

# Impact of Russia-Ukraine War On Foreign Trade

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**Abstract**— This paper is an overall exploratory analysis of foreign trade between growing nations across Asia, Europe and the United States. The extensive analysis includes gathering data of the most imported and exported commodities by nation over the last two to three decades and in the last nine months since the Russia-Ukraine war in February 2022. Existing papers analyzing the Russia-Ukraine conflict employ economically backed methodologies such as global average from cumulative average abnormal returns (CAAR) and follows a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)<sup>[5]</sup> that includes a panel conducting e-Delphi method and gray literature search. This paper employs forecast and prediction models specifically for the time series data to highlight variation in import of the crude and mineral oil, iron ore amidst a global energy crisis.

**Keywords**—crude oil, regression model, export, trade, GDP

## I. INTRODUCTION

Global trade across borders has experienced one of the most catastrophic changes in last few years; Covid-19 pandemic from 2020 till this year, 2022 and Russia's attack on Ukraine in Feb 2022. Relative to Russia, smaller country like Ukraine is one of the largest Iron Ore exporters and the war has left the country with a long-lasting impact on its Iron manufacturing and export<sup>[8]</sup>. Post Russia's debilitating attack on Ukraine, the EU, and the US<sup>[7]</sup> had passed trade control sanctions towards Russian Federation, to cut down Russia's biggest export of natural gas and Crude oil & petroleum export to member countries. The paper tends to explore in statistical terms the magnitude of import changes in recent times for following nations: the US, India, China, Germany, Italy and so on countries with trade sanctions, post two yearlong pandemic and then the on-going Russia-Ukraine conflict.

Apart from the big nations undergoing trade and energy supply change, an overall raw material endangerment has been observed for the first half of this year.<sup>[10]</sup>

To understand the amount of variation in crude petroleum import to the US, European and Asian nations over the last couple decades we did a multiple linear regression over annual crude oil and petroleum import data along with national economic indicators as independent variable. Additionally, ARIMA model was utilized to register the trend change after the initial phase of the war and its impact on this year's crude oil and iron ore export from Russian Federation and Ukraine to above mentioned country.

## II. RELATED WORK

Russia-Ukraine conflict has been analyzed by few papers taking its economic, geo-political effects including effects on the food-supply chain<sup>[1][2][5][6]</sup>. Researchers and economists have predicted the impact on GDP for major countries that have immediately seen a shift in trade relations.<sup>[6]</sup> The papers take a purely economic path to analyze the various growth and economic indicators to forecast the GDP and raise in interest rate taking the energy crisis into account. Notably, one of the recent studies on the food supply chain disruption due to the conflict, published in MDPI. A Preferred Reporting Items for Systematic Reviews and Meta-Analyses approach including grey literature is deployed to investigate key areas of food supply chain that has been impacted in on-going war.<sup>[5]</sup> The paper explores the difference in impact taking the COVID-19 pandemic into account<sup>[9]</sup> and incorporating different search strategies which included the usage Google search engine and news reports in that timeline.

## III. LEARNING METHODS

We apply four methodologies for our analysis.

### A. Exploratory Data Analytics

#### 1. Russia with Other Countries

##### a. USA

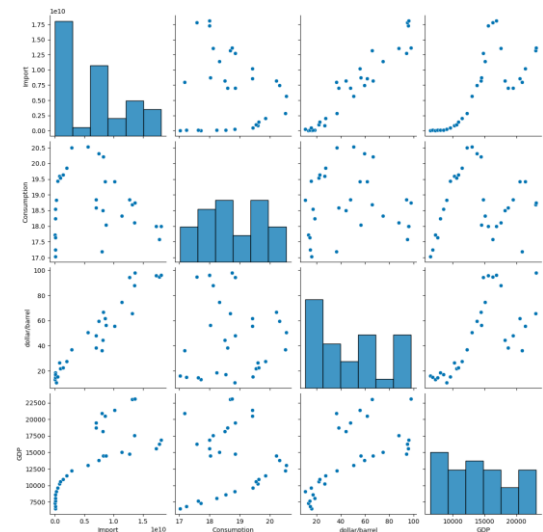


Fig 1: RUSSIA - USA

We can see that import has strong positive correlation with GDP and price ( dollar/barrel), while there is no clear correlation between import and consumption.

