How did EU economies and commodity prices react to the 2022 Russian invasion?

<u>Quantitative Method in Finance</u>

[redacted]

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<u>PART 1:</u> We study the impact of the war on the commodities

A rolling event-study analysis of the Russian war's impact on commodity markets

The Russian invasion of Ukraine has had enormous impact on commodity prices across the globe, specifically on food prices because of Ukraine's important role in agriculture and also on energy prices because of sanctions on Russian energy exports. In this section, we use a rolling-event study analysis of the Russian invasion's impact on more than 20 commodity prices, and we show that a large proportion of commodities experienced abnormal increases in prices in days following the start of the invasion and rapid announcements of global sanctions on Russian energy exports. Specifically, we show that energy, industrial metals, precious metals, and good related commodities experienced jumps in prices. This price increases have been the highest for the wheat with an average of 6% increase in daily price for 14 day period after the start of the invasion. Our important innovation is our rolling event-study methodology which allows for elimination of noise associated with daily trading and clean detection of the commodity market's reaction to the shock of the war. Furthermore, this methodology ensures that we detect no abnormal activity in the market prior to the invasion or after the initial shock of the invasion.

Literature Review

The ongoing Russia-Ukraine war is one of the most prominent war in Europe since the second world war, changing among other the dynamics of the commodity market (Adekoya et al., 2022). According to Prokopczuk et al. (2019) commodity market volatility comoves strongly with economic and financial uncertainty, especially during recessions. While strategic commodities such as crude oil and gold are highly sensitive to the effect of intensified geopolitical risk, the fact that Russia and Ukraine are two major producers and exporters of commodities such as crude oil, natural gas, wheat, and aluminium, has amplified the effect on commodity prices (Wang et al., 2022).

There are different approaches to investigate the impact of the Russian war on the commodity prices, we will be using of the daily data of clean energy stock indices, the conventional energy indices , and the metal indices. Energy, metals (precious and industrial), and agriculturals are three groups of commodities investigated by Wang et al. (2022). Yang et al. (2022) have taken into consideration four groups of commodity indices including energy, agriculture, industrial metals and precious metals, and so we will follow their methodology.

Discussing models that were used to investigate the reaction of the market, there two main approaches: ARMA models (Adekoya et al. (2022), Wang et al. (2022), Yang et al. (2022)) and Event study approach (Umar et al. (2022), Yousaf et al. (2022), Boubaker et al. (2022)).

Data and methodology: Rolling event-study method

In this section, we will explain our data and our general methodology. Our methodology is event study which is widely used by different literature in order to measure the impact of unexpected shocks on variables of interest. The main assumption of this methodology is that markets do not expect the specific event of study (the start of Russian invasion for this study) prior to its occurrence, and consequently, any reaction by the market in the early days of that event will indicate the market's reaction to that specific event. Although, the signs and warnings for a Russian buildup of forces were evident prior to start of the invasion, the events and European sanctions between 24th of February and early March were surprising enough for the markets that our analysis yields tangible results and partially satisfies the assumption of unexpectedness of event study.

To study the impact of the Russian invasion of Ukraine on global commodity prices, we obtain daily prices of 24 commodities in Euros. We focus our study period on the interval between 1st of January 2022 and end of March 2022. The reason for the choice of this specific interval is that first, we do not want the price volatility of COVID-19 to impact our ARMA models, secondly, we do not want the developments of the Russian war after its initial shock to impact our ARMA models, and thirdly, selecting a study period of roughly one year is widespread in event-study methodologies. Our study includes the global prices of the following commodities in Euros: Natural Gas, Gold, WTI Crude, Brent Crude, Soybeans, Corn, Copper, Silver, Low Sulphur Gas Oil, Live Cattle, Soybean Oil, Aluminium, Soybean Meal, Zinc, Uls Diesel, Nickel, Wheat, Sugar, Gasoline, Coffee, Cotton.

