The impact of the Russia-Ukraine war on American, European and Russian stock markets

Author: Robin de Ruiter
University of Twente
P.O. Box 217, 7500AE Enschede
The Netherlands

ABSTRACT

This thesis examines the impact of the Russia-Ukraine war on the volatility of American, European, and Russian stock markets. The central research question aims to explore how this conflict influences stock exchanges worldwide, focusing on different periods between 2018 and 2025. Using a quantitative research design, the study analyses financial market volatility indices like VIX, VSTOXX and RVI for American, European and Russian stock exchanges respectively. Geopolitical risks are measured using the GPR index created by Caldara and Iacoviello (2022), which quantifies geopolitical tensions based on news articles. Preliminary findings suggest a close relationship between geopolitical risks and stock market volatility, aligning with previous research. The methodology examines potential correlations and causality between the dependent variable: volatility in different stock markets; and the independent variable: GPR index. Ultimately, this thesis aims to contribute to understanding the economic consequences of geopolitical risks on financial markets.

Graduation Committee members:
1st Supervisor: Dr. Frédérik Sinan Bernard
2nd Supervisor: Dr. Lingbo Shen

Keywords
Geopolitical risk, GPR index, stock market volatility, correlation, DID regression, Russia-Ukraine war.

During the preparation of this work, the author used Microsoft Copilot and ChatGPT in order to improve the overall quality of the paper, including refining spelling and grammar. Furthermore, these tools helped in performing the analyses in RStudio (e.g. aiding when code is not functioning). After using these tools/services, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

1. INTRODUCTION

The Russia-Ukraine conflict has been going on for many years. In 1991, after being Soviet republics for 70 years, Ukraine and Russia became independent states (Kappeler, 2014, p. 107). However, the relationship between the two had many issues from the very beginning, since there were many problems for example regarding territory (Ibid., p. 108-109). What belongs to who? In 2013, former Ukraine President Viktor Yanukovych refused to sign an association agreement with the EU, opting for closer ties with Russia. That led to the Euromaidan protests, since Yanukovych promised the Ukrainian people that he would sign the association agreement (Kvit, 2014, p. 28). After the many protests, Yanukovych was ousted. Crimea, a peninsula in Eastern Europe which is located in the Black Sea, was annexed by Russia in 2014 after Yanukovych's ousting, together with other regions including parts in Donbas, Donetsk and Lugansk (Kostanyan & Meister, 2016, p. 1). Later, the Minsk I and II agreements were made, in order to create peace and a ceasefire between Russia and Ukraine (Wittke, 2019, p. 268). However, the agreement was never fully implemented, and both parties continued fighting.

The most recent highlight of this conflict that is still going on between Russia and Ukraine started on February 24, 2022. Russia started to invade parts of Ukraine, as Russian President Vladimir Putin authorised what he referred to as a "special military operation". After this happened, many western countries imposed sanctions against Russia. Since the start of the war, the EU adopted 16 sanction packages on Russia, such as taking away the ability of Russian state and government to access capital and financial markets from the EU and banning imports and exports from Russia. [1] Russia responded by implementing counter sanctions. Even though Russia was suffering the most from the sanctions, the global economy is not immune and inflation increased worldwide because of the sanctions (Pereira et al., 2022, p. 2). The sanctions against Russia and the increased worldwide geopolitical tensions are just a few examples of how big the impacts of this conflict are. The energy and food markets are an example to look at of how severely disrupted they were after the war began. The EU area has been more vulnerable to the economic consequences of this conflict compared to other economic regions (Arce et al., 2022, p. 17). The EU area very strongly depended on energy imports, notably from Russia (Adolfsen et al, 2022). The war led to a substantial rise in energy prices and significant instability in energy markets (Ibid.). Prior to the war, most EU countries heavily relied on energy supply from Russia. Russia provided 24.4% of the EU's total available energy (Papunen, 2024, p. 6). The sanctions thus created significant challenges when they were imposed to Russia. Additionally, the EU implemented a ban on the import of Russian coal as of August 2022 (Adolfsen et al., 2022). Energy inflation accounted for more than half of headline inflation in February 2022. It reached a historical high of 32% in that month (Nickel et al., 2022, p. 70). The surge in energy inflation indirectly affects the pricing chain via higher input costs to food and non-energy industrial goods and services (Koester et al., 2021). The combination of geopolitical risks, increasing commodity prices, sanctions and regional business disruptions have significantly influenced financial market prices and volatility (OECD, 2022, p. 7).

In 2025, the situation is still tense. Ukraine became (and still is) the focal point of contention between Russia and the West (Safranchuk, 2022, p. 2-3). For the past couple of years, most NATO countries stood consistently by Ukraine's side. From February 24, 2022, until March 12, 2025, the United States have provided 66.5 billion USD in military assistance to Ukraine since Russia launched its invasion (U.S. Department of State, 2025). The EU provided approximately 145 billion USD in aid to Ukraine during this period, with additional support in 2025, increasing the total to nearly 198 billion USD (EEAS, 2025). However, on January 20, 2025, United States President Donald Trump took over from the Biden administration. That marked a significant shift in U.S. foreign policy. Trump is known for his critical stance against foreign aid, maintaining an "America First" policy (Taim, 2024, p. 15). After publicly clashing in an Oval Office meeting with Ukraine President Volodymyr Zelenskyy on February 28, 2025, Trump decided to suspend all military aid to Ukraine. It was a fierce exchange, with U.S. President Trump and Vice President J.D. Vance asserting that Zelenskyy should be more grateful towards the U.S. and their financial and military aid. Trump insisted that Zelenskyy should pursuit more towards a peace agreement with Russia, while Zelenskyy emphasised the need for more military aid from the U.S. (The White House, 2025). This public fallout intensified global tensions, with the European leaders raising concerns about Ukraine's ability to sustain its military actions against Russia. Following a period of relative "status quo", geopolitical tensions started to rise again. The ongoing conflict in Ukraine continues to impact numerous countries in different ways. A potential further escalation of the war or other heightened geopolitical tensions could reduce economic activity and drive global inflation higher again (Federal Reserve, 2023, p. 60).

As explained earlier, geopolitical risks have numerous influences on market volatility, supply chains, inflation and many other factors. Given the recent nature of the Ukraine war, this thesis seeks to explore the consequences of this conflict on financial markets, in particular the correlation and causation. Examples of major stock exchanges are Euronext, the New York Stock Exchange (NYSE), NASDAQ and the Moscow Stock Exchange (MOEX). Investigating how this conflict and its geopolitical implications impact stock exchanges in regions affected by the war could give a good understanding of the global economic landscape. This topic discusses economics, finance and international relations, giving a comprehensive analysis of this global conflict. Consequently, this thesis aims to provide an answer to the following research question:

"What impact does the war in Ukraine have on the volatility and fragility of different stock exchanges worldwide?"