b. Poland

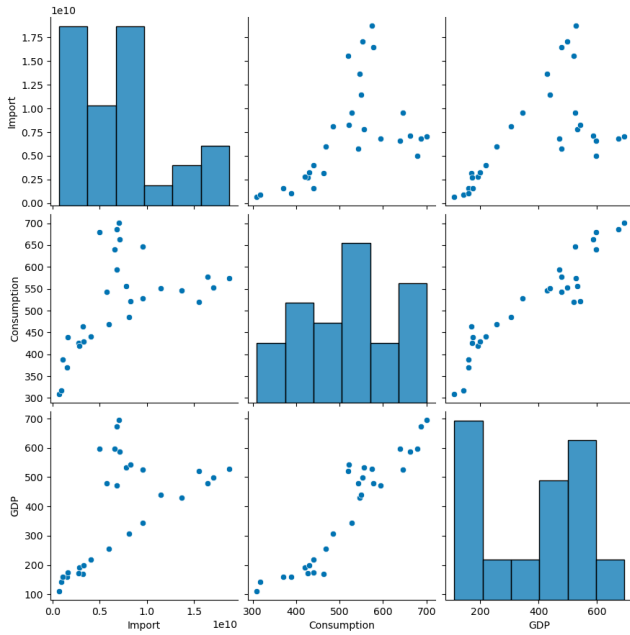


Fig 2: RUSSIA - POLAND

Import, consumption and GDP have strong positive correlation with respect to each other.

c. China

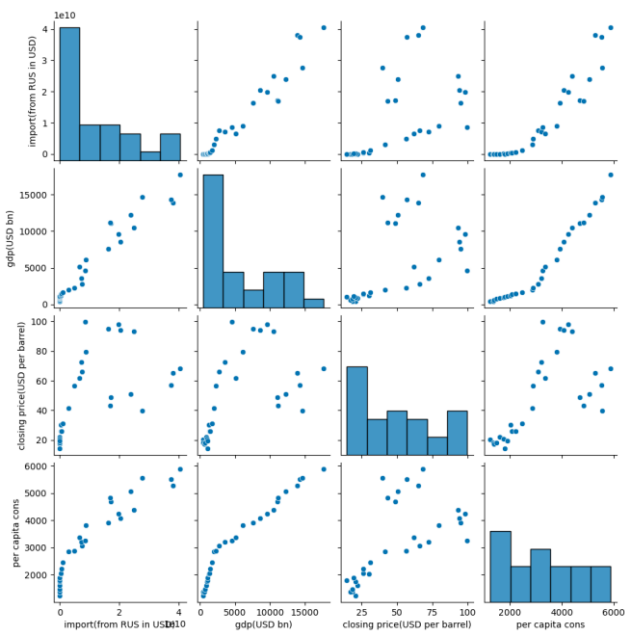


Fig 3: RUSSIA - CHINA

Closing price have a strong correlation for the initial 10 years after which it tends to go down with respect to import, GDP and per capita consumption. Import has a strong positive correlation with respect to all other variables.

d. UK

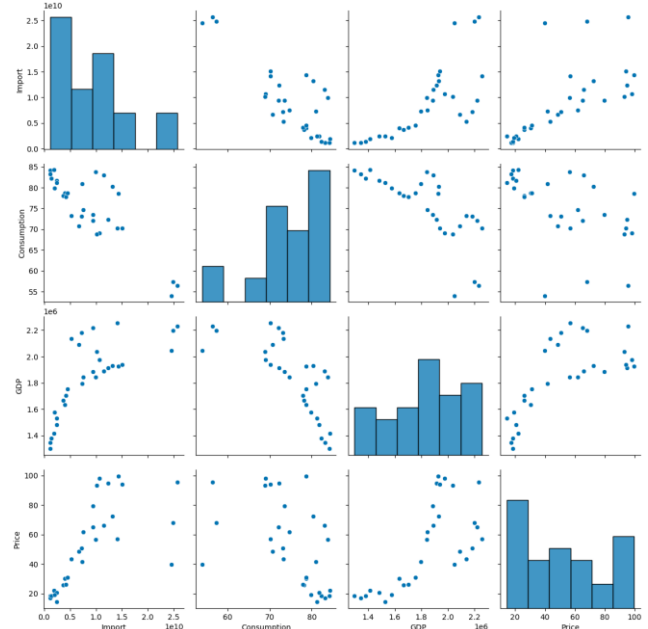


Fig 4: RUSSIA - UK

As import increases, GDP of the country increases while price has a negative correlation with consumption