To prepare our data, we begin by checking for stationarity of our time series of commodity prices using Augmented Dickey Fuller. As expected, price time series are not stationary. We generate the daily rate of change in prices of each commodity as our main variable of analysis.

Our identification strategy for identifying the impact of the Russian invasion's start is to use event study methodology applied to an ARMA model. More specifically, we will select an ARMA model of order p and q for each commodity's rate of change in prices and include a dummy variable for the start of the Russian invasion. However, we do two things differently. Firstly, to reduce the impact of noises associated with daily trading, we select a time interval of 14 days where the dummy variable for the war's start turns to 1 during those 14 days and stays 0 for any other day. In other words, if T is the date of the start of the war, the dummy variable for the event is 1 for any date within [T-7, T+7] and is 0 for other dates outside of this interval. Secondly and most importantly, to clearly identify the impact of the war and to ensure that no abnormal reaction is detected by our model prior to the start of the war or days past the initial shock of the war, we will run multiple ARMA(p,q) regressions where the difference between each regression will be the fact that we move T from 1st of February 2022 one day by one day until later in March 2022. Our model specification would be as following then:

$$\left[r_t = \alpha + \rho . \sum_{p=0}^{t-1} r_p + \theta . \sum_{q=0}^{t-1} \varepsilon_q + \beta . W_T + \varepsilon_t \right]_T \quad where\ T \in [1st\ of\ FEB\ 2022, 17\ MAR\ 2022]$$

Where r_t is the rate of change on commodity price, ρ denotes a vector of coefficients for the AR component, $\sum_{p=0}^{t-1} r_p$ denotes the number of the AR components in the AR model, θ denotes a vector of coefficients for MA component, $\sum_{q=0}^{t-1} \varepsilon_q$ denotes the number of MA components in the ARMA model, W_T denotes the dummy variable that turns to 1 for dates within the [T-7, T+7] interval and β is the coefficient of interest that will capture the reaction of the commodity market to the Russian invasion's start. The key to this model is that this ARMA model is ran T times for each day between 1st of February 2022 and 17th March 2022, and we report the resulting β coefficients of interest for each T regressions in graphs with 95% confidence interval. This visualization will allow us to detect the market reaction more clearly and ensures that we do not detect any abnormality in dates prior to the start of the war or in days where the initial shock of the war has past, and markets have priced in the Russian invasion into commodity prices.

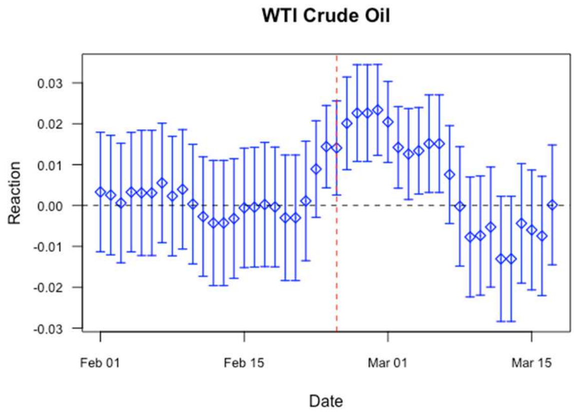
Finally, we mention that we follow the standard ARMA model literature in detecting the proper order of the ARMA model. We use autocorrelation functions, partial autocorrelation functions, AIC, BIC, and parameter significance to detect the best order of the ARMA model.

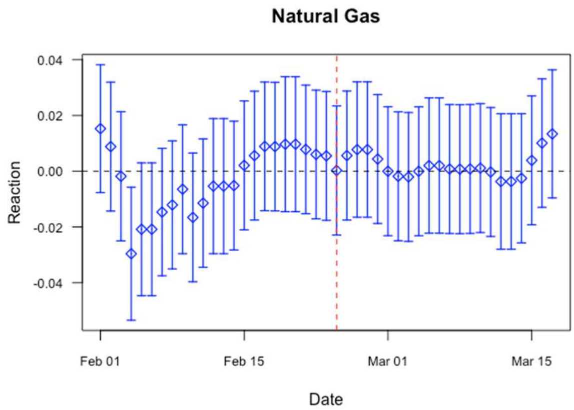
Results:

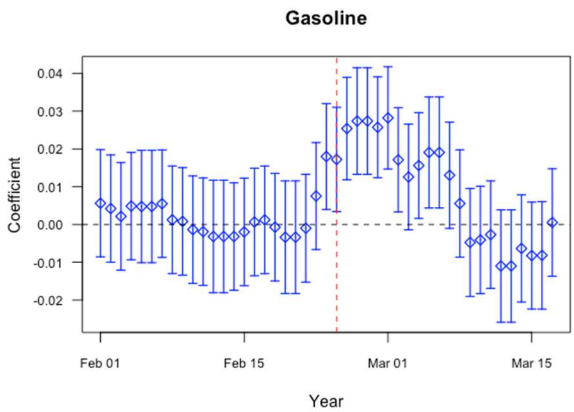
In this section, we report our results for the coefficient of interest that captures the impact of the start of Russian invasion in form of graphs for each commodity. As expected, most commodities that are tied to Ukraine or Russia show the most reaction to start of the invasion and this reaction continues well into starting days of March where Europe and U.S were announcing numerous sanctions. These sanctions include first package of sanctions against Russia announced on 23 February, the second and third package of sanctions in response to Russia's invasion of Ukraine announced on 25th February and 28th February respectively and further sanctions on 2nd and 3rd of March.

First, we start with energy section where we analyze WTI crude oil, natural gas, and gasoline with ARMA models of order (2,2), (0,1), and (1,0) detected for each respectively. The graphs below demonstrate the coefficient for the shock period (event period) estimated in each T regressions while moving the date T forward. The start of the war on 24th is market with a red dashed line and the coefficient is reported with 95% confidence interval. As seen on the graphs, the rate of change in prices of crude oil and gasoline jumps to roughly 2% to 3% as early as 23rd of February (the date for first package of sanctions) and remains high afterwards, but this effect is not detected for natural gas. This reaction which is in form of a jump in prices is highly statistically significant.

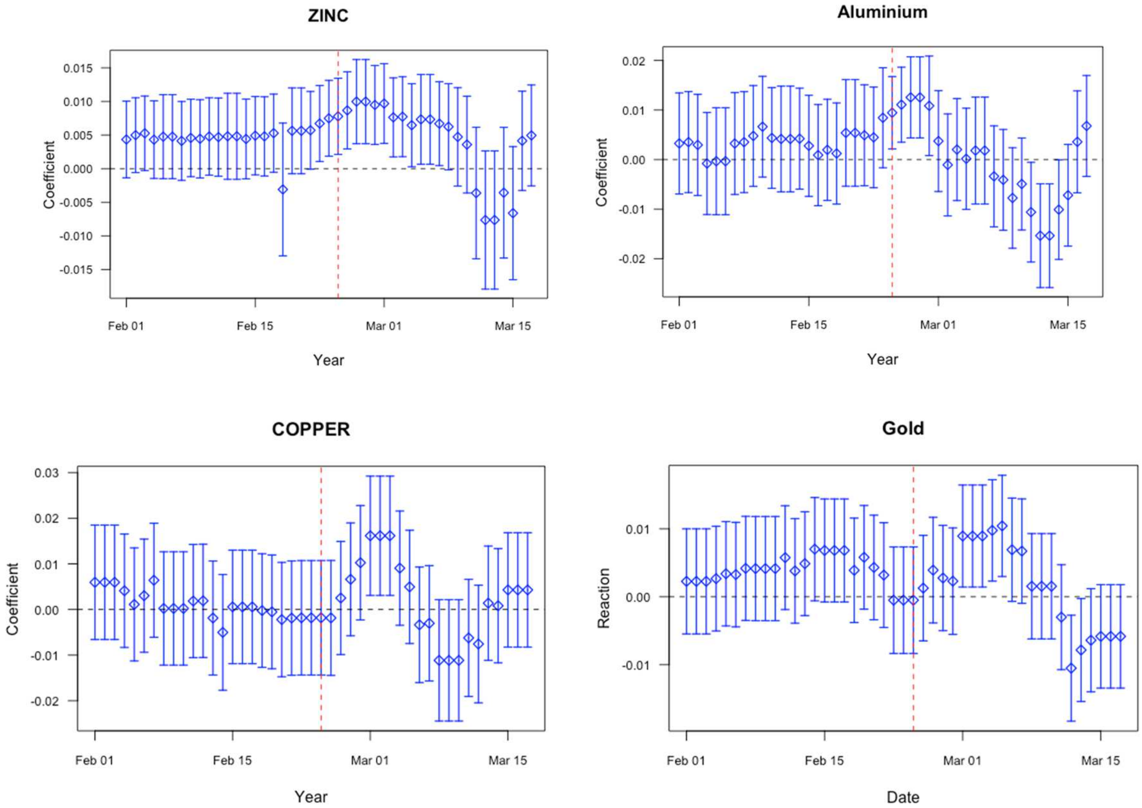
It is important to note that the coefficient of interest is not statistically significant in any date prior to start of the war and it returns to statistical insignificance after the first week of March where the initial shock of the war has passed. This ensures that the reaction that we have detected is indeed caused by the significance evets that took place at the start of invasion and no other confounding news has had impact in any other date.