Building on existing literature and theoretical frameworks, this thesis formulates the next hypotheses to examine the relationship between geopolitical risks and stock market volatility:

H1: There is a significant positive correlation between geopolitical risks, as measured with the GPR index and the volatility of American, European and Russian stock markets.

H2: Russian stock markets experience greater volatility due to the Russia-Ukraine war, compared to European and American stock markets, since Russia is directly involved in the conflict.

The reason for choosing these specific regions is because the war takes place in Eastern Europe; the Russian, and European stock markets are thus more likely to be affected by this conflict than for instance the Tokyo Stock Exchange (TSE). Also, since the U.S. are a member of NATO as well, it could be considered that they will also be affected by the war, albeit to a different extent than European and Russian counterparts.

[1] See https://www.consilium.europa.eu/en/policies/sanctions-against-russia/, as well as *Economic impact of Russia's war on Ukraine: European Council response* (Papunen, 2024, p. 5).

This thesis examines market volatility across American, European and Russian stock exchanges, considering major geopolitical events as treatment periods. Here, key periods are analysed, focusing on the effect of geopolitical risks on financial markets. Trends or patterns are identified and analysed to address the research question. This thesis will aim to address how this conflict influenced stock markets from regions that are affected the most by this conflict, making it relevant for this topic.

2. THEORETICAL FRAMEWORK

2.1 Geopolitical tensions and risks

2.1.1 Definition of "geopolitical risk"

When conducting this research, certain questions need to be addressed first, such as: What is geopolitical risk exactly, and how is it measured? The term "geopolitical risk" has been given multiple definitions by entrepreneurs, market participants and central bank officials (Caldara & Iacoviello, 2018, p. 2). Caldara & Iacoviello (2018) define geopolitical risk as: "the threat, realisation, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations" (p. 4-5). Their definition includes terrorism, conflict over influences that do not involve acts of violence and territorial rivalry, as well as covering a broad spectrum of geopolitical events, ranging from potential threats, to their realisation, to escalation (Caldara & Iacoviello, 2018, p. 5). This definition was guided by journalistic practices and measurement considerations (Ibid.). Therefore, this paper will adopt this definition throughout its analysis.

2.1.2 Measurement of GPR

Geopolitical risk is measured by the so-called "GPR index". The index measures geopolitical risk on a monthly basis by counting the number of news articles that discuss rising geopolitical risks, divided by the total amount of published news articles (Caldara & Iacoviello, 2018, p. 5-6). A dictionary-based method is used to count the number of words that are related to geopolitical risk. Words that closely align with the definition of geopolitical risk such as 'war' and 'terror' are selected. Afterwards, a text mining approach is performed by looking at the frequency of those selected words. This is an information retrieval measure called 'term frequency' (TF). For every word or term that occurs in a document, TF scores can be computed. Caldara & Iacoviello (2018, p. 6) give the example of the word 'crisis'. On days of high geopolitical tensions, 'crisis' has a relative TF of 0.25%, compared to 0.04% on a normal day. Of course, looking at one word at a time leads to misclassification and measurement error (Ibid.). However, to minimise measurement error in the GPR index, researchers use many more strategies such as exclusion of false positives and robustness analysis to improve the accuracy and reliability of the GPR index (Caldara & Iacoviello, 2022, p. 1197-1200).

Their GPR index also have country-specific measures, where the GPR index in 44 different countries are measured including Russia, Ukraine, and several other countries.[2]

2.1.3 Formulation and improvements over other definitions of "geopolitical risk"

Caldara and Iacoviello (2022) built their definition on the historical usage of the term and captures a wide range of different geopolitical events (p. 1197). This was opposed other, more narrow interpretations of the term "geopolitical risk" (Ibid.) Their definition encompasses non-violent power struggles and territorial disputes, with as example the Cuban Missile Crisis, or the tensions with the U.S. and Iran (Ibid.).

Their paper made several contributions, such as introducing a novel measure of adverse geopolitical events, which also includes important information about geopolitical events that is not reflected in indicators from other researchers (Ibid., p. 1196). Furthermore, they also distinguish the threats of adverse geopolitical events from their actual realisation (Ibid.).

Caldara and Iacoviello (2022) do extensive robustness analyses around their strategies and confirm that in their application, it provides better outcomes than analyses of other researchers (Ibid., p. 1200).

2.2 Market volatility and fragility

2.2.1 Volatility in financial markets

Volatility is the variation or instability in the prices of economic goods or assets, for example a share. Consequently, a high volatility is associated with higher risk of a share, since the share has stronger price fluctuations, which could be seen as a form of risk. (Mieg, 2022, p. 1952-1953). Volatility in financial markets is one of the most important factors because it is directly related to market uncertainty and investment behaviour of individuals and organisations (Bhowmik & Wang, 2020, p. 1). Financial market volatility also has a profound influence on macroeconomics and financial stability of the global economy. For that reason, research on volatility is a main target of focus for researchers and analysts (Ibid. p. 2).

Financial market volatility can be measured in several ways; however, two measures are most commonly used. Firstly, volatility is computed as the standard deviation of asset returns over a specific period. This method uses historical price movements to calculate volatility. A high standard deviation indicates a high probability of significant gains or losses (Schwert, 1990, p. 26). The simplicity and transparency of this method contribute to its widespread use. Secondly, there are more advanced and complex methods to compute volatility with econometric models such as GARCH models. GARCH models are superior and useful for forecasting and predicting volatility in financial markets (Chi & Hao, 2020, p. 2). For the earlier mentioned stock exchanges, there are several indices that imply volatility. For instance, the index that provides the volatility for Euronext is called "VSTOXX", which is based on the prices on the EURO STOCK 50 index. For the U.S., the VIX index is used. This index is created by the Chicago Board Options Exchange. It estimates the 30-day expected volatility of U.S. stock markets using real-time prices of the Standard & Poor's (S&P) 500 options. It serves as a key daily indicator of volatility of U.S. stock markets (CBOE, 2023). For Russian stock exchanges, the Russian Volatility Index (RVI) is used, replacing the former RTSVX index (Moscow Exchange, 2014).

2.2.2 Market fragility

The term "fragility" is referred to as the possibility of stock prices experiencing widespread instability on a global scale due to a local negative shock (Lin & Guo, 2019, p. 132). Financial market fragility stems from exposure to systematic risks, which refers to the likelihood that a negative local shock could disrupt normal operations for a significant portion of institutions, possibly causing global instability (Haldane & May, 2011; Acemoglu et al., 2015, as cited in Lin & Guo, 2019, p. 132).

Measuring how fragile or instable a financial system is, is challenging due to the interdependence and complex interactions between different elements of the financial system and their links

[2] See https://www.matteoiacoviello.com/gpr_country.htm

to the real economy (Gadanecz & Jayaram, 2009, p. 365). A financial system can be called "stable" when there is no excessive volatility, stress or crises (Ibid., p. 365-366).

