | .0127017 | -.0820205 | .0948433 | N=89 |
| | between | | .0010919 | -.0000508 | .0036949 | n=1 |
| | within | | .0126594 | -.0000508 | .0036949 | T=8 |
| Google Trends | overall | 46.16111 | 31.23294 | 0 | 100 | N=90 |
| | between | | 27.18137 | 3.333333 | 74.88889 | n=1 |
| | within | | 17.60151 | -.3277778 | 142.8278 | T=9 |
| Region_id | overall | 5.5 | 2.873878 | 1 | 10 | N=90 |
| | between | | 3.02765 | 1 | 10 | n=1 |
| | within | | 0 | 5.5 | 5.5 | T=9 |

## 7.3. Appendix C

### Summary Statistics for time series

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| AEX | 117 | 0.0022509 | 0.0229192 | -0.0771038 | 0.0615886 |
| SP500 | 117 | 0.0019376 | 0.0248253 | -0.057961 | 0.0658225 |
| FTSE100 | 117 | 0.001176 | 0.0184563 | -0.0670703 | 0.0407468 |
| CAC40 | 117 | 0.0018679 | 0.0240091 | -0.1022995 | 0.0598091 |
| JSE | 117 | 0.000897 | 0.024145 | -0.0615712 | 0.053064 |
| SPASX200 | 117 | 0.0010992 | 0.0178262 | -0.065955 | 0.0445769 |
| NIKKEI225 | 117 | 0.0036426 | 0.0247948 | -0.0668944 | 0.0661552 |
| SPBMV | 117 | 0.0008427 | 0.021811 | -0.0437477 | 0.0674036 |
| Bitcoin | 117 | 0.0078677 | 0.0789998 | -0.3315413 | 0.3149676 |
| Oil | 117 | 0.0001722 | 0.0564797 | -0.1296296 | 0.26302 |
| Google Trends: Netherlands | 118 | 22.45763 | 13.13744 | 9 | 100 |
| Google Trends: USA | 118 | 15.16102 | 13.00162 | 6 | 100 |
| Google Trends: Japan | 118 | 16.20339 | 12.92156 | 5 | 100 |
| Google Trends: France | 118 | 21.28814 | 13.06205 | 10 | 100 |
| Google Trends: South Africa | 118 | 14.76271 | 13.68178 | 5 | 100 |
| Google Trends: Mexico | 118 | 15.98305 | 12.89072 | 0 | 100 |
| Google Trends: United Kingdom | 118 | 17.72881 | 12.27161 | 8 | 100 |
| Google Trends: Australia | 118 | 18.16102 | 12.79621 | 8 | 100 |
| Google Trends: World | 118 | 14.18644 | 12.95815 | 6 | 100 |

lag1 – a one-period lag of the variable is considered; lag2- a two-period lag of the variable is considered. lead1 - a one-period lead of the variable is considered.

For convenience, the variable of return on index is denoted by the index name: e.g., one-week return on AEX index is denoted by AEX.

## 7.4. Appendix D

### Time series testing procedure

#### Model №1, dependent variable: one period lagged AEX

Dickey-Fuller tests

```
. dfuller lag1AEX

Dickey-Fuller test for unit root                   Number of obs   =       115

                         ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -11.571            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag2AEX

Dickey-Fuller test for unit root                   Number of obs   =       114

                         ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -11.469            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag1GT_Netherlands

Dickey-Fuller test for unit root                   Number of obs   =       116

                         ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.551            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lead1GT_Netherlands

Dickey-Fuller test for unit root                   Number of obs   =       116

                         ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.512            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1AEX

         chi2(1)      =     1.02
         Prob > chi2  =   0.3118
```

Breusch-Godfrey

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
---------------------------------------------------------------------------
    lags(p)  |          chi2               df                 Prob > chi2
-------------+-------------------------------------------------------------
       1     |          0.048               1                   0.8268
---------------------------------------------------------------------------
```

#### Model №2, dependent variable: one period lagged S&P 500

Dickey-Fuller tests

```
. dfuller lag1SP500

Dickey-Fuller test for unit root                   Number of obs   =       115

                         ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -11.151            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag2SP500

Dickey-Fuller test for unit root                   Number of obs   =       114

                         ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -11.131            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lead1GT_USA

Dickey-Fuller test for unit root                   Number of obs   =       116

                         ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -19.044            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag1GT_USA

Dickey-Fuller test for unit root                   Number of obs   =       116

                         ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -9.820            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

---

lag1 - a one-period lag of the variable is considered; lag2 - a two-period lag of the variable is considered. lead1 - a one-period lead of the variable is considered.
For convenience, the variable of return on index is denoted by the index name: e.g., one-week return on AEX index is denoted by AEX.

