Geopolitical Risks and US Market Dynamics

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1. Introduction and background

In this report, we will investigate the impact of geopolitical risks on the dynamics of US markets using data science techniques, and connect our results with empirical observations. Following a brief overview of recent geopolitical events, we will conduct an exploratory analysis of the relevant datasets. Then we will present our main hypothesis, outline the methodologies used, and discuss our results along with their interpretations. The report will conclude with a brief summary of the findings.

Geopolitical risks are known to have significant impact on global markets. In recent years, major events have heightened the relevance and importance of accounting for geopolitical risks in asset allocation, policy decisions, and economic analyses. Significant recent themes include the Ukraine war, tensions between China, Russia, and NATO, de-dollarisation efforts, and shifting global influences. One of the most pronounced geopolitical shocks on markets has been the escalation in Ukraine, which led to a politically-motivated decision by Russia to cut off and reduce gas supplies to European countries, leading to disruption of European energy markets, inflation, and heightened instability, which spilled over into other markets and globally. In the wake of the Russian invasion, disruptions of supplies of Ukrainian goods for export drove up commodity prices sharply, and sanctions on Russian products exacerbated commodity market volatility, with lasting impacts on non-commodity asset classes across countries and macroeconomic relevance for policy-making decisions.

These shocks, originating from geopolitical developments and considerations rather than purely economic forces, have reverberated across markets and asset classes, highlighting the need for comprehensive approaches that factor in geopolitical risk. In a world increasingly influenced by geopolitcal interactions, traditional financial or market tools must be supplemented by developing methods to quantify and understand geopolitical risks for informed decision-making.

2. Description of the data

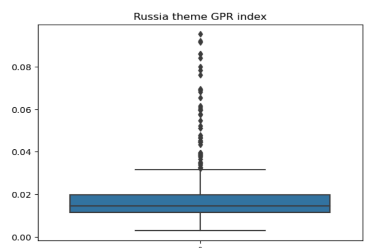
a. Geopolitical Risks Data Source

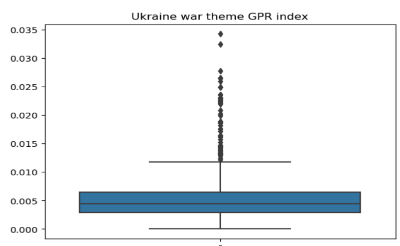
A tool found at https://search.mediacloud.org/about-search has been used to scrap newspapers/websites and to build geopolitical risk (GPR) indices by themes and an aggregated GPR index. The web-scraped aggregated geopolitical risk index was benchmarked against a built-in GPR index, developed by Dario Caldara and Matteo Iacoviello that can be found at Geopolitical Risk (GPR) Index (https://www.matteoiacoviello.com/gpr.htm) .

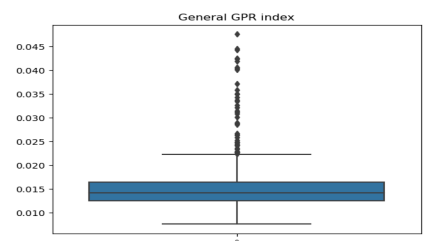
In this report, we will use the GPR index that we constructed using the *mediacloud* tool. While some results are illustrated using different-themed indices alongside the aggregated index, the emphasis of this report is on two key themes: the Ukraine war and Russia. The built-in GPR index does not have publicly available data for these specific themes. It is an index calculated daily with a general version, called GPRD, and a decomposition into two components GPRD_ACT and GPRD_THREAT. The data is available both at world and country levels.

The *mediacloud* tool has been run with specific sets of keywords to produce several datasets, which have been downloaded as csv or excel files. They have been aggregated further into five GPR indices for five main themes (Ukraine war, Russia, China, de-dollarization, geopolitical – the last index being used to encompass the overall consideration of geopolitical factors in media). The aggregated GPR index is an average of all these five themes. An average was used for aggregation to lower the potential risk of overcounting. The time frame used in the report is from the end of Oct 2021 to the end of Apr 2023. This time period specifically captures the key developments in our area of focus: Ukraine and Russia.