e. India

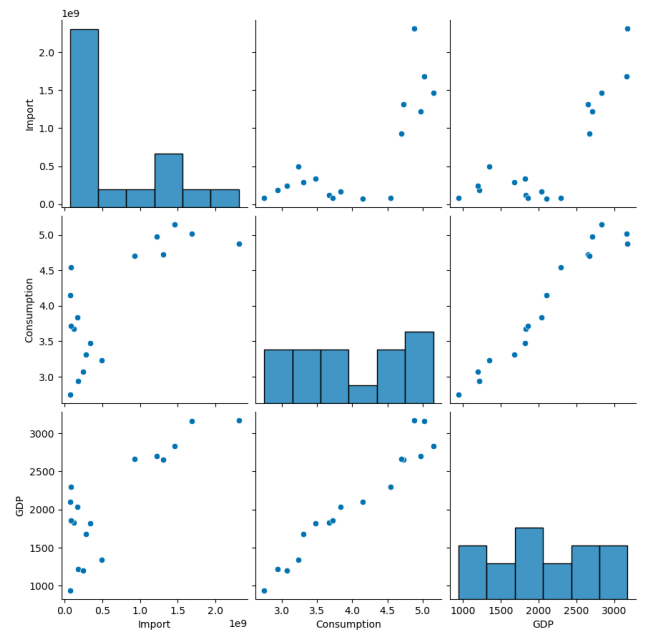


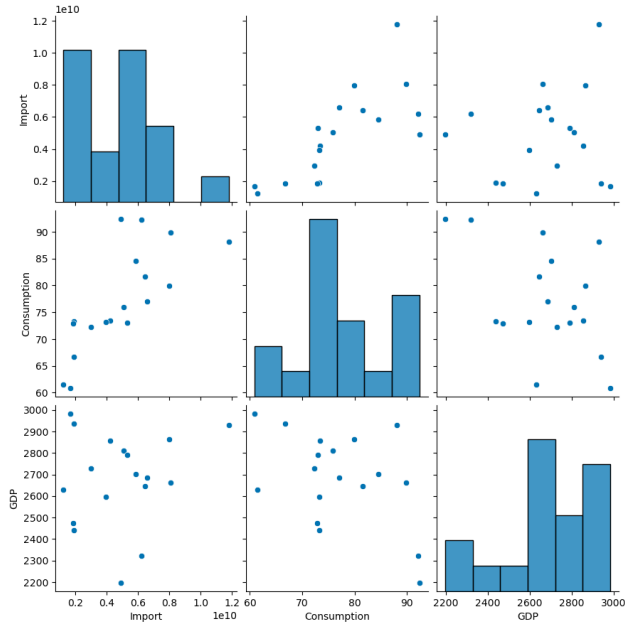
Fig 5: RUSSIA - INDIA

GDP and consumption have a strong positive correlation. For the initial years, as import increases consumption stays constant after which

a strong positive correlation with all other variables except per capita consumption where no relation is observed.