However, there are several ways to try and measure financial market stability or fragility such as looking at variables that explain conditions on financial markets like equity indices, volatility and corporate spreads (Gadanecz & Jayaram, 2009, p. 370). Even though some central banks have tried to measure financial stability with single aggregate measures, those cannot be used without knowledge and use of other quantitative or qualitative instruments (Ibid., p. 378). This thesis will use volatility as the main indicator to assess stock market fragility, since volatility reflects fluctuations in market prices that are closely tied to systemic risks and is a potential precautionary signal for the lack of resilience of a financial market (Mieg, 2022, p. 1962).

2.3 Relationship of geopolitical risks and financial markets

The link between geopolitical risks and financial markets has been a recurring topic among researchers over the past couple of years (Elsayed & Helmi, 2021, p. 1). The recent increase of geopolitical risks is a potential disruptive factor to financial stability. Adding to that, geopolitical risks can affect capital flows and asset valuations, potentially triggering volatility in commodities, currencies, equities, interest rates and credit spreads. (Dieckelmann et al., 2024). Factors that influence stock market dynamics include shocks that create uncertainty among investors (Antonakakis et al., 2017, as cited in Salisu et al., 2022, p. 2). A key factor among these disruptions that influence investment decisions and stock market dynamics are geopolitical risks (Alqahtani et al., 2020; Baur & Smales, 2020; Caldara & Iacoviello, 2018, as cited in Salisu et al., 2022, p. 2). As mentioned before, geopolitical risk is measured with the GPR index. Geopolitical risks can affect the stock market in several ways: they can create uncertainty among market participants and investors, a decline in global trade and investment, and increasing risks of investing in certain financial markets (Salisu et al. 2022; Bloom, 2009; Eckstein & Tsiddon, 2004, as cited in Zhang et al., 2023, p. 1). Geopolitical risks and uncertainty cause negative reactions to the international market and financial market performance (Schneider & Troeger, 2006, as cited in Gong et al., 2025, p. 2; as well as Ahmed et al., 2022, p. 1079). Heightened geopolitical risks can result in reduced economic activity, lower stock returns (Caldara & Iacoviello, as noted in Gong et al., 2025, p. 1) and an increased buildup of systemic financial vulnerabilities (Ibid., p. 1-2). Extensive research consistently demonstrates a close relationship between geopolitical risks and equity prices, gold and oil (Maghyereh et al., 2017; as well as Morales & Andreosso O'Callaghan, 2014, as mentioned in Shaik et al., 2023, p. 3). Further empirical evidence shows that geopolitical risks have a significant positive effect on stock market volatility (Zhang et al., 2023, p. 6).

3. METHODOLOGY

3.1 Research design

The research design of this thesis was quantitative, which means that this research is numeric and objective. A comparative approach is used to analyse the effects of the war in Ukraine to different stock markets worldwide. As mentioned in the introduction, the market volatility of European, Russian and American stock markets will be analysed from different timeframes. This paper will test the correlation between geopolitical risks (in this case specifically the war in Ukraine) and the volatility of different stock markets worldwide. Furthermore, it is examined whether the Russian stock markets were more affected by the war than the American and European stock markets, by using volatility as a fragility measure of a stock market.

3.2 Data sources and preprocessing

As previously mentioned, some stock exchanges have specific indices that reflect the volatility for those specific stock markets. This paper will use the earlier-mentioned VSTOXX and VIX indices to analyse the volatility of European and American stock markets respectively. For Russian stock markets, the RVI is used to analyse the volatility of MOEX. The VIX historical data will be downloaded from the CBOE website itself. The data from the other two indices are obtained from the Refinitiv Eikon database the University of Twente provides. Furthermore, the historical data from the GPR indices will be used from Caldara and Iacoviello's own website. These datasets allow for exploring correlations between volatility and geopolitical risk indices. After that, the data will be cleaned, so that there is minimal chance of error in the calculations.

3.2.1 Volatility indices

The three volatility indices used in this thesis are VIX, VSTOXX, and RVI. All three indices convert option prices into a 30-day standard deviation forecast that is annualized, meaning that their levels are directly comparable.

The VIX was developed on January 19, 1993 by the Chicago Board Options Exchange (CBOE) and is based on the real-time mid-quotes of call and put options on the S&P 500 (SPX) that bracket 30 calendar days to expiry (CBOE, 2023). Since the S&P 500 is the most liquid equity-derivatives market in the world, the VIX is commonly accepted as the international standard for forward-looking volatility (Kuepper, 2024). The CBOE's back-cast series provides historical data up to 1990, however only data from 1993 onwards correspond to the officially published index. Therefore, this thesis will use the VIX data from 1993.

VSTOXX, like the VIX, measures 30-day implied volatility. The VSTOXX indices are based on the real-time option prices of the EURO STOXX 50 and are intended to reflect the market expectations of volatility ranging from the short term to the long term (Eurex, 2025a). The VSTOXX indices were introduced on April 20, 2005 (Eurex, 2025b). It was quickly adopted as the EU's unchallenged indicator of market stress. Furthermore, the VSTOXX also made volatility a more accessible asset class for European investors and enabled a variety of volatility trading strategies (Ibid.).

The Russian Volatility Index (RVI) was introduced on April 16, 2014 by the Moscow Exchange (Moscow Exchange, 2022). As mentioned before, the RVI replaced the former RTSVX. The new RVI measures market expectation of 30-day volatility, just like the VIX and VSTOXX.

3.3 Data analysis

The next step is to test if there is any correlation. A Pearson's correlation test will be performed in RStudio to test if there is a correlation between the historical data from the GPR indices and the volatility indices.

To measure whether the Russian stock markets are/were more affected by the war than the American and European stock markets, a Difference-in-Difference (DID) regression approach in will be used. This will also be performed in RStudio.

The reason for adopting both Pearson's correlation test and DID regression is to make sure that there is a definite relationship between the GPR index and volatility in stock markets, and that there not a potential third variable that influences the relationship. By using both Pearson's correlation test and DID regression, this thesis examines both correlation and causal impact. Correlation is frequently associated with causality. Naser (2022, p. 3) gives the example of an experimental intervention that shows it correlates with a response, thus labelled as causal. The effect could be misleading, since correlation might only reflect marginal associations rather than conditional associations. Therefore it is important to note that if there is correlation, it does not necessarily mean that there is also causality (Ibid.).

3.3.1 Correlation

Correlation is defined as a statistical measure that determines a relationship between two variables, and is used to analyse the strength of a relationship between two numerical variables (Elmahmoudy, 2024, p. 2). In this case it is examined if there is a relationship between the GPR index and the volatility in stock markets. To test correlation, a commonly used method is Pearson's correlation test. Here, a formula is used that gives an output "r" between 1 and -1. An r between 1 implies a perfect positive relationship between the two variables and move in the same direction, while -1 also implies a perfect relationship, but then negative (Emerson, 2015, p. 242-244). When it is close to zero, there is little to no relationship. To estimate the correlation coefficient visually, the results are put into a scatterplot. If the dots sit close to the straight line (which goes up- or downwards), there is a strong correlation, and if the dots are scattered randomly there is a weak correlation (Elmahmoudy, 2024, p. 2). Pearson's r is calculated as follows:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \Sigma(y_i - \bar{y})^2}}$$

Here, x_i represents GPR index values and y_i represents stock market volatility index values at a specific time i.