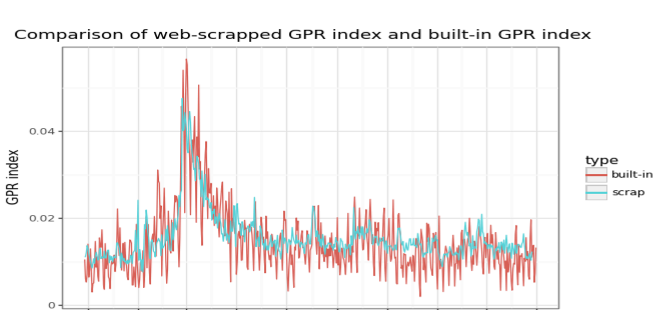
We present time series plots, boxplots and histograms for GPR indices below. The shape of the GPR indices curves is the most critical part. Multiplying these numbers by 100 converts the data into percentages representing the daily attention observed in newspapers and articles to various events and news related to the specific geopolitical theme under consideration.

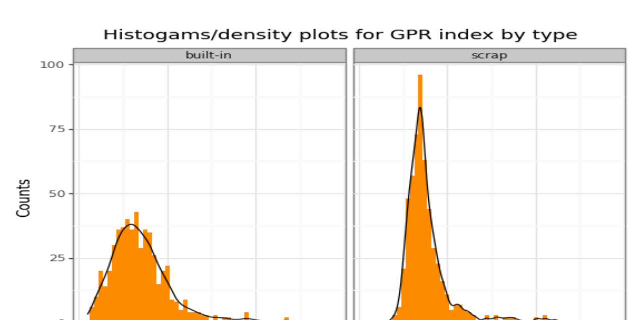




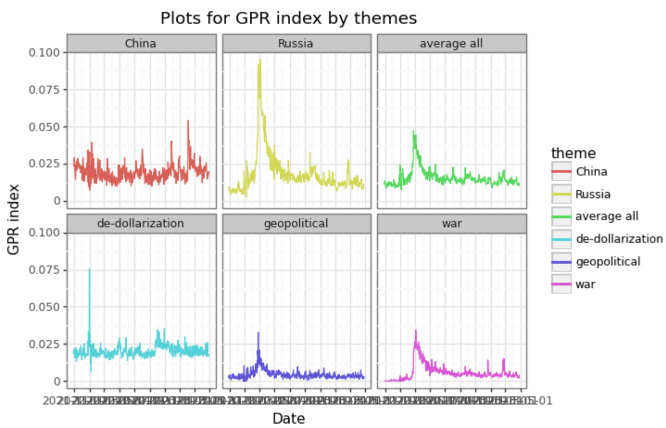


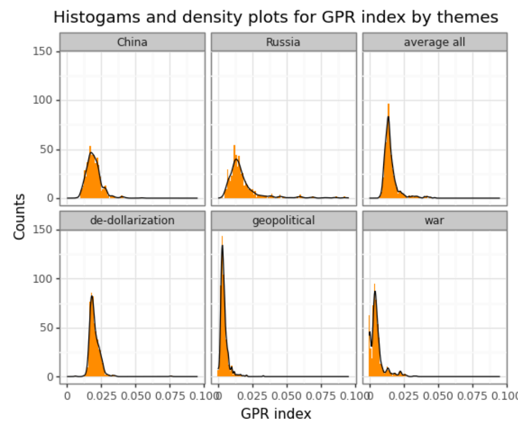
These boxplots above reveal significant outliers. While some extreme outliers will be removed, others will be retained to consider the concept of two regimes for the GPR index: a semi-stressed regime (covering periods further from significant one-time events) and a stressed regime (covering periods closer to significant events). These regimes are separated by an observed threshold that will depend on the theme used. For example, for the Ukraine theme, this threshold is between 0.005 and 0.01, while for the Russia theme, the threshold is between 0.015 and 0.025. These outliers are an indication of the extreme magnitude values for attention, indicating periods of heightened focus in media. Retaining some of these outliers is important for our analysis because they can signal moments of strong geopolitical impact on markets.





The two charts above compare the web-scraped GRP index and built-in GRP index. To ensure consistency, some scaling was applied prior to plotting. The web-scraped GPR index has a distribution exhibiting a taller profile with a sharper peak, while being less volatile than the built-in index. The comparison indicates that the built-in index is more responsive, while the web-scraped index maintains a steadier measure over time, though they generally move together on significant swings.