## 2. Ukraine with Other Countries

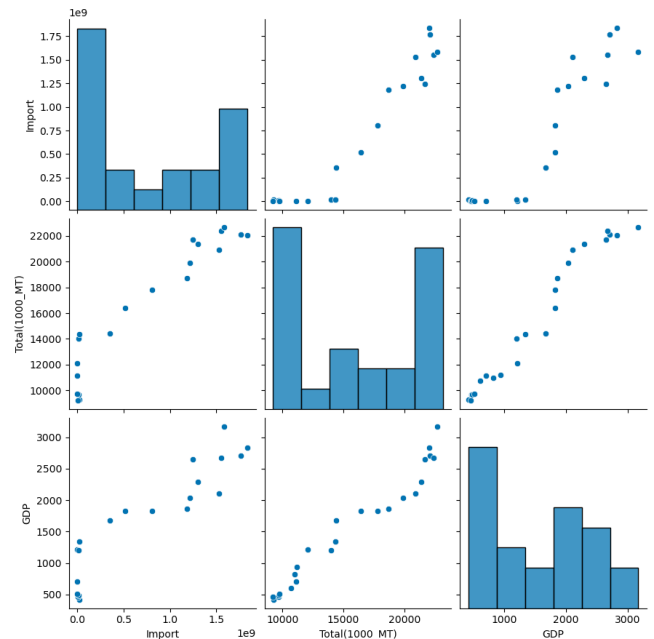
### f. France



**Fig 6: RUSSIA - FRANCE**

For France, GDP has no clear relation with consumption and import while import and consumption have a strong positive correlation.

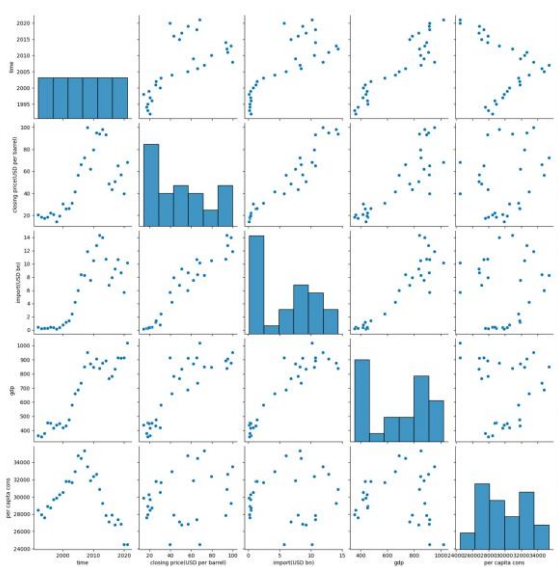
### a. India



**Fig 8: UKRAINE - INDIA**

Here we look at Ukraine export to other countries and identify trends and meaningful insights out of it. In case of India, all parameters have a strong correlation with respect to each other.

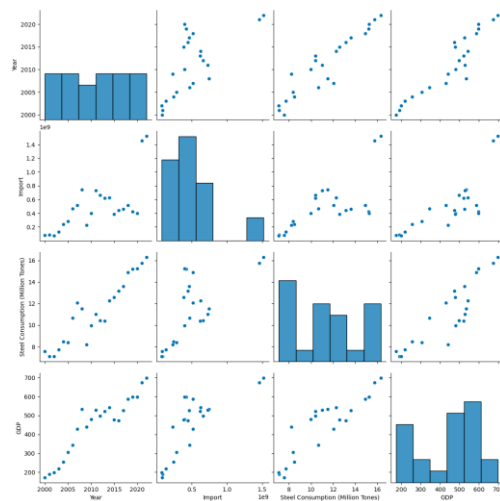
### g. Netherlands



**Fig 7: RUSSIA - NETHERLANDS**

For Netherlands, with time per capita consumption increased for the initial 10 years after a drop was observed. Import has

### b. Poland



**Fig 9: UKRAINE - POLAND**

Similar to India, all parameters have an overall strong positive correlation with respect to each other.

### c. USA

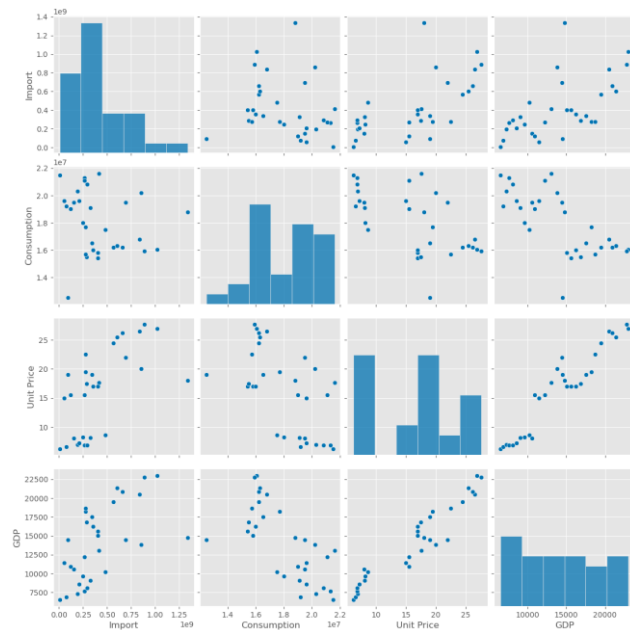


Fig 10: UKRAINE - USA

Similar to India, all parameters have an overall strong positive correlation with respect to each other.