For these tests, monthly data is used, since daily data gives a lot of samples. With extremely large samples, p-values can quickly go to zero, potentially leading to the researcher claiming support for results with no practical significance (Lin et al., 2013, p. 906). With such a significantly large sample size, disparities could become more noticeable and highlight statistical differences that are not clinically significant (Faber & Fonseca, 2014, p. 27).

Although it does not imply causation, this correlation test helps in determining whether geopolitical risks are statistically associated with market volatility. To address causality, DID regression is performed.

3.3.2 Difference-in-difference (DID) regression

DID regression is used to examine the causal impact of an event where the set of units where the event occurred (treatment group) are compared to the set of units where the event did not occur (control group)(Torres-Reyna, 2015). DID regression is based on the idea that the discrepancies between the treatment and control groups should not change over time if the event never occurs (Ibid.). DID regression could be used in situations where the event occurred at the same time for all treated groups, and where the event is staggered across groups (Ibid.). In this case, DID regression helps in assessing whether the volatility of Russian stock markets changed more during specific geopolitical shocks than for example American and European stock markets. The war in Ukraine (event), occurred for all treated groups (Russian, European and American stock exchanges) at the same time. DID regression is used to determine causality by comparing stock market volatility before and after disruptive geopolitical events in different regions.

In this thesis, the RVI, VSTOXX and VIX indices are used to measure stock market volatility. The dependent variable in the model is stock market volatility, while the explanatory variables include binary indicators for the post-conflict period. The model also includes a categorical variable that distinguishes the Russian stock market (treatment group) and the European and American markets (control groups).

Daily data will be used in this analysis rather than monthly data, as in the previous analysis. This is to identify the spikes in geopolitical tensions this analysis tries to capture. With monthly data, those spikes would smooth away.

In this analysis, three different DID tests will be done. Firstly, a general DID regression will be performed, capturing the whole testing period from 2018 to 2025. The motivation for choosing this timeframe is because this timeframe captures a pre-war period of more than four years, and a post-war timeframe of more than three years. The pre-treatment baseline from 2018 till the end of 2021/beginning of 2022 is to examine the behaviour of volatility in financial markets prior to the war. The core treatment period begins with February 2022, when Russia invaded Ukraine, triggering relative uncertainty in global markets. Finally, by looking at more recent years, it is examined whether Russian stock markets normalised after the event. By using this timeframe, the general DID regression evaluates post-war adjustments, validates trends before the event and minimises short-term biases. For extra robustness checks, a placebo test is to be performed. This is the same test, but then selecting a time period with relatively no geopolitical tensions. Here, 2019 is chosen as the placebo year. The reason 2019 was chosen as the placebo year in this analysis is because in 2019, financial circumstances in advanced economies were eased because of steep drops in market interest rates (IMF, 2019, p. 3). Also, since 2019 is before the COVID-crisis in 2020, COVID can be taken out of account as a potential underlying factor for heightened volatility in financial markets. Finally, a DID event study will be performed. Event studies have been performed to a number of firm specific and economy wide events in accounting and finance research (Craig, 1997, p. 13). Here, the behaviour of Russian stock market volatility after the beginning of the war in Ukraine on 24th February 2022 (event) is assessed, to measure for abnormal RVI quotes (Ibid., p. 14).

By clearly defining the groups and specifying the interactions, these analyses allow to test whether the volatility of Russian stock markets react more strongly to geopolitical events compared to European and American stock markets.

4. RESULTS

Firstly, this thesis examined whether there is a positive correlation (or any correlation at all) between the GPR index and the three earlier-mentioned volatility indices. The data was downloaded from their respective sources and was cleaned after that. For the test, the GPR index was put next to the indices in three different Excel files.

The data from the GPR and the market volatility indices are available in daily and monthly data.. For the second test, daily data is used to measure whether spikes in geopolitical tensions affect volatility in stock markets.

To answer H1, three tests were done to test correlation. The GPR index was tested with the VIX, VSTOXX and RVI. The data from the indices were put together into an Excel file and after that imported into RStudio.

4.1 Pearson correlation coefficient test

To examine the linear relationship between GPR and VIX, a Pearson's correlation test was performed in RStudio using monthly data from the introduction of the VIX, February 1993, to April 2025. For VSTOXX, monthly data was used from May 2005 till March 2025, while for RVI, monthly data was used from May 2014 till April 2025. The analysis provided the following results:

Market	r	t	df	p-value	95% CI (low)	95% CI (high)
USA	0.031	0.599	385	0.549	-0.069	0.130
EU	-0.182	-2.851	238	0.005	-0.301	-0.056
RUS	0.484	6.299	130	4.263e-09	0.341	0.605

Results from correlation test in RStudio

Firstly, for the GPR and VIX, the correlation coefficient is near-zero, meaning that a change in GPR is not linearly related to changes in the VIX. The p-value of 0.5991 drastically exceeds the conventional significance threshold of 0.05, meaning that the relationship between GPR and VIX is not statistically significant. Consequently, there is insufficient evidence to reject the null hypothesis that the true correlation between the two are zero. The 95% confidence interval includes zero [-0.069, 0.130]. This indicates that the true correlation between the two could possibly be zero. The analysis does not provide a statistically significant linear relationship between GPR and VIX over the period since 1993. These findings suggest that, at least on a linear basis, changes in GPR do not seem to correspond to with changes in VIX.

After testing the potential correlation between GPR and VIX, another test was performed, looking at the country-specific GPR index (U.S.) and VIX. This was to examine whether GPR rooted in domestic events influence the VIX. The results were similar:

Pair	r	t	df	p-value	95% CI (low)	95% CI (high)
GPRUSA-VIX	0.032	0.631	385	0.529	-0.068	0.131

USA-specific GPR index with VIX

Here, the correlation coefficient was 0.032. The test gave a t-value of 0.631 with a corresponding p-value of 0.5287, which is well above the typical significance threshold of 0.05. Furthermore, the 95% confidence interval ranged from -0.068 to 0.131, thus including zero. These findings suggest that this lack of statistically significant relationship between GPR, and USA-specific GPR indices with the VIX, implies that financial market volatility in the United States is not affected by geopolitical risks in any matter.

The second correlation test performed was between GPR and European market volatility, the Pearson correlation test in RStudio used a sample of 239 observations (df = 238) covering the available time periods. The statistically significant negative correlation of $r \approx -0.182$ with a p-value of 0.005, implies that within this data set, a higher GPR index is associated with a modest decrease in the VSTOXX index.