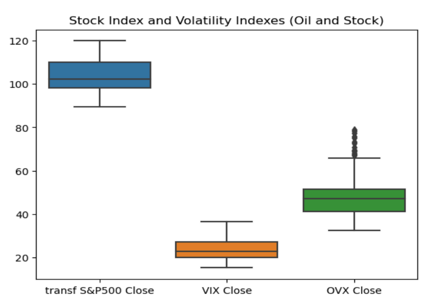


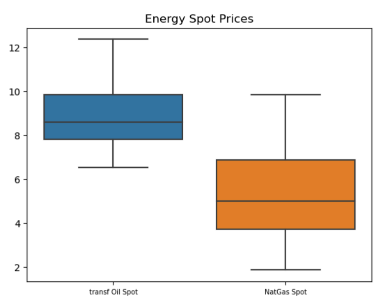
In the charts above, the time series plots and their distributions are shown for each selected theme and for the aggregated index. They show that the dominant themes over the timeframe considered are related to the Russia-Ukraine conflict, which we will focus on.

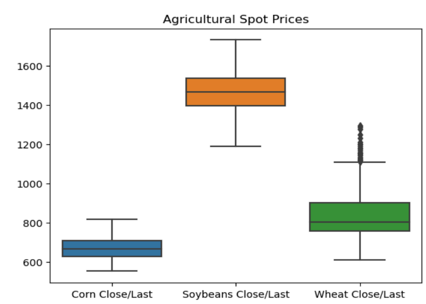
b. US Markets (Stocks & Commodities Markets) Data Source

In this report, we will focus on US markets, though similar methods may also be applied to European markets, which were more directly affected by the geopolitical risk during this time period. We use daily time series prices for two two equity-related series (S&P 500 Index, VIX Volatility Index Spot), three energy-commodity series (WTI Oil Spot, HH NatGas Spot, OVX Volatility Oil Index Spot), and one agriculture-commodity series (Corn Spot, with empirical observations for Wheat Spot and Soybeans Spot).

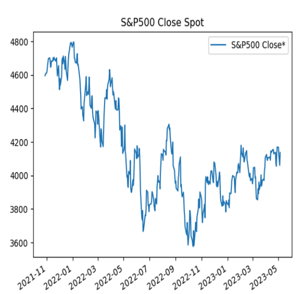
Historical daily prices for US Stock markets and agricultural commodities – S&P 500 Index price, Volatility index for stock markets (VIX) , Oil Volatility index (OVX), as well as for Corn, Wheat, and Soybeans Spot – have been downloaded from [Yahoo Finance - Stock Market Live, Quotes, Business & Finance News](). The daily historical prices for US energy commodities – Oil (US) WTI Spot and (Henry Hub) Natural Gas Spot prices – have been obtained from [www.eia.org](). After downloading the historical time series as csv or excel files, the data has been aggregated by market into energy, agriculture and stock indices. Below, we present box plots and times series plots of Close prices.

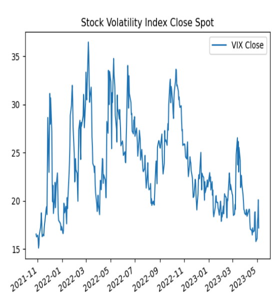


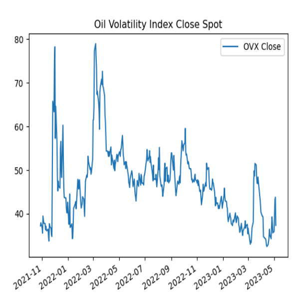


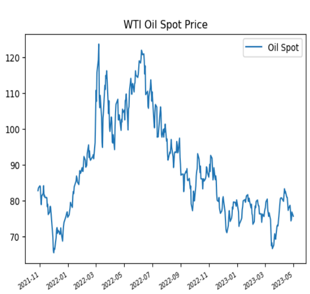


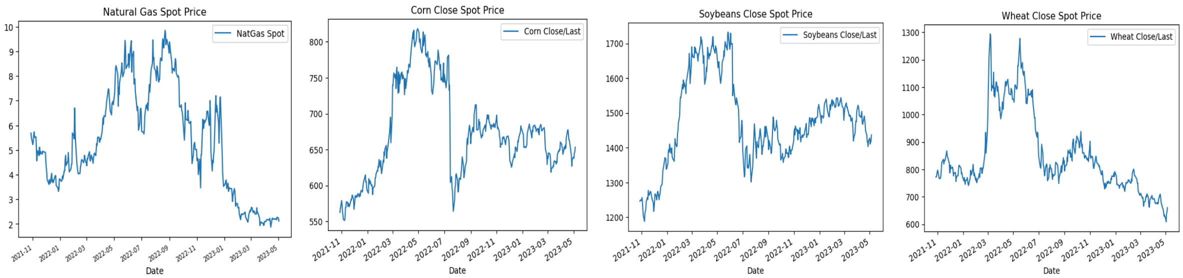
In the box plots above, some of the variables have been transformed such that we have similar magnitude scales. The time frame of analysis is from the end of Oct 2021 to the end of Apr 2023. For all variables the interquartile range and the overall spread is wide.