### B. Autoregressive integrated moving average (ARIMA)

First, an autoregressive integrated moving average model is executed. This allows us to impute missing data values in the dataset by considering the data points preceding the year of interest. In addition, we apply ARIMA to forecast the value of GDP, imports, etc. for 2022.

### C. Multiple Linear Regression

Multiple linear regression is employed to determine the association between two or more independent variables and a single dependent variable. The regression coefficient or R squared value allows us to make conclusions from the regression model's outcome. R squared is the correlation coefficient between the observed (observed) values of the outcome variable (y) and the predicted (fitted) values of y. R squared is the proportion of variation in the outcome variable y that can be predicted by knowing the values of the independent variables x. A close R squared score to 1 implies that the model explains a substantial proportion of the variance in the outcome variable.

### D. Analysis of Variance (ANOVA)

In multi-linear regression, analysis of variance (ANOVA) can be used to determine whether our complex model outperforms a simpler model (e.g. model with only one independent variable). With the ANOVA, we may determine the significance of our model by calculating the likelihood of

observing an F-statistic that is as least as high as our model's value.

## IV. RESULTS

### A. Import of Crude Oil to different countries from Russia

Now that we have talked about data extraction, exploratory data analysis and learning methods, here we will look at the results for each country separately.

The most important metric to look at is R-squared value. Higher the value, better is the model performance. For USA, model behaves correctly as can be seen from the value 0.976. Similar trend is observed for countries like China. While it is the opposite case with countries like Poland where value is much smaller.

In that case, it would make sense to add dimensionality to the data in order to improve the model performance.

Below are all the model results at country level for the import of crude oil from Russia to these countries

#### 1. USA

OLS Regression Results						
=====						
Dep. Variable:	Import	R-squared:	0.976			
Model:	OLS	Adj. R-squared:	0.973			
Method:	Least Squares	F-statistic:	351.5			
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	3.75e-21			
Time:	16:10:07	Log-Likelihood:	-661.23			
No. Observations:	30	AIC:	1330.			
Df Residuals:	26	BIC:	1336.			
Df Model:	3					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	1.137e+10	3.37e+09	3.373	0.002	4.44e+09	1.83e+10
Consumption	-8.905e+08	1.8e+08	-4.956	0.000	-1.26e+09	-5.21e+08
dollar/barrel	1.686e+08	8.4e+06	20.079	0.000	1.51e+08	1.86e+08
GDP	2.876e+05	4.98e+04	5.777	0.000	1.85e+05	3.9e+05
=====						
Omnibus:	0.460	Durbin-Watson:	1.658			
Prob(Omnibus):	0.795	Jarque-Bera (JB):	0.432			
Skew:	-0.259	Prob(JB):	0.806			
Kurtosis:	2.721	Cond. No.	2.77e+05			

Fig 11: ARIMA (RUSSIA – USA)

#### 2. Poland

OLS Regression Results						
Dep. Variable:	Import	R-squared:	0.426			
Model:	OLS	Adj. R-squared:	0.380			
Method:	Least Squares	F-statistic:	9.291			
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	0.000961			
Time:	16:59:27	Log-Likelihood:	-657.91			
No. Observations:	28	AIC:	1322.			
Df Residuals:	25	BIC:	1326.			
Df Model:	2					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	5.319e+09	6.63e+09	0.803	0.430	-8.33e+09	1.9e+10
Consumption	-1.666e+07	2.06e+07	-0.808	0.427	-5.91e+07	2.58e+07
GDP	2.777e+07	1.2e+07	2.313	0.029	3.04e+06	5.25e+07
Omnibus:	2.292	Durbin-Watson:	0.596			
Prob(Omnibus):	0.318	Jarque-Bera (JB):	2.039			
Skew:	0.596	Prob(JB):	0.361			
Kurtosis:	2.430	Cond. No.	5.65e+03			