In the following test, the GPR index and RVI were tested to examine the potential correlation between the two variables. This sample size (df = 130) was significantly smaller than the previous two samples, since the RVI only exists since 2014. The Pearson correlation coefficient was r = 0.484, indicating a significant positive linear relationship between the two variables. The t-value was 6.299 with a highly significant p-value of 4.263e-09, which is well below the conventional significance threshold of 0.05. The 95% confidence interval was [0.341, 0.605], which does not include zero. These findings suggest that higher levels of GPR are correlated with increased RVI levels. The highly positive correlation implies that sudden heightened periods of geopolitical risks are accompanied by greater volatility in Russian financial markets.

Finally, a correlation test was performed to see whether the Russian-specific GPR index also has a significant positive correlation with the RVI, just like was done previously with USA-specific GPR index and the VIX.

Pair	r	t	df	p-value	95% CI (low)	95% CI (high)
GPRRUS-RVI	0.647	9.674	130	<2.2e-16	0.535	0.736

Russian-specific GPR index with RVI

The results gave an even stronger positive correlation than the previous test, giving a correlation of $r \approx 0.647$. Additionally, the test gave a t-value of 9.674 with 130 degrees of freedom and a p-value that is nearly zero. These results confirm that the correlation is statistically significant. The 95% confidence interval of [0.535, 0.736] does not include zero, further confirming that the true correlation is positive and substantial. These results suggest that Russian stock markets are very prone to any geopolitical risks, whether they are global or regional.

Of course, a simple correlation test does not tell the whole story. There could be underlying factors that are not included in the analysis as mentioned before. However, these correlation tests gave a first and general insight into how strongly associated geopolitical risks and volatility in financial markets are. To make this analysis more robust, DID regression is performed.

4.2 DID analysis

In this analysis, it is examined whether this specific conflict in Ukraine has an effect on American, European and Russian stock markets. In specific, this is to answer the second hypothesis, to see whether Russian stock markets are more influenced by the war in Ukraine than European and American stock markets.

The three volatility indices examined in this paper have different numeric scales from each other. While the VIX and VSTOXX usually sit around 20 to 40 points, the RVI is quoted in the tens of thousands, therefore potentially causing problems for the analysis. The RVI dominates the residual variance when estimating the DID in raw levels. For example, an increase in 10.000 points could be difficult to interpret. To solve this, the dependent variable will be converted into a logarithmic value. The natural logarithm compresses each series onto the same order of magnitude, meaning that the regression now explains relative movements instead of absolute movements. For an input with a large amount of relative variation, like in this case with the different indices, it makes sense to work with logarithms (Gelman et al., 2020, p. 195) . Additionally, a logarithmic model gives an approximate percentage change as an output, which is ideal for this analysis (Ibid. p. 190).

4.2.1 General DID

To ensure that all volatility levels are mapped onto a comparable scale, for every observation, log-volatility level is defined as:

$$logvol_{it} = \ln(vol_{it})$$

Here, i is the type of market in question (USA, EU, RUS). Date is indexed with t, while vol_{it} is the original volatility index value, with ln being the natural logarithm.

For the general DID regression, the following formula was formulated:

$$logvol_{it} = a + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 (Treat_i \times Post_t) + \gamma_t + \varepsilon_{it}$$

Here, $Treat_i$ = 1 if the market *i* is Russia (RVI), otherwise it is 0. $Post_t$ = 1 for dates on or after 24th February 2022, before it is 0. ($Treat_i \times Post_t$) captures the war-specific effect for the RVI. γ_t represents the daily fixed effects, absorbing common shocks, while ε_{it} is the error term. The key coefficient β_3 represents the percentual change in Russian volatility due to the war. The formula for the war effect is as follows:

$$War\ Effect = 100\ \times (e^{\beta_3} - 1)$$

The dependent variable is the natural logarithm of each index's volatility (*logvol*), so all coefficients can be interpreted as approximate percentual changes. The results were as following:

General DID	*Output*
Treat	7.260011
Treat x Post	0.309661
R^2	0.99887
Effect	36.3%
95% CI	[31.6;41.2%]

DID-regression output in RStudio

The *Treat* coefficient ($\beta \approx 7.26$), captures the average pre-invasion gap between the RVI and the other two control indices. Because the three indices are quotes on significantly different scales, the gap is huge. However, this is purely a level effect, not a treatment effect.

The difference-in-difference analysis estimate of the war shock (*Treat × Post)* gave a standard error of 0.018 and a t-value of around 17.1, with a p-value of under 0.001. Furthermore, the test gave a RMSE of 0.118 log points, converted to percentages it is around 12%, and an adjusted R^2 of 0.998. These estimates show that the daily fixed effects with the treatment terms explain almost all variation in *logvol*. The true effect is very likely to be below 32% or above 41%. The t-value of around 17.1 with ($p < 0.001$) confirms that the result is statistically decisive, while the within R^2 of nearly 0.999 indicates that once common day shocks are removed, the regression model explains almost all residual variation across markets. To conclude, the assumption that can be made here is that on and after 24th February 2022, the RVI increased by roughly 36% relative to the VIX and VSTOXX benchmarks, indicating that the invasion in Ukraine had a highly significant effect on the RVI.

4.2.2 Placebo test

For the placebo test, the same formula is used as with the general DID, however there is one change. $Post_t^{pl}$ = 1 for dates on or after 24th February 2019 and 0 before. β_3 now captures any false treatment effect in percentages from using an incorrect war timing. The formula is now as follows:

$$logvol_{it} = a + \beta_1 Treat_i + \beta_2 Post_t^{pl} + \beta_3 (Treat_i \times Post_t^{pl}) + \gamma_t + \varepsilon_{it}$$

To examine whether the analysis falsely detects a "treatment effect" in a period when there were less conflicts compared to 2022, the log-specific DID is re-run, using 24th February 2019 as a fake event date. The test gave the following results:

Placebo DID	*Output*
Treat	7.325693
Treat × Post_pl	0.081552
R^2	0.998446
Effect	8.5%
95% CI	[3.5;13.8%]

Placebo-DID test in RStudio

The test gives the key interaction coefficient β_3 of around 0.0816, with a standard error of around 0.0243 (t = 3.36, $p \approx 0.0008$). The RMSE is 0.138 log points, which is around 14.7%. The within R^2 is 0.998446, while the adjusted R^2 is 0.997688. Converting the log-point of the key interaction coefficient to a percentage, the effect is around 8.5%. This means that if we pretend the war started in 2019, the model would attribute around 8.5% of an increase in the RVI. Comparing this to the true-event estimate of around 36%, the placebo test indicates an effect of roughly one quarter of the actual shock, confirming that the event in 2022 is far greater than any spurious difference generated by slow pre-existing drift between the indices. Additionally, the t-statistic of 3.36 shows that the placebo difference is statistically different from zero, indicating that the RVI was already going modestly upwards even before the war. Nevertheless, the magnitude is small compared to the true event shock, and the event study graph (see Appendix), also shows no extremely sharp increase around 2019.