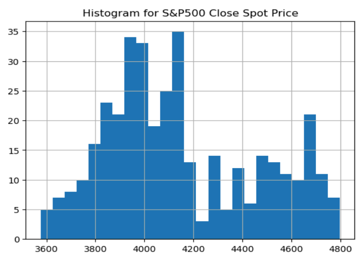


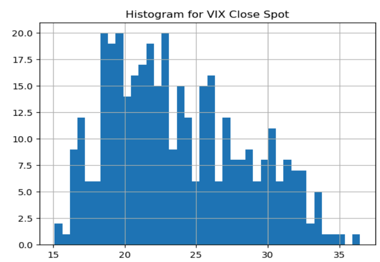


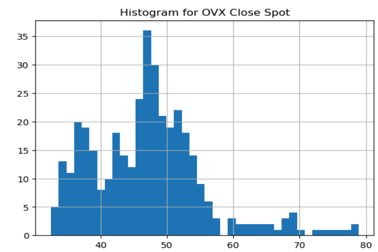


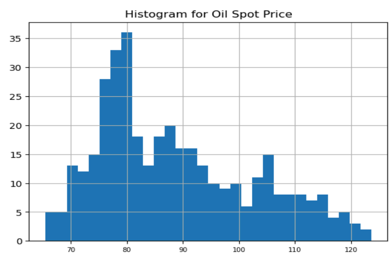
The historical data plots of the US market variables show a pronounced impact from the Ukraine conflict during early 2022, though some variables continued to be affected over an extended period. Across 2022, varying sanctions were imposed at different times on different Russian commodities by the US and Europe, including a cap on oil price later in the year. Gas supply disruptions in Europe were affected both by Russian cuts of supply and by European sanctions and disinvestment, leading to increased reliance on American natural gas exports. While Europe was most directly affected, the resulting shocks from the Ukraine war had ripple effects across global markets, including the US. The above charts capture these events and their associated market impacts.

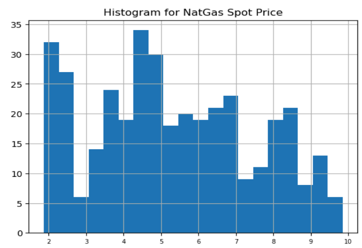
The histograms below present the distributions of US market variables. Most distributions appear approximately bimodal, which in some cases suggests the presence of a two-regime structure in the observed time frame: a semi-stressed regime and a stressed regime. This is clearly interpretable in the case of agricultural commodities, which were most affected by the geopolitical events. The assets most affected present a more distinct threshold separating these two regimes, marking the area of transition between typical and heightened market responses. To quantify this, we calculated day-over-day price spreads across the period under analysis, which reveal high maxima and minima and high standard deviations for the US market variables. Additionally, we calculated 30-day rolling volatilities for all variables, except VIX and OVX, and found that this data also showed high minima and maxima.