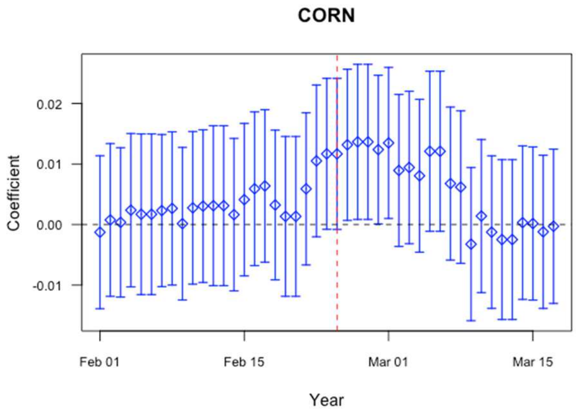


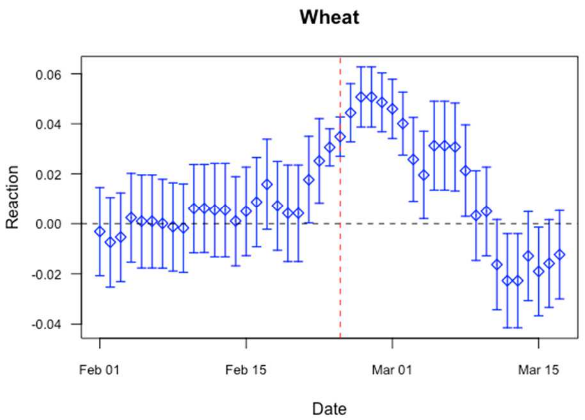


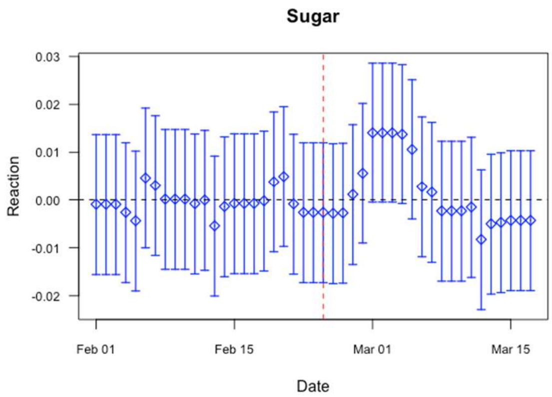
Next, we analyze three important industrial metals and gold as precious metal. The industrial metals are Zinc, Aluminum, and copper. Again, as seen from the graphs and in line with previous results, all metals demonstrate significant increase in prices at the start of the Russian invasion, however the size of this increase, specifically for zinc and aluminum, is much smaller than energy prices studies in previous graphs.