Fig 12: ARIMA (RUSSIA – POLAND)

### 3. China

```
china
Intercept:
-443638430.71977806
Coefficients:
[-936154.67252789 2577757.72016498]

=====
OLS Regression Results
=====
Dep. Variable:   import(from RUS in USD)   R-squared:      0.943
Model:          OLS                      Adj. R-squared:  0.939
Method:         Least Squares             F-statistic:    223.2
Date:           Sun, 11 Dec 2022           Prob (F-statistic): 1.61e-17
Time:           01:31:27                   Log-Likelihood: -697.33
No. Observations: 30                     AIC:           1401.
Df Residuals:   27                       BIC:           1405.
Df Model:        2
Covariance Type: nonrobust

=====
              coef    std err          t      P>|t|      [0.025    0.975]
-----
const          -4.436e+08    3.09e+09    -0.144    0.887    -6.79e+09    5.9e+09
per capita cons -9.362e+05    1.7e+06     -0.551    0.586    -4.42e+06    2.55e+06
gdp(USD bn)     2.578e+06    4.62e+05     5.585    0.000    1.63e+06    3.52e+06
=====
Omnibus:            2.600   Durbin-Watson:      1.510
Prob(Omnibus):      0.272   Jarque-Bera (JB):  1.430
Skew:               0.037   Prob(JB):          0.489
Kurtosis:           4.067   Cond. No.          4.49e+04
=====
```

Fig 13: ARIMA (RUSSIA – CHINA)

### 4. UK

```
=====
OLS Regression Results
=====
Dep. Variable:   Import   R-squared:      0.734
Model:          OLS      Adj. R-squared:  0.702
Method:         Least Squares   F-statistic:    22.96
Date:           Sun, 11 Dec 2022   Prob (F-statistic): 2.34e-07
Time:           17:37:09           Log-Likelihood: -675.66
No. Observations: 29          AIC:           1359.
Df Residuals:   25          BIC:           1365.
Df Model:        3
Covariance Type: nonrobust

=====
              coef    std err          t      P>|t|      [0.025    0.975]
-----
const          3.982e+10    1.46e+10     2.719    0.012    9.66e+09    7e+10
Consumption   -4.994e+08    1.24e+08    -4.036    0.000    -7.54e+08    -2.45e+08
GDP            1337.5412    3999.910     0.334    0.741    -6900.428    9575.510
Price          7.694e+07    3.1e+07     2.481    0.020    1.31e+07    1.41e+08
=====
Omnibus:            1.593   Durbin-Watson:      0.441
Prob(Omnibus):      0.451   Jarque-Bera (JB):  1.429
Skew:               0.423   Prob(JB):          0.489
Kurtosis:           2.316   Cond. No.          4.25e+07
=====
```

Fig 14: ARIMA (RUSSIA – UK)

### 5. India

```
=====
OLS Regression Results
=====
Dep. Variable:   Import   R-squared:      0.643
Model:          OLS      Adj. R-squared:  0.589
Method:         Least Squares   F-statistic:    11.73
Date:           Sun, 11 Dec 2022   Prob (F-statistic): 0.00123
Time:           18:02:28           Log-Likelihood: -338.98
No. Observations: 16          AIC:           684.0
Df Residuals:   13          BIC:           686.3
Df Model:        2
Covariance Type: nonrobust

=====
              coef    std err          t      P>|t|      [0.025    0.975]
-----
const          -6.343e+07    9.85e+08    -0.064    0.950    -2.19e+09    2.07e+09
Consumption   -5.988e+08    5.81e+08    -1.031    0.321    -1.85e+09    6.56e+08
GDP            1.49e+06    6.99e+05     2.132    0.053    -1.99e+04    3e+06
=====
Omnibus:            6.674   Durbin-Watson:      0.877
Prob(Omnibus):      0.036   Jarque-Bera (JB):  1.608
Skew:               -0.062   Prob(JB):          0.448
Kurtosis:           1.452   Cond. No.          2.25e+04
=====
```

Fig 15: ARIMA (RUSSIA – INDIA)