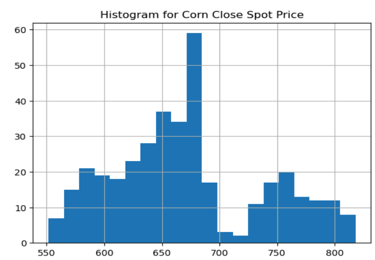




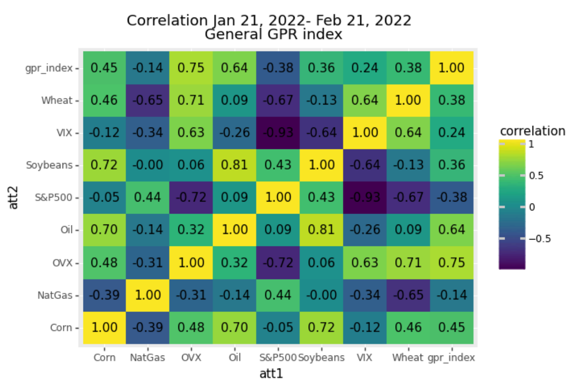


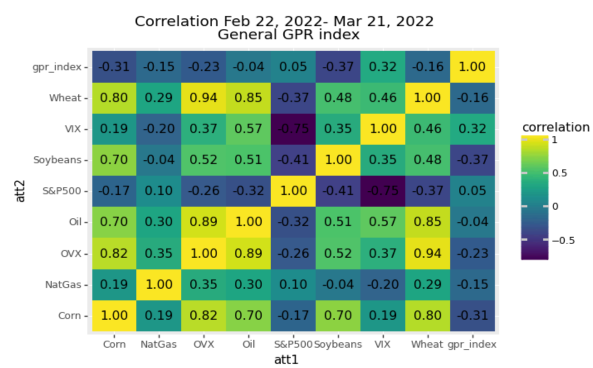






c.Dynamics of the US markets and Geopolitical Risks- empirical observations





The correlations between the price trends of US markets variables and the aggregated GRP index are presented for the month before and the month after the start of the Ukraine war. The comparison shows that the correlations with the aggregated GRP index switched signs for most variables during this transition. One significant exception is Natural Gas, for which the correlation remained mostly stable around -0.14 to -0.15. US Natural Gas was affected more later in the year rather than immediately around the start of the conflict. Another exception is VIX: the correlation of VIX became slightly more positive, aligning with the GDP index representing market shock. These changes in correlation indicate that geopolitical risks have significant impacts on US markets, representing shifts in market perception of the impact of geopolitical effects on prices.

3. Hypothesis and Description of the Methodologies

***a. Hypothesis*: ** Geopolitical Risks have a strong impact on US markets, leading to two distinct regimes: a semi-stressed and stressed regime. The regimes represent periods of moderate reaction and heightened volatility triggered by specific geopolitical events. Transitions between regimes can be defined by an observable threshold. Price trends for some or all US market variables should change according to the nature and magnitude of geopolitical shocks, and these dynamics can be predicted with random forest models. Further, the sign of the difference of means for prices under the two regimes is statistically significant for all US market variables under analysis. The difference of variance for prices under the two regimes is also statistically significant for almost all US market variables under analysis.

As mentioned, the analysis will focus on a specific stock markets index, two volatility indices (for stocks and oil), energy markets, and agricultural markets, and a subset of geopolitical risks. This provides a strong basis for hypothesis testing, encompassing key market areas and key risks relevant during the period. We aim to extract sufficient statistically significant evidence from the data in order to support the hypothesis.

b. Methodology used to build the GPR

The datasets for geopolitical risk indices have been built using a web scraping tool. For each theme, several key words were inputted, and the tool searched multiple US news sites for the given keywords. The tool then counts the number of times the given set of keywords appear in articles each day, and the total number of articles searched is stored as well. A ratio is produced of successful matches over total counts representing the attention of media and other sources to the combination of keywords. In this report, this ratio will be interpreted as the Geopolitical Risk Index, or the GPR index.

c. Methodology for hypothesis testing

To test the hypothesis stated in Section 3.a., we use a cointegration technique to show that the GPR index moves in the same direction as most US market variables, and machine learning models (random forest classifiers) to show that we can predict prices trends in US market variables with high accuracy using the GPR index. We also investigate the two-regime framework defined by an observed threshold using a modified regression with discontinuity design. To assess the differences between the regimes, we use both a one sided T-test and the Levene test. In this section, we focus on describing these methodologies.

Cointegration is a method used to determine whether two stationary and/or non-stationary time series move together in the same direction, maintaining an almost constant distance across time. We use the *coint* method from *statsmodels.tsa.stattools* to test cointegration of the aggregated GPR index with US market variables. The cointegration test examines a null hypothesis of no cointegration and the alternative of cointegration, and *coint* uses the augmented Engle-Granger two-step cointegration test. The decision is based on the p-value result: if p-value is less than 1%, 5% or 10%, this indicates that we have sufficient evidence to reject the null hypothesis at the corresponding significance level, indicating that the two times series variables are cointegrated. The analysis confirms the existence of cointegration between the GPR index and most US market variables. Since GPR index exhibits several significant outliers, cointegration implies that these market variables also attain extreme values during situations of elevated geopolitical risk.