Finally, we focus on the food related commodities, of which wheat is the most important one because Ukraine is a major global producer of wheat. We analyze corn, wheat, and sugar and find significant reactions to the start of the war. We also analyzed the prices for other commodities such as cattle and coffee but did not find impact of the war on these commodities. The most reactive commodity is wheat which experiences daily change of roughly 6% in days at the beginning of Russian invasion of Ukraine which is the highest rate of reaction among all commodities studied in this paper.







To sum up this section, we used a rolling event study ARMA methodology where we rolled the event date forward in an ARMA model in order to detect the reaction of the commodity markets to Russian invasion of Ukraine in form of a wave. We selected an interval of event date because the news of the invasion and also the announcement of sanctions took multiple days to be announced and also, we wanted to reduce the impact of daily trading noises. We tested more than 20 commodities ranging from industrial metals to food commodities and reported the results for commodities impacted significantly by the Russian war. Our methodology successfully picked up the impact of the Russian Invasion on commodity markets after the 24th of February. We identified wheat as the commodity with the highest reaction to the Russian invasion with wheat prices jumping by 6% on average for the 14-day period after the start of the Russian invasion, which shows the food security related concerns were correctly placed. We also detected significant reaction in energy markets, however most surprising, our methodology did not detect any reaction in natural gas prices. In general, our methodology has been successful in detecting the impact of Russian invasion on commodity markets.

PART 2: we study the impact of the war on the EU economies (using time series model)

The ongoing war between Russia and Ukraine is an unprecedented one. Not only has this war affected Russia and Ukraine, but it has also had an impact on the rest of the world, particularly in Europe due to its high reliance on Russia's gas, crude oil and food supplies, almost half of the EU's imports of natural gas comes from Russia. The EU regions expect a significant increase in energy prices to approach $140 per barrel (Liadze et al, 2022). Additionally, the ECB anticipates a 0.2% increase in manufactured goods prices this year as a result to the increase in energy costs in the Eurozone (Lloyd, 2022). According to a statement made by the ECB on May 15, 2022, the increase in energy prices and commodity prices will worsen the situation in the region , increase inflation , volatile stock prices and in slow economic growth. Slow growth will impact financial corporations particularly those that were unable to expand following the COVID-19 financial crisis (ECB, 2022) given that the world bank anticipates that economic activity will remain weak through 2023 since the EU is faced with oil supply shortages and trade disruptions brought on by the War (World Bank , 2022). (Ahmed et al, 2022) try to study the impact of the Russia-Ukraine war on the European stock markets. They expect that the European stock market will react negatively to this crisis due to the sanctions imposed on Russia, political uncertainty and instability risk. To examine the effect of the war on the stock market they used firms belonging to STOXX Europe 600 index which represent publicaly traded firms with large medium and small capital from the major European Countries, and they used the event study methodology they found that there is significant negative average abnormal returns, they observe 0.41% negative average abnormal return on the day of invasion (event day) the highest drop in stock prices in this period.

This paper aims to study the impact of the war on the EU economies. To study this impact we used the consumer price index, interest rates, unemployment, industrial confidence and current account values. The variables used within this paper were extracted from the Eurostat and represent the data regarding the years between 2018 and 2022. It is also worth noting that our data set runs on a monthly frequency.

A monthly frequency allows us to better focus on important variations in the data. It also allows us to increase the sample size which in turn improves the accuracy of the average values. The programming language Python was used to run the empirical analysis.

The consumer Price Index (CPI) is a gauge of how prices for a market basket of consumer goods and services have changed on average over time for urban consumers.

Interest rates can be a measure of economic growth because a rise in interest rates can lead to a rise of the cost of capital which leads to a reduction in investment within the economy.

Unemployment is highly dependent on economic activity, when economic activity is high, new opportunities are high , production is high and more people are needed to produce new goods whereas when the economic activity is low less people are needed to produce new goods and service.