### 6. France

```
=====
OLS Regression Results
=====
Dep. Variable:   Import   R-squared:      0.848
Model:          OLS      Adj. R-squared:  0.826
Method:         Least Squares   F-statistic:    39.05
Date:           Sun, 11 Dec 2022   Prob (F-statistic): 1.87e-06
Time:           18:21:21           Log-Likelihood: -377.05
No. Observations: 17          AIC:           760.1
Df Residuals:   14          BIC:           762.6
Df Model:        2
Covariance Type: nonrobust

=====
              coef    std err          t      P>|t|      [0.025    0.975]
-----
const          -3.916e+10    5.51e+09    -7.109    0.000    -5.1e+10    -2.73e+10
Consumption    2.916e+08    3.45e+07     8.451    0.000    2.18e+08    3.66e+08
GDP             8.058e+06    1.47e+06     5.478    0.000    4.9e+06    1.12e+07
=====
Omnibus:            0.277   Durbin-Watson:      2.429
Prob(Omnibus):      0.871   Jarque-Bera (JB):  0.447
Skew:               -0.094   Prob(JB):          0.800
Kurtosis:           2.228   Cond. No.          5.31e+04
=====
```

Fig 16: ARIMA (RUSSIA – FRANCE)

### 7. Netherlands

```
netherlands
Intercept:
[-0.17453994]
Coefficients:
[[ 0.12648896  0.00625257 -0.00015098]]

=====
OLS Regression Results
=====
Dep. Variable:   import(USD bn)   R-squared:      0.962
Model:          OLS              Adj. R-squared:  0.958
Method:         Least Squares     F-statistic:    222.4
Date:           Sun, 11 Dec 2022   Prob (F-statistic): 1.20e-18
Time:           21:49:35           Log-Likelihood: -40.088
No. Observations: 30          AIC:           80.18
Df Residuals:   26          BIC:           93.78
Df Model:        3
Covariance Type: nonrobust

=====
              coef    std err          t      P>|t|      [0.025    0.975]
-----
const          -0.1745    2.622    -0.067    0.947    -5.565    5.216
closing price(USD per barrel)  0.1265    0.015     8.383    0.000    0.095    0.158
gdp             0.0063    0.002     3.341    0.003    0.002    0.010
per capita cons -0.0002    7.65e-05    -1.973    0.059    -0.000    6.3e-06
=====
Omnibus:            1.700   Durbin-Watson:      1.307
Prob(Omnibus):      0.427   Jarque-Bera (JB):  0.645
Skew:               0.220   Prob(JB):          0.724
Kurtosis:           3.568   Cond. No.          4.37e+05
=====
```

Fig 17: ARIMA (RUSSIA – NETHERLANDS)

### B. Import of Iron and Steel to different countries from Ukraine

Similarly, now we will look at the model results at country level for the import of crude oil from Ukraine to these countries

### 1. USA

```
=====
OLS Regression Results
=====
Dep. Variable:   Import   R-squared:      0.346
Model:          OLS      Adj. R-squared:  0.265
Method:         Least Squares   F-statistic:    4.241
Date:           Sun, 11 Dec 2022   Prob (F-statistic): 0.0154
Time:           20:30:33           Log-Likelihood: -578.62
No. Observations: 28          AIC:           1165.
Df Residuals:   24          BIC:           1171.
Df Model:        3
Covariance Type: nonrobust

=====
              coef    std err          t      P>|t|      [0.025    0.975]
-----
const          -1.041e+09    7.2e+08    -1.444    0.162    -2.53e+09    4.46e+08
Consumption    46.4971    29.580     1.572    0.129    -14.552    107.546
Unit Price     1.77e+07    2.3e+07     0.769    0.449    -2.98e+07    6.52e+07
GDP             2.26e+04    3.83e+04     0.590    0.561    -5.65e+04    1.02e+05
=====
Omnibus:            22.494   Durbin-Watson:      1.529
Prob(Omnibus):      0.000   Jarque-Bera (JB):  30.059
Skew:               1.719   Prob(JB):          5.44e-09
Kurtosis:           7.561   Cond. No.          2.84e+08
=====
```

Fig 18: ARIMA (UKRAINE – USA)