<u>Regression discontinuity design</u> is a regression method used to assess whether there exists an observed threshold splitting the underlying data into two distinct groups with significant difference. This method can help mitigate selection bias. In this report, a dummy variable is introduced based on an observed threshold related to the theme-based GPR index; the dummy variable takes the value of 1 if the predictor variable is bigger than the threshold, and 0 otherwise. Running the regression with this dummy variable and GPR index allows us to see if the difference of the means of the two regimes (defined by the observed threshold) is statistically significant. This occurs if the coefficient of the threshold dummy is statistically significant. We also add an interaction term between GPR index and the dummy variable. This will allow us to investigate whether the impact on prices comes solely from the threshold effect or also from the overall level of the GPR index. The regression model therefore takes the form:

$$f(\text{Price}) = \boldsymbol{\alpha} + \boldsymbol{\beta}\,(\text{GRP index}) + \boldsymbol{\delta}(\text{Dummy Var}) + \boldsymbol{\gamma}(\text{GRP index})*(\text{Dummy Var})+\text{Error}$$

Two regimes defined by a threshold implies two distinct regression lines, each with its own slope. These slopes represent the average price trends per regime and the difference in slopes represents the change in average behaviour across regimes. To assess the accuracy of the model, we look at the regression summary, focusing on an R-squared of at least 60%-70%, along with reasonable values for other statistics. For each US market variable, we then compare regression-derived trends with the empirically observed average trends (separated by the threshold) as seen in the charts in Section 2. We conclude that there is a strong agreement between them. The presence of different slopes indicates that there exists a breaking point in time where regimes change. For natural gas, we take a slightly different approach: we used a shifted GPR index proxy to perform the regression. However, the general methodology remains the same.

One-sided T-test and the Levene test are used to test if the difference of means and variances of prices in the two regimes are statistically significant. Before conducting the tests, we check whether the variances between the groups are equal or unequal. For the t-test, we examine whether the difference in means is positive or negative. For the Levene test, we assess whether the difference in variances is non-zero with the decision being made by comparing p-value at the 5% significance level. For datasets of sufficient size, these tests do not require the assumption of normal distribution.

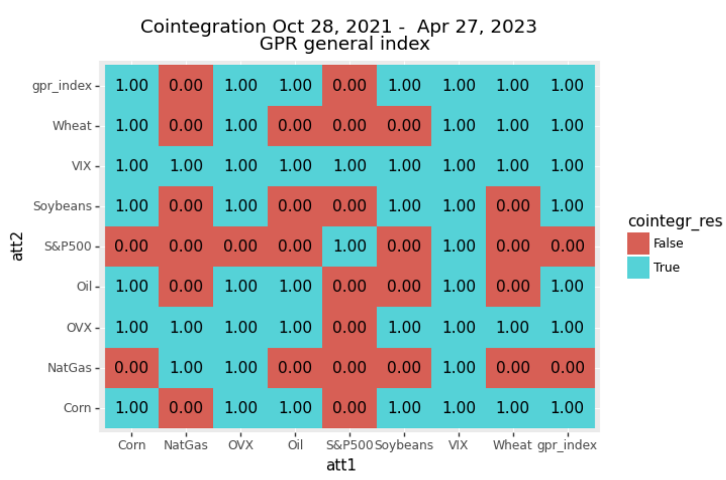
Random forests classifiers are used to predict the price trends, with the GPR index as the predictor variable. The class (0 or 1) variable is defined as follows: 1 if the price increases from the previous day, or 0 if it stays the same or decreases from previous day (based on observations, when the value is 0, it is most likely that the price has decreased, rather than remaining unchanged). First, we check if the classes are balanced. In most cases, they are slightly imbalanced, so we apply upsampling to the minority class to address this issue. We use cross validation specific to time series data (TimeSeriesSplit with gap = 0) with n_splits = 10. This method is chosen because the k-fold method performs random splits, which may disrupt patterns in time series data. We run the random forest classifier to a maximum depth level of 40, with a step of 2. To assess the accuracy of the model's predictions we use the 'Accuracy' score, available with TimeSeriesSplit_, which measures the percentage of correctly predicted observations across the dataset. The curve of the accuracy score is plotted via depth level. In most cases, we observe that after a certain depth level, the 'Accuracy' score stabilises and remains approximately the same, effectively converging to a value, indicating further depth does not significantly improve predictive performance. We also tested the k-nearest neighbor classifier adapted for time series and the support vector classifier, but these models produced slightly lower accuracy scores and so we do not include their results here.

As mentioned before, histograms are used to investigate the distributions of US market variables under stress from geopolitical risks events, while correlations with GRP index are used to see if there are sign changes from these events. Additionally, we analyze the presence of extreme values and standard deviations for spreads and 30-day rolling volatilities around geopolitical events in the historical data.