With log specification, heteroskedasticity is tamed and the within R^2 is around 0.999 in both tests, because logs compress the huge level spread. When comparing the results from the general DID test and the placebo test, in both tests there was a significant increase in RVI. However, 8.5% is much smaller than 36.3%. That indicates that the RVI was already increasing in comparison to the VIX and VSTOXX before the war started. Yet after the war, the effect became 4 times larger. Therefore we can conclude that growth rates are not flat, but the shock because of the war is clearly an outlier in magnitude.

4.2.3 Event study

For further robustness, an event study was performed, with a total window of 60 days (30 before and after 24th February 2022). This is the output for the test:

Event study	*Output*
RMSE	0.352755
Adjusted R^2	0.97383
Within R^2	0.991131

Event study output

The event study fits the data extremely well. The output gave a RMSE of 0.352755 (output in log points), with an R^2 of around 0.991. The within R^2 shows that more than 99 percent of the day-by-day gap between the RVI and the other two control indices are captured by the model. The adjusted R^2 of around 0.974 indicates that roughly 97 percent of the total variation in log-volatility across both time and markets is explained once common day effects and the relative-day treatment dummies are included. The output of RSME, converted back to levels corresponds a typical prediction error of around 42 percent on any single observation, which is larger than on the previous two tests.

The visual results from the test suggest that Russian volatility levels spiked significantly more than American and European volatility levels. They also indicate that the RVI had already been trending upward prior to February 24th, 2022.

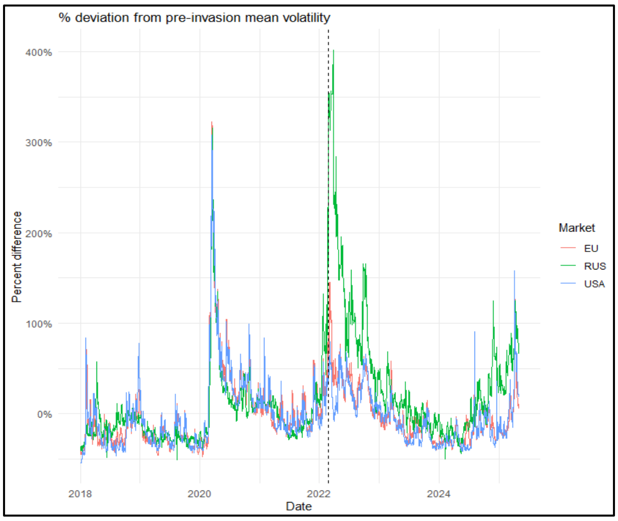

Figure 1: Percentual differences of volatility levels of different stock markets during the period 2018-2025.

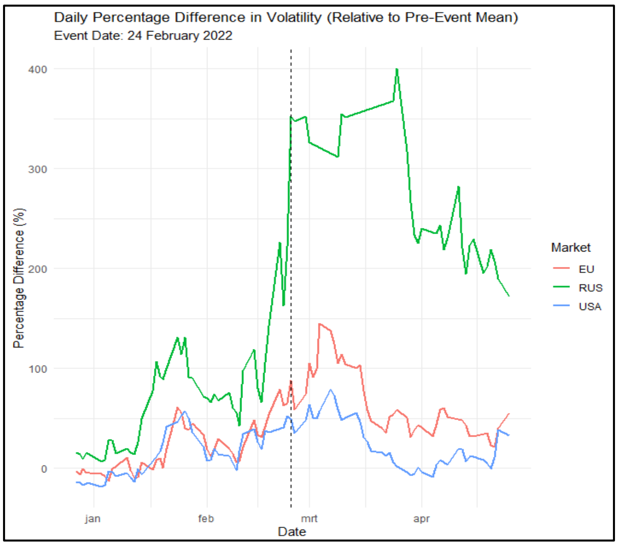

Figure 2: Percentual differences of volatility levels of different stock markets from January till April 2022.

All in all, these results confirm that the event study curve built from the relative-day coefficients provide a statistically tight description of the data. Pre-event differences are effectively zero, while the post-invasion coefficients reveal a sharp increase unique to the RVI.

5. DISCUSSION

The goal of this research was to examine the effects of the war in Ukraine on the volatility levels of different stock exchanges worldwide. Two hypotheses were formulated to reach this objective. The first hypothesis, which was "*There is a significant positive correlation between geopolitical risks, as measured with the GPR index and the volatility of American, European and Russian stock markets*.", was examined with a Pearson's correlation test in RStudio. The results were interesting, as American stock markets experience little to no increase in volatility after times of geopolitical tensions, as measured with the GPR index, meaning that the relationship between the two is not statistically significant. Even after taking the USA-specific GPR index, which only measures the geopolitical tensions based in the United States, the correlation test showed that there is little positive correlation between the USA-specific GPR index, and the volatility based index in the United States, the VIX. Even more surprising was that there even was a negative correlation between the GPR index, and the European volatility index, as measured with VSTOXX. This goes against the research of Zhang et al. (2023), where it is mentioned that geopolitical risks have a significant positive effect on stock market volatility. Furthermore, Zhang et al. (2023) found that geopolitical risks, as measured with the GPR index by Caldara & Iacoviello (2022), positively affects stock market volatility significantly, even including VIX as a control variable. That is different from what the results from this paper suggest. However, it must be acknowledged that Zhang et al. (2023) used different methods to measure the impact of geopolitical risks on stock market volatility and also looked at it from a global perspective, whereas this paper has not. In addition, since this analysis only looked at the effects of geopolitical risks on stock market volatility, other factors that can influence volatility in stock markets like monetary policies, regional economic conditions or other macroeconomic factors have been left out of the analysis. However, the research of Amengual & Xiu (2019) suggests that downward volatility jumps are just as common as upward ones. Furthermore, the majority of volatility jumps are associated with Central Bank interventions (Amengual & Xiu, 2019, p. 314).

The RVI was the only index that had a significant positive relationship with the GPR index, based on the Pearson correlation tests performed in RStudio, therefore being the only index that conforms with the first hypothesis. Now the question arises: why are Russian stock markets so heavily influenced by geopolitical risks, in contrast to American and European stock markets? Russia is directly involved in this conflict, therefore you could draw the conclusion that the MOEX is affected more by the war than other stock exchanges. The ECB found that stock market losses rise sharply with physical proximity to Kyiv and that stock prices in countries in the vicinity of the war, were hit harder than those that are further away from the conflict (Chițu et al., 2022). With Russia sitting close of Ukraine, this could explain the fragility in their stock markets. Figures 1 and 2 also show that the RVI remains relatively higher than the VIX and VSTOXX, which could be an effect of the Western sanctions following Russia's invasion of Ukraine. Furthermore, Russia's heavy reliance on commodities leaves its economy less diversified and more susceptible to sanctions and global price fluctuations (Allianz, 2024). These results do conform with the second hypothesis, which was: *Russian stock markets experience greater volatility due to the Russia-Ukraine war, compared to European and American stock markets, since Russia is directly involved in the conflict.* The analysis, accompanied by several other sources, confirms that the RVI is uniquely responsive to changes of the GPR index. Consequently, each change or shock in global geopolitical tensions translates into a disproportionate jump in Russian implied volatility, whereas the VIX and VSTOXX remain buffered because of geographical insulation and other policy offsets.