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1SP500

         chi2(1)      =     0.59
         Prob > chi2  =   0.4438
```

Breusch-Godfrey

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

| lags(*p*) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 0.278 | 1 | 0.5981 |

## Model №3, dependent variable: one period lagged NIKKEI225

Dickey-Fuller tests

```
. dfuller lag1NIKKEI225

Dickey-Fuller test for unit root                   Number of obs   =       115
```

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -11.994 | -3.505 | -2.889 | -2.579 |

```
. dfuller lag2NIKKEI225

Dickey-Fuller test for unit root                   Number of obs   =       114
```

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -11.944 | -3.505 | -2.889 | -2.579 |

```
. dfuller lead1GT_Japan

Dickey-Fuller test for unit root                   Number of obs   =       116
```

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -11.452 | -3.505 | -2.889 | -2.579 |

```
. dfuller lag1GT_Japan

Dickey-Fuller test for unit root                   Number of obs   =       116
```

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -6.567 | -3.505 | -2.889 | -2.579 |

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1NIKKEI225

         chi2(1)      =     1.78
         Prob > chi2  =   0.1822
```

Breusch-Godfrey

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

| lags(*p*) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 0.422 | 1 | 0.5160 |

## Model №4, dependent variable: one period lagged S&P/ASX 200

Dickey-Fuller tests

```
. dfuller lag1SPASX200

Dickey-Fuller test for unit root                   Number of obs   =       115
```

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -10.244 | -3.505 | -2.889 | -2.579 |

```
. dfuller lag2SPASX200

Dickey-Fuller test for unit root                   Number of obs   =       114
```

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -10.204 | -3.505 | -2.889 | -2.579 |

```
. dfuller lead1GT_Australia

Dickey-Fuller test for unit root                   Number of obs   =       116
```

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -13.105 | -3.505 | -2.889 | -2.579 |

```
. dfuller lag1GT_Australia

Dickey-Fuller test for unit root                   Number of obs   =       116
```

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -5.556 | -3.505 | -2.889 | -2.579 |

---

lag1 - a one-period lag of the variable is considered; lag2 - a two-period lag of the variable is considered. lead1 - a one-period lead of the variable is considered.
For convenience, the variable of return on index is denoted by the index name: e.g., one-week return on AEX index is denoted by AEX.

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1SPASX200

         chi2(1)      =     0.63
         Prob > chi2  =   0.4286
```

Breusch-Godfrey

```
. estat bgodfrey
```

Breusch-Godfrey LM test for autocorrelation

| lags(p) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 2.732 | 1 | 0.0984 |

## Model №5, dependent variable: one period lagged S&P/BMV

Dickey-Fuller tests

. dfuller lag1SPBMV

Dickey-Fuller test for unit root — Number of obs = 115

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -10.018 | -3.505 | -2.889 | -2.579 |

. dfuller lead1GT_Mexico

Dickey-Fuller test for unit root — Number of obs = 116

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -11.456 | -3.505 | -2.889 | -2.579 |

. dfuller GT_Mexico

Dickey-Fuller test for unit root — Number of obs = 117

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -8.725 | -3.504 | -2.889 | -2.579 |

. dfuller lag2SPBMV

Dickey-Fuller test for unit root — Number of obs = 114

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -9.960 | -3.505 | -2.889 | -2.579 |

. dfuller lag1GT_Mexico

Dickey-Fuller test for unit root — Number of obs = 116

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -8.716 | -3.505 | -2.889 | -2.579 |

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1SPBMV

         chi2(1)      =     0.06
         Prob > chi2  =   0.8090
```

Breusch-Godfrey

```
. estat bgodfrey
```

Breusch-Godfrey LM test for autocorrelation

| lags(p) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 2.126 | 1 | 0.1448 |

## Model №6, dependent variable: one period lagged JSE

Dickey-Fuller tests

. dfuller lag1JSE

Dickey-Fuller test for unit root — Number of obs = 115

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -12.964 | -3.505 | -2.889 | -2.579 |

. dfuller lag2JSE

Dickey-Fuller test for unit root — Number of obs = 114

| | Test Statistic | Interpolated Dickey-Fuller 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -12.949 | -3.505 | -2.889 | -2.579 |

lag1 - a one-period lag of the variable is considered; lag2 - a two-period lag of the variable is considered. lead1 - a one-period lead of the variable is considered.