4. Results and Interpretation

In this section, we will present evidence showing that the results are statistically significant and align with what was empirically observed in Section 2. Conclusions are based on combining all methodologies described in Section 3. Based on the analysis, we find that the hypothesis proposed in Section 3 is supported at a significance level of 5% in most cases.

a. Statistical Analysis: Cointegration with theme of general geopolitical risk



The above cointegration tiles show that prices for most of the US market variables are cointegrated with GPR index (some at the 5% significance level and most others at least at the

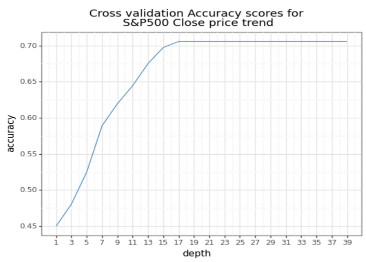
10% level). Despite the tiles showing 0 for two of the variables, the Natural Gas Spot Price is co-integrated with GPR index up to approximately a 12% significance level, while the S&P 500 Close Spot Price is cointegrated with GPR index up to approximately a 11% significance level. We also see that US market variables tend to display bimodal distributions when geopolitical events occur, and that the correlations signs with the GPR index change for most of the variables under consideration. This suggests that geopolitical risks, represented by the GPR index, have a statistically significant impact on the variables discussed in this report. Since the GPR index generally moves in the same direction as prices, this indicates that geopolitical events are perceived as strong shocks. The bimodal distributions also suggest the existence of a two-regime structure defined by an observed threshold across most US market variables, depending on the types of geopolitical risks involved. Additionally, the presence of high positive and negative values with high standard deviations for spreads around the Ukraine war are indicators of strong impact on US markets.

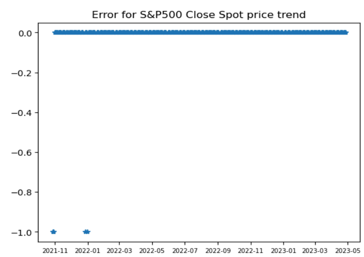
b. Machine Learning: Random Forest Classifier

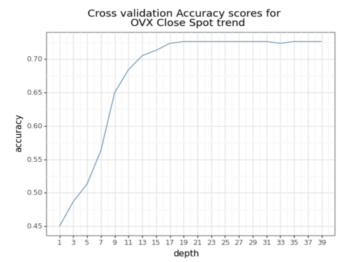
We run random forest classifier models as described in the methodology for all US market variables discussed in this report, namely for: S&P500 ,VIX, OVX, WTI Oil, Henry Hub NatGas and Corn. The GPR index corresponds to the Ukraine war theme, except for NatGas, which is run under the Russia theme. OVX was additionally run under Russia theme, with similar results. The results of the random forest classifier models are shown in the table below.

	S&P500	VIX	OVX	Oil	NatGas	Corn
Accuracy	71%	72%	73%	69%	71%	70%
Depth	17	15	19	17	15	15

We present the accuracy scores curve for the S&P 500 Close Spot price trend (theme: Ukraine war) and OVX Close Spot price trend (theme: Russia) below, along with the error results for the S&P 500 Close Spot price trend. The accuracy scores curves for the other variables exhibit similar patterns. These results demonstrate that we can predict price trends using the GPR index to an accuracy of approximately 71%-73% for the US market variables under study by using the random forest classifier models with the corresponding depth indicated by the table above.





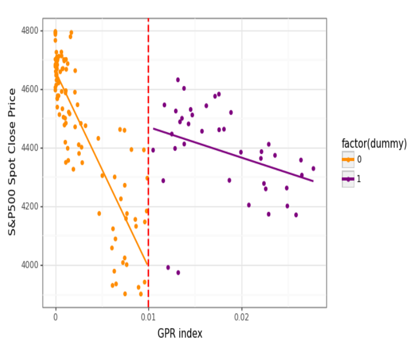


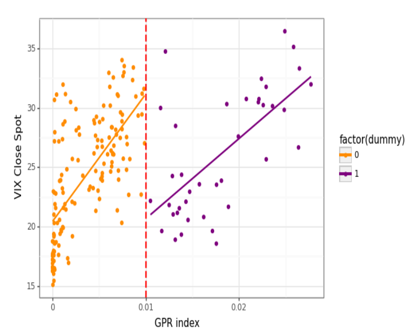
<u>c. Machine Learning: Regression regression discontinuity design with T-test and Levene test</u>

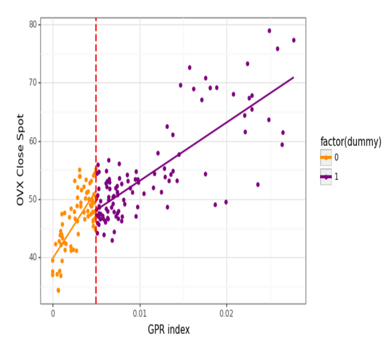
We run a modified method of regression discontinuity design model as outlined in the methodology for all US market variables, namely for: S&P500,VIX, OVX, WTI Oil, Henry Hub NatGas, and Corn, with the GPR index as independent variable for the Ukraine theme. OVX and WTI were also run under the Russia theme with similar results. As a reminder, a modified GPR index is used for NatGas.