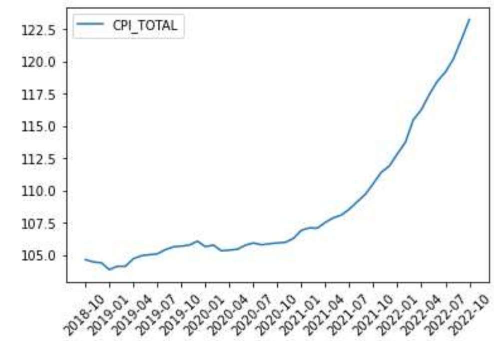
Industrial confidence reflects the trusts of investors, when business confidence is high in the economy there will be higher level of investment and hence a higher economic growth and vice versa.

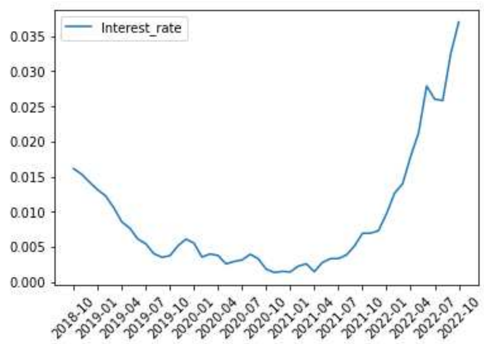
Finally, the current account of a country balance of payment can give an idea about the economic activity remaining in the country. It contains activities about a country's industries, capital market services , the money entering the country from other countries and remittances.

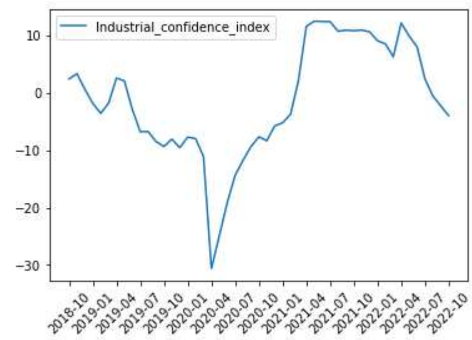
Testing for Stationarity

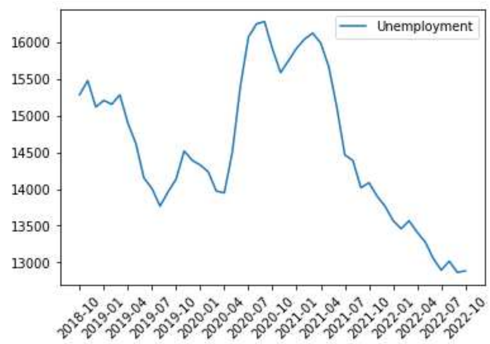
We start off by installing the necessary libraries. Following, the five series are imported and introduced as times series.

We first plot our data to have a first look to study the shape of the curve before applying any transformation.









For the CPI total index, we notice that we have a positive trend throughout the years which can indirectly mean that the inflation has been increasing during the years

As for the current account we notice a big fall during 2020 that can be due to the COVID-19 crisis, and then there is an increase in the current account, but we can notice that in the period of the war there was a negative shock which led to the fall of the current account.

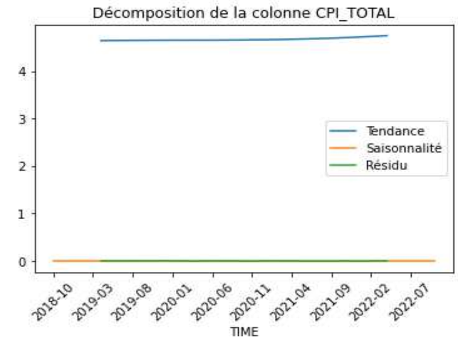
For the interest rates we can see a negative trend followed by a positive since April 2021, this trend kept increasing but in almost March 2022 precisely there was a negative shock in interest rates and this might be due to the War between Ukraine and Russia