For convenience, the variable of return on index is denoted by the index name: e.g., one-week return on AEX index is denoted by AEX.

```
. dfuller lag1GT_SA

Dickey-Fuller test for unit root                   Number of obs   =       116

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.728            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1JSE

         chi2(1)      =     0.29
         Prob > chi2  =   0.5891
```

Breusch-Godfrey

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

| lags(*p*) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 1.031 | 1 | 0.3100 |

## Model №7, dependent variable: one period lagged FTSE100

### Dickey-Fuller tests

```
. dfuller lag1FTSE100

Dickey-Fuller test for unit root                   Number of obs   =       115

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -11.318            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag2FTSE100

Dickey-Fuller test for unit root                   Number of obs   =       114

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -11.149            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lead1GT_GB

Dickey-Fuller test for unit root                   Number of obs   =       116

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -14.532            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag1GT_GB

Dickey-Fuller test for unit root                   Number of obs   =       116

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -11.115            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1FTSE100

         chi2(1)      =     1.60
         Prob > chi2  =   0.2054
```

Breusch-Godfrey

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

| lags(*p*) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 0.087 | 1 | 0.7675 |

## Model №8, dependent variable: one period lagged CAC40

### Dickey-Fuller tests

```
. dfuller lag1CAC40

Dickey-Fuller test for unit root                   Number of obs   =       115

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -12.448            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag2CAC40

Dickey-Fuller test for unit root                   Number of obs   =       114

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -12.270            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

---

lag1 - a one-period lag of the variable is considered; lag2 - a two-period lag of the variable is considered. lead1 - a one-period lead of the variable is considered.
For convenience, the variable of return on index is denoted by the index name: e.g., one-week return on AEX index is denoted by AEX.

```
. dfuller lead1GT_France

Dickey-Fuller test for unit root                   Number of obs   =       116

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)             -9.802            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller GT_France

Dickey-Fuller test for unit root                   Number of obs   =       117

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)             -6.272            -3.504            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag1GT_France

Dickey-Fuller test for unit root                   Number of obs   =       116

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)             -6.284            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1CAC40

         chi2(1)      =     1.66
         Prob > chi2  =   0.1974
```

Breusch-Godfrey

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

| lags(p) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 0.777 | 1 | 0.3781 |

## Model №9, dependent variable: one period lagged Oil

### Dickey-Fuller tests

```
. dfuller lag1Oil

Dickey-Fuller test for unit root                   Number of obs   =       115

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)            -13.998            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag1GT_World

Dickey-Fuller test for unit root                   Number of obs   =       116

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)             -9.553            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag2Oil

Dickey-Fuller test for unit root                   Number of obs   =       114

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)            -13.953            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lag1Oil

         chi2(1)      =     0.09
         Prob > chi2  =   0.7589
```

Breusch-Godfrey

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

| lags(p) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 0.756 | 1 | 0.3845 |

lag1 - a one-period lag of the variable is considered; lag2 - a two-period lag of the variable is considered. lead1 - a one-period lead of the variable is considered.
For convenience, the variable of return on index is denoted by the index name: e.g., one-week return on AEX index is denoted by AEX.

## Model №10, dependent variable: Bitcoin

### Dickey-Fuller tests

```
. dfuller Bitcoin

Dickey-Fuller test for unit root                   Number of obs   =       116

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -11.152            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag2Bitcoin

Dickey-Fuller test for unit root                   Number of obs   =       114

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -10.971            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller lag1GT_World

Dickey-Fuller test for unit root                   Number of obs   =       116

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -9.553            -3.505            -2.889            -2.579
------------------------------------------------------------------------------
```

```
. dfuller GT_World

Dickey-Fuller test for unit root                   Number of obs   =       117

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -9.572            -3.504            -2.889            -2.579
------------------------------------------------------------------------------
```

### Breusch-Pagan

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of Bitcoin

         chi2(1)      =     0.03
         Prob > chi2  =   0.8661
```