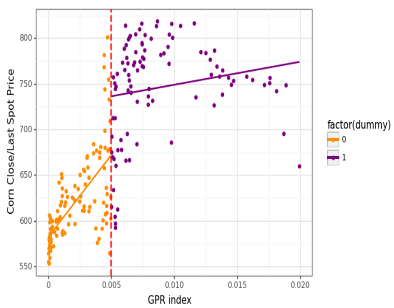
We will present the main findings from the regression analysis. We have found that the difference of means and variances of the prices in the pre-threshold and post-threshold regimes are non-zero at the 5% significance level, based on the regressions summaries and p-values. The slopes of regression lines can be interpreted as the average trends in prices in the two regimes. The difference in slopes implies that the GPR index has a statistically significant impact on the price movements of variables under consideration. The transition from one regime to the next occurs at breaking points in time corresponding to moments where geopolitical risk spikes. The regressions use several months of time series data around the start of the Ukraine war. Since we are also interested in the magnitude of the impact, only some far outliers have been removed. Performing a one sided T-test with unequal variance further confirmed that, for all US market variables, the mean of the prices after threshold are statistically significantly higher than the mean of the prices before the threshold. The exception is for S&P 500, where this trend is found in the reverse. Additionally, a Levene test was used to assess the difference in variance between the two regimes, confirming that the difference in variance between the two regimes is also statistically significant. However, for VIX and OVX, we have not tested variances since they are volatility indices. The results of the regressions and statistical tests are presented in the charts and table below.

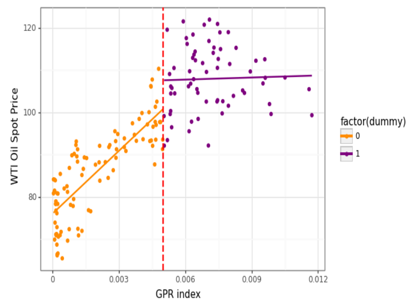
After-Before Threshold	S&P500	VIX	OVX	Oil	NatGas	Corn
Difference in Means	< 0	> 0	> 0	> 0	> 0	> 0
Difference Variances	$\neq 0$	N/a	N/a	$\neq 0$	$\neq 0$	$\neq 0$

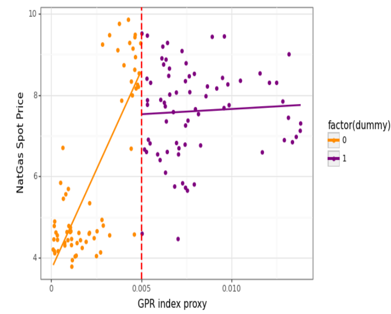












5. Discussion and Summary

The analysis presented in this report has shown that geopolitical risks have a significant impact on US markets as a whole. By the use of cointegration analysis, regression discontinuity design, machine learning models, and statistical tests, we present a strong framework for quantifying this relationship.

The GPR index, web-scraped from US news sources, was used as a proxy for the assessment of geopolitical tensions and risk and consistently shows strong relationships to market variables, evident through both correlation and cointegration. Findings confirm that price trends change significantly across periods of elevated geopolitical risk. Through a threshold analysis, we confirm the existence of a two-regime model for the passthrough of geopolitical risk into asset prices: a semi-stressed regime, where the market reacts moderately to risk, and a stressed regime, where markets are characterised by heightened volatility.

Our methodologies have been effective at predicting and capturing these dynamics. The random forest classifiers accurately predict price trends at accuracy rates of 71-73% for US market variables, and the regression discontinuity design and further T-test and Levene test validation successfully demonstrate statistically significant differences in means and variances between regimes.

While this report focuses on the impact of the Ukraine war and Russia-related risks on US stocks and commodities, the methodology can be applied to other markets, countries, and types of geopolitical risks. Our findings underscore the need to consider geopolitical risk assessments in models where traditional tools alone may fail to account for shocks. As the global landscape continues to shift, integrating some form of geopolitical risk analysis into financial modeling may become increasingly important for effective forecasting and risk management.