6. LIMITATIONS AND FUTURE RESEARCH

Of course, this bachelor thesis has some limitations. Firstly, the methods used in this analysis are robust, however the analysis does not account for other factors as mentioned in the discussion. Addressing that would strengthen the conclusions and add more relativity to it. Furthermore, because of the negative correlation of the VSTOXX with the GPR index, there was some initial confusion and doubt about the analysis. However, after some further research, it was concluded that there could be many more factors that caused the negative correlation that were not included in this analysis. Secondly, this analysis relied on Pearson's correlation and Difference-in-Difference regression. These assume linear relationships and parallel trends. They assume that

American, European and Russian volatility levels would have followed parallel paths. Non-linear and more complex models like GARCH models were not used. These could have captured more complex dynamics between volatility and geopolitical risks, therefore providing a more thorough analysis. Thirdly, even though four years of pre-treatment and three years of post-treatment data was used, other important events like the annexation of Crimea were not captured. These would have given the analysis more events to examine whether volatility levels of the different stock exchanges were affected by them.

For future research, incorporating non-linear techniques such as GARCH models will help in capturing more complex dynamics and asymmetric volatility responses. In addition, including other macroeconomic events in the analysis such as central bank interventions and oil price shocks for example, will make sure the analysis captures more major events that could influence stock market volatility. Finally, expanding the analysis to include other countries that are affected by this conflict would help test whether the patterns seen in Russia are unique or more general.

7. CONCLUSION

This thesis tried to examine how geopolitical risks, in this case the war in Ukraine that started in February 2022, affects stock market volatility across different regions. Performing a Pearson correlation test, a Difference-in-Difference regression using log-transformed volatility indices and an event study, the analysis identified a statistically significant rise in volatility in Russian markets. The estimated effect was a rise of around 36% of the Russian Volatility Index (RVI). The effect is robust across multiple specifications and time windows.

While the VIX (U.S.) and VSTOXX (European) indices also showed temporary reactions, their movements showed no significant, or significant but negative relationship with the GPR index. The RVI however, displayed a strong and stable correlation, confirming that markets closer to the conflict area are disproportionately exposed to conflict-driven risk.

While these findings only conformed with the second hypothesis, they highlight the significance of geographic proximity and economic structure in determining how global markets respond to geopolitical shocks. Despite certain limitations, mainly related to measurement lag, overlapping shocks and the exclusion of the use of non-linear models, the results provide a useful contribution to the general understanding of financial markets under stress. By incorporating other types of statistical models and potential confounding variables, future research can expand on this research.

8. ACKNOWLEDGEMENTS

I would like to express my sincere thanks to Dr. Frédérik Bernard for his consistent help, support and guidance throughout this entire process. I would also like to thank Dr. Lingbo Shen for the initial introduction to the topic and guidance in the beginning of the bachelor thesis process.

9. REFERENCES

Adolfsen, J. F., Kuik, F., Schuler, T., & Lis, E. (2022, June 21). *The impact of the war in Ukraine on euro area energy markets*. European Central Bank. https://www.ecb.europa.eu//press/economic-bulletin/focus/2022/html/ecb.ebbox202204_01~68ef3c3dc6.en.html

Allianz. (2024, December). *Allianz | Country Risk Report Russia*. Allianz.com. https://www.allianz.com/en/economic_research/country-and-sector-risk/country-risk/russia.html

Arce, Ó., Koester, G., & Pierluigi, B. (2022). Challenges for global monetary policy in an environment of high inflation: the case of the euro area. *ICE Revista De Economía*, *929*. https://doi.org/10.32796/ice.2022.929.7531

Bhowmik, R., & Wang, S. (2020). Stock Market Volatility and Return Analysis: A Systematic Literature Review. *Entropy*, *22*(5), 522. https://doi.org/10.3390/e22050522

Caldara, D., & Iacoviello, M. (2018). Measuring Geopolitical Risk. *International Finance Discussion Paper*, *2018*(1222), 1–66. https://doi.org/10.17016/ifdp.2018.1222

Caldara, D., & Iacoviello, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, *112*(4), 1194–1225. https://doi.org/10.1257/aer.20191823

CBOE. (2023). *VIX Index*. Www.cboe.com. https://www.cboe.com/tradable_products/vix/

Chi, Y., & Hao, W. (2020). A Horserace of Volatility Models for Cryptocurrency: Evidence from Bitcoin Spot and Option Markets. *ArXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2010.07402

Chițu, L., Eichler, E., McQuade, P., & Ferrari Minesso, M. (2022). How do markets respond to war and geopolitics? Www.ecb.europa.eu. https://www.ecb.europa.eu/press/blog/date/2022/html/ecb.blog220928~a4845ecd8c.en.html

Craig, M. A. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, *35*(1), 13–39. JSTOR. https://doi.org/10.2307/2729691

Dieckelmann, D., Kaufmann, C., Larkou, C., McQuade, P., Negri, C., Pancaro, C., & Rößler, D. (2024). Turbulent times: geopolitical risk and its impact on euro area financial stability. *Www.ecb.europa.eu*. https://www.ecb.europa.eu/press/financial-stability-publications/fsr/special/html/ecb.fsrart202405_01~4e4e30f01f.en.html

EEAS. (2025, February 25). *EU assistance to Ukraine (in U.S. dollars)*. European External Action Service. https://www.eeas.europa.eu/delegations/united-states-america/eu-assistance-ukraine-us-dollars_en?s=253

Elsayed, A. H., & Helmi, M. H. (2021). Volatility transmission and spillover dynamics across financial markets: the role of geopolitical risk. *Annals of Operations Research*, *305*. https://doi.org/10.1007/s10479-021-04081-5

Emerson, R. W. (2015). Causation and Pearson's Correlation Coefficient. *Journal of Visual Impairment & Blindness*, *109*(3), 242–244. https://doi.org/10.1177/0145482x1510900311

Eurex. (2025a). *VSTOXX derivatives*. Deutsche Börse Group. https://www.eurex.com/ex-en/markets/vol/vstoxx

Eurex. (2025b). *VSTOXX turns 20: Experts appraise the volatility index's standing in equity markets*. Deutsche Börse Group. https://www.eurex.com/ex-en/find/news-center/news/navigating-volatility-4416712

European Council. (2024). *EU Sanctions against Russia*. Consilium. https://www.consilium.europa.eu/en/policies/sanctions-against-russia/

Faber, J., & Fonseca, L. M. (2014). How Sample Size Influences Research Outcomes. *Dental Press Journal of Orthodontics*, *19*(4), 27–29. NCBI. https://doi.org/10.1590/2176-9451.19.4.027-029.ebo

Federal Reserve. (2022, May). *Financial Stability Report: 5. Near-Term Risks to the Financial System*. https://www.federalreserve.gov/publications/2022-may-financial-stability-report-near-term-risks.htm

Federal Reserve. (2023, May). *Financial Stability Report: 5. Near-Term Risks to the Financial System*. Board of Governors of the Federal Reserve System. https://www.federalreserve.gov/publications/2023-may-financial-stability-report-near-term-risks.htm

Gadanecz, B., & Jayaram, K. (2009), Measures of financial stability - a review, p. 365-380 in Settlements, Bank for International eds., Proceedings of the IFC Conference on , vol. 31, Bank for International Settlements, https://EconPapers.repec.org/RePEc:bis:bisifc:31-26.