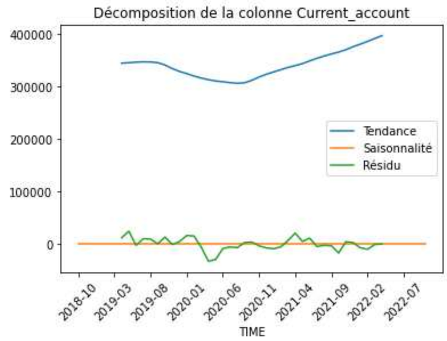
We notice a high rise in unemployment rates between the end of 2019 and 2021 this might be due to the COVID- Crisis as well, followed by a fall in unemployment rate, this might be due to new job opportunities after the big lockdown, but we can notice a small increase in unemployment between March 2022 and July 2022 which might be due to the war as well.

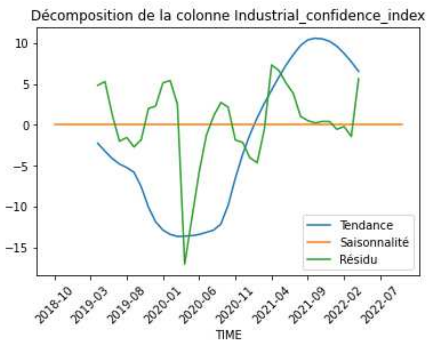
Industrial confidence which is a sign of investment during the COVID-19 crisis then there is a positive trend.

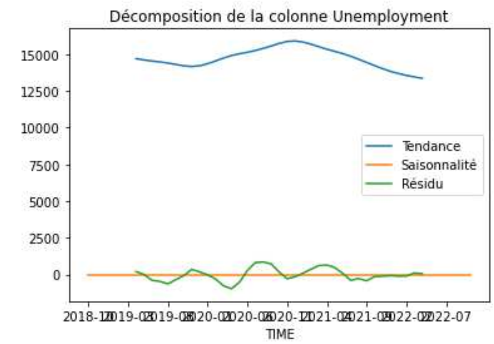
Decomposition and Analysis of Series

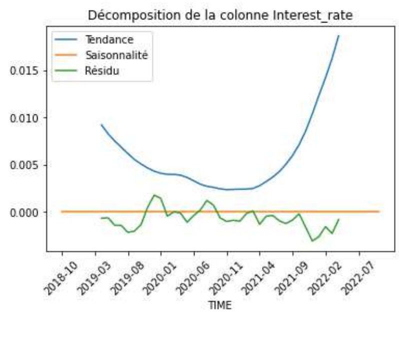
Using non-stationary time series data in financial models produces unreliable and spurious results This consequently leads to poor forecasting finding. The presence of deterministic trends and/or seasonality can lead to non-stationarity. We investigate that.











No Seasonal behaviour was detected in all series plots. A deterministic trend was inspected for by decomposing the time series. A deterministic trend was detected in all series.

The augmented dickey fuller test was run on each of the five series to test for the assumption of stationary within the series. The null hypothesis states that a unit root is present within the time series. Hence, **H0:** The time series is non-stationary. In other words, it has some time-dependent structure and does not have constant variance over time and **H1**: The time series is stationary.

If the p-value from the test is less than some significance level (e.g. α = .05), then we can reject the null hypothesis and conclude that the time series is stationary**.**