### 2. Poland



OLS Regression Results					
Dep. Variable:	Import	R-squared:	0.756		
Model:	OLS	Adj. R-squared:	0.726		
Method:	Least Squares	F-statistic:	24.83		
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	1.24e-05		
Time:	07:15:43	Log-Likelihood:	-378.11		
No. Observations:	19	AIC:	762.2		
Df Residuals:	16	BIC:	765.1		
Df Model:	2				
Covariance Type:	nonrobust				
	coef	std err	t	P> t	[0.025 0.975]
const	-1.321e+08	1.29e+08	-1.028	0.319	-4.05e+08 1.4e+08
Steel Consumption (Million Tones)	-4.836e+06	2.12e+07	-0.228	0.822	-4.97e+07 4e+07
GDP	1.445e+06	3.58e+05	4.033	0.001	6.85e+05 2.2e+06
Omnibus:	0.288	Durbin-Watson:	1.465		
Prob(Omnibus):	0.866	Jarque-Bera (JB):	0.428		
Skew:	-0.225	Prob(JB):	0.808		
Kurtosis:	2.420	Cond. No.	2.09e+03		

**Fig 19: ARIMA (UKRAINE – POLAND)**

### C. Import of edible oil to India from Ukraine

OLS Regression Results					
Dep. Variable:	Import	R-squared:	0.750		
Model:	OLS	Adj. R-squared:	0.499		
Method:	Least Squares	F-statistic:	2.994		
Date:	Sun, 11 Dec 2022	Prob (F-statistic):	0.250		
Time:	20:34:06	Log-Likelihood:	-81.597		
No. Observations:	5	AIC:	169.2		
Df Residuals:	2	BIC:	168.0		
Df Model:	2				
Covariance Type:	nonrobust				
	coef	std err	t	P> t	[0.025 0.975]
const	2.557e+07	1.07e+08	0.240	0.833	-4.34e+08 4.85e+08
Total(1000_MT)	8357.7980	1.49e+04	0.562	0.631	-5.57e+04 7.24e+04
GDP	-2.093e+05	1.09e+05	-1.927	0.194	-6.77e+05 2.58e+05
Omnibus:	nan	Durbin-Watson:	2.167		
Prob(Omnibus):	nan	Jarque-Bera (JB):	0.552		
Skew:	-0.380	Prob(JB):	0.759		
Kurtosis:	1.561	Cond. No.	4.86e+05		

**Fig 20: ARIMA (UKRAINE - INDIA)**

### D. ANOVA

#### Russia – Other Countries

Country	Probability of observing value at least as high as F-statistic
USA	3.750769564780047e-21
Poland	0.0009614731349273523
China	6.573233392719949e-17
UK	2.338970757524524e-07
India	2.338970757524524e-07
France	1.8748699208138517e-06

**Fig 21: ARIMA (RUSSIA – ALL OTHER)**

#### Ukraine – Other Countries

Country	Probability of observing value at least as high as F-statistic
USA	0.015383983979007247
Poland	1.2426757824960272e-05
India	0.25039658746558413

**Fig 22: ARIMA (UKRAINE – ALL OTHER)**

The table above shows probability of observing F-statistic value. Lower F value means we can reject the null hypothesis and say all coefficients contribute to the prediction of target variable.

### V. CONCLUSION

In this overall study of trade impact of the on-going Russia-Ukraine conflict on major energy trade depicts an overall decline in cross-border trade, derived from the negative coefficients for trade indicators from the time series and regression models. The analysis also establishes that there has been a close correlation between the countries GDP and growing fossil fuel price to the import quantity for the nation. We have also compared the performance of Autoregressive integrated moving average model, linear and multiple linear regression model based on confidence statistic (f-statistic and p-value), AIC. The trained model included various trade indicators to best predict the import quantity for present and next timelines. There has been an evident long-term impact of the war as shown in other studies[3][5] published and an overall snowballing effect of the economy recuperating from the COVID-19 pandemic. With more recent data on energy trade, we would expect a more robust model that can capture the timeline in detail and forecast a more reliable.

### VI. FUTURE SCOPE

When data of import value is released for every product for 2022, using the predicted value for import of the respective product from the ARIMA model, we will be able to calculate evaluation metrics such as sum of squared error. On the basis of that we can evaluate our model. Also, the model can be trained on a monthly basis for the months just before and after the war to pinpoint the exact changes in trade. As of now, as data is not available, this method cannot be implemented.

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