Gelman, A., Aki Vehtari, & Hill, J. (2020). *Regression and other stories*. Cambrige Universiy Press.

Iacoviello, M. (n.d.). *Country-Specific Geopolitical Risk Index*. Www.matteoiacoviello.com. https://www.matteoiacoviello.com/gpr_country.htm

IMF. (2019). *Global Financial Stability Report: Lower for Longer* (pp. 1–23). International Monetary Fund. https://www.imf.org/-/media/Files/Publications/GFSR/2019/October/English/ch1.ashx

Kappeler, A. (2014). Ukraine and Russia: Legacies of the Imperial past and Competing Memories. *Journal of Eurasian Studies*, *5*(2), 107–115. https://doi.org/10.1016/j.euras.2014.05.005

Koester, G., Rubene, I., Gonçalves, E., & Nordeman, J. (2021, August 5). *Recent developments in pipeline pressures for non-energy industrial goods inflation in the euro area*. European Central Bank. https://www.ecb.europa.eu/press/economic-bulletin/focus/2021/html/ecb.ebbox202105_07~d799754f4e.en.html

Kostanyan, H., & Meister, S. (2016). *Ukraine, Russia and the EU : Breaking the deadlock in the Minsk process*. Ugent.be. https://biblio.ugent.be/publication/8514008

Kuepper, J. (2024, August 7). *CBOE Volatility Index (VIX) Definition*. Investopedia. https://www.investopedia.com/terms/v/vix.asp

Kvit, D. S. (2014). The Ideology of the Euromaidan. *Social, Health, and Communication Studies Journal*, *1*(1), 27–40. https://journals.macewan.ca/shcsjournal/article/view/245/196

Lin, L., & Guo, X.-Y. (2019). Identifying fragility for the stock market: Perspective from the portfolio overlaps network. *Journal of International Financial Markets, Institutions and Money*, *62*, 132–151. https://doi.org/10.1016/j.intfin.2019.07.001

Lin, M., Lucas, H. C., & Shmueli, G. (2013). Research Commentary: Too Big to Fail: Large Samples and the p-Value Problem. *Information Systems Research*, *24*(4), 906–917. https://www.jstor.org/stable/24700283

Mieg, H. A. (2020). Volatility as a Transmitter of Systemic Risk: Is there a Structural Risk in Finance? *Risk Analysis*, *42*(9). https://doi.org/10.1111/risa.13564

Moscow Exchange - *Новости и пресс-релизы Московской биржи*. (2014). Moscow Exchange. https://www.moex.com/n5321

Moscow Exchange. (2022). *Московская Биржа - Index*. Московская Биржа. https://www.moex.com/s381

Naser, M. Z. (2024). Causality and causal inference for engineers: Beyond correlation, regression, prediction and artificial intelligence. *WIREs Data Mining and Knowledge Discovery*, *14*(4). https://doi.org/10.1002/widm.1533

Nickel, C., Koester, G., & Lis, E. (2022). Inflation Developments in the Euro Area Since the Onset of the Pandemic. *Intereconomics*, *57*(2), 69–75. https://doi.org/10.1007/s10272-022-1032-y

OECD (2022), Impacts of the Russian Invasion of Ukraine on Financial Market Conditions and Resilience: Assessment of Global Financial Markets, OECD Publishing, Paris, https://doi.org/10.1787/879c9322-en.

Papunen, A. (2024, February). *Economic impact of Russia's war on Ukraine: European Council response | Think Tank | European Parliament*. Www.europarl.europa.eu. https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2024)757783

Pereira, P., Bašić, F., Bogunovic, I., & Barcelo, D. (2022). Russian-Ukrainian war impacts the total environment. *The Science of the Total Environment*, *837*, 155865. https://doi.org/10.1016/j.scitotenv.2022.155865

Safranchuk, I. (2022). The Conflict in Ukraine: Regional and Global Contexts. *Policy Perspectives*, *19*(1). https://doi.org/10.13169/polipers.19.1.ca1

Salisu, A. A., Ogbonna, A. E., Lasisi, L., & Olaniran, A. (2022). Geopolitical risk and stock market volatility in emerging markets: A GARCH – MIDAS approach. *The North American Journal of Economics and Finance*, *62*, 101755. https://doi.org/10.1016/j.najef.2022.101755

Schwert, G. W. (1990). Stock Market Volatility. *Financial Analysts Journal*, *46*(3), 23–34. https://doi.org/10.2469/faj.v46.n3.23

Shaik, M., Jamil, S. A., Hawaldar, I. T., Sahabuddin, M., Rabbani, M. R., & Atif, M. (2023). Impact of geo-political risk on stocks, oil, and gold returns during GFC, COVID-19, and Russian – Ukraine War. *Cogent Economics & Finance*, *11*(1). https://doi.org/10.1080/23322039.2023.2190213

Taim, A. (2024). The Impact of Realism on U.S. Foreign Policy during the Trump Presidency. *Journal of International Relations*, *4*(2), 14–29. https://doi.org/10.47604/jir.2552

The White House. (2025, February 28). *President Trump and Ukrainian President Zelenskyy in Oval Office, Feb. 28, 2025* [Video]. YouTube. https://www.youtube.com/watch?v=ajxSWocbye8

Torres-Reyna, O. (2015). *Differences-in-Differences (using Stata)*. https://www.princeton.edu/~otorres/DID101.pdf

U.S. Department of State. (2025, March 12). *U.S. Security Cooperation with Ukraine*. https://www.state.gov/bureau-of-political-military-affairs/releases/2025/01/u-s-security-cooperation-with-ukraine

Wittke, C. (2019). The Minsk Agreements – more than "scraps of paper"?. *East European Politics*, *35*(3), 264–290. https://doi.org/10.1080/21599165.2019.1635885

Zhang, Y., He, J., He, M., & Li, S. (2022). Geopolitical risk and stock market volatility: A global perspective. *Finance Research Letters*, *53*, 103620. https://doi.org/10.1016/j.frl.2022.103620