### Breusch-Godfrey

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

| lags(p) | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 0.441 | 1 | 0.5064 |

## The testing results of variance inflation factors (VIF)

TABLE 1. Correlation Test for model 1

. estat vif

| Variable | VIF | 1/VIF |
|---|---|---|
| lead1GT_Ne~s | 2.42 | 0.413388 |
| lag1GT_Net~s | 2.41 | 0.415022 |
| lag2AEX | 1.06 | 0.945044 |
| Mean VIF | 1.96 | |

TABLE 2. Correlation Test for model 2

. estat vif

| Variable | VIF | 1/VIF |
|---|---|---|
| lead1GT_USA | 3.38 | 0.295701 |
| lag1GT_USA | 3.28 | 0.304999 |
| lag2SP500 | 1.06 | 0.945721 |
| Mean VIF | 2.57 | |

TABLE 3. Correlation Test for model 3

. estat vif

| Variable | VIF | 1/VIF |
|---|---|---|
| lead1GT_Ja~n | 2.33 | 0.428309 |
| lag1GT_Japan | 2.32 | 0.430640 |
| lag2NIKK~225 | 1.01 | 0.991532 |
| Mean VIF | 1.89 | |

TABLE 4. Correlation Test for model 4

. estat vif

| Variable | VIF | 1/VIF |
|---|---|---|
| lag1GT_Aus~a | 6.76 | 0.147867 |
| lead1GT_Au~a | 6.75 | 0.148093 |
| lag2SPASX200 | 1.03 | 0.972293 |
| Mean VIF | 4.85 | |

lag1 - a one-period lag of the variable is considered; lag2 - a two-period lag of the variable is considered. lead1 - a one-period lead of the variable is considered.

For convenience, the variable of return on index is denoted by the index name: e.g., one-week return on AEX index is denoted by AEX.

TABLE 5. Correlation Test for model 5

```
. estat vif
```

| Variable | VIF | 1/VIF |
|---|---|---|
| GT_Mexico | 3.50 | 0.285910 |
| lag1GT_Mex~o | 3.24 | 0.308536 |
| lead1GT_Me~o | 2.79 | 0.359051 |
| lag2SPBMV | 1.03 | 0.969513 |
| Mean VIF | 2.64 | |

TABLE 6. Correlation Test for model 6

```
estat vif
```

| Variable | VIF | 1/VIF |
|---|---|---|
| GT_SA | 1.01 | 0.993119 |
| lag2JSE | 1.01 | 0.993119 |
| Mean VIF | 1.01 | |

TABLE 7. Correlation Test for model 7

```
estat vif
```

| Variable | VIF | 1/VIF |
|---|---|---|
| lead1GT_GB | 2.27 | 0.439920 |
| lag1GT_GB | 2.27 | 0.440913 |
| lag2FTSE100 | 1.05 | 0.952716 |
| Mean VIF | 1.86 | |

TABLE 8. Correlation Test for model 8

```
. estat vif
```

| Variable | VIF | 1/VIF |
|---|---|---|
| GT_France | 6.36 | 0.157223 |
| lag1GT_Fra~e | 3.97 | 0.251943 |
| lead1GT_Fr~e | 3.53 | 0.283270 |
| lag2CAC40 | 1.09 | 0.919006 |
| Mean VIF | 3.74 | |

TABLE 9. Correlation Test for model 9

```
. estat vif
```

| Variable | VIF | 1/VIF |
|---|---|---|
| lag2Oil | 1.02 | 0.984121 |
| lead1GT_Wo~d | 1.02 | 0.984121 |
| Mean VIF | 1.02 | |

TABLE 10. Correlation Test for model 10

```
. estat vif
```

| Variable | VIF | 1/VIF |
|---|---|---|
| GT_World | 11.24 | 0.088999 |
| lag1GT_World | 11.22 | 0.089149 |
| lag2Bitcoin | 1.01 | 0.990256 |
| Mean VIF | 7.82 | |

lag1 - a one-period lag of the variable is considered; lag2 - a two-period lag of the variable is considered. lead1 - a one-period lead of the variable is considered.

For convenience, the variable of return on index is denoted by the index name: e.g., one-week return on AEX index is denoted by AEX.