ADF test for the CPI:

```
CPI_TOTAL
1
(-2.597555030875201, 0.09350364649812282, 1, 47, {'1%': -3.5778480370438146, '5%': -2.925338105429433, '10%': -2.6007735310095064},
-325.4765797708255)
2
(0.3429745695911788, 0.9792324691441947, 10, 38, {'1%': -3.6155091011809297, '5%': -2.941262357486514, '10%': -2.6091995013850418},
-323.9239657063345)
3
(0.1278875873494208, 0.9679143335299231, 3, 45, {'1%': -3.584828853223594, '5%': -2.9282991495198907, '10%': -2.6023438271604937},
-317.92739358067365)
4
(-0.747169175503243, 0.8341505513889933, 11, 37, {'1%': -3.6209175221605827, '5%': -2.9435394610388332, '10%': -2.6104002410518627},
-316.45050998791766)
5
(1.2190369000992376, 0.9961148068235416, 10, 38, {'1%': -3.6155091011809297, '5%': -2.941262357486514, '10%': -2.6091995013850418},
-312.0394375749793)
6
(-2.844595908393321, 0.052180502607612284, 0, 48, {'1%': -3.5745892596209488, '5%': -2.9239543084490744, '10%': -2.6000391840277777},
-313.1180420708807)
7
(-0.49763001649774596, 0.8924781538209055, 11, 37, {'1%': -3.6209175221605827, '5%': -2.9435394610388332, '10%': -2.6104002410518627},
-326.56544818302325)
8
(-2.349318564106834, 0.15655449014368333, 0, 48, {'1%': -3.5745892596209488, '5%': -2.9239543084490744, '10%': -2.6000391840277777},
-310.9240178367572)
9
(-3.9503152141870927, 0.0016942269956985911, 6, 42, {'1%': -3.596635636000432, '5%': -2.933297331821618, '10%': -2.6049909750566895},
-308.0983592920721)
```

Regarding the time series of our first indicator, CPI, we record that the p-value of the coefficient equals to 0.016 < 0.05 (critical value at 5%). In that case, we can reject the null hypothesis no unit root remains present in the time series which means that the time series is stationary at lag 9 .

```
Current_account
1
(-288.0520966249725, 0.0, 0, 48, {'1%': -3.5745892596209488, '5%': -2.9239543084490744, '10%': -2.6000391840277777}, -127.59409328606608)
```

Regarding the time series of our second indicator, current account, we record that the p-value of the coefficient equals to 0 < 0.05 (critical value at 5%). In that case, we can reject the null hypothesis no unit root remains present in the time series which means that the time series is stationary at the first lag .

ADF test for the industrial confidence index:

```
Industrial_confidence_index
1
(-5.65211943324811, 9.806298521541573e-07, 0, 48, {'1%': -3.5745892596209488, '5%': -2.9239543084490744, '10%': -2.6000391840277777},
218.7932022960806)
```

Regarding the time series of our second indicator, current account, we record that the t-value of the coefficient equals to -5.65 < -2.92 (critical value at 5%). In that case, we can reject the null hypothesis no unit root remains present in the time series which means that the time series is stationary at the first lag .

ADF test for the interest rate

```
Interest_rate
1
(-0.2520320713546198, 0.932028625748505, 7, 41, {'1%': -3.60098336718852, '5%': -2.9351348158036012, '10%': -2.6059629803688282},
-363.6038926927617)
2
(-0.654737041138878, 0.8581280044993025, 6, 42, {'1%': -3.596635636000432, '5%': -2.933297331821618, '10%': -2.6049909750566895},
-364.08079653733245)
3
(0.12618756094231676, 0.967804223876021, 6, 42, {'1%': -3.596635636000432, '5%': -2.933297331821618, '10%': -2.6049909750566895},
-358.1241813648936)
4
(-0.9383399025392611, 0.7750845560975153, 4, 44, {'1%': -3.5885733964124715, '5%': -2.929885661157025, '10%': -2.6031845661157025},
-366.996296666396)
5
(-1.5505957467003606, 0.5083505993015609, 0, 48, {'1%': -3.5745892596209488, '5%': -2.9239543084490744, '10%': -2.6000391840277777},
-359.72359171817925)
6
(-1.2743875263803708, 0.6408070895298158, 2, 46, {'1%': -3.5812576580093696, '5%': -2.9267849124681518, '10%': -2.6015409829867675},
-352.62508888912686)
7
(1.702380918460855, 0.9981344117630147, 7, 41, {'1%': -3.60098336718852, '5%': -2.9351348158036012, '10%': -2.6059629803688282},
-359.5037976489445)
8
(-0.45099321701533446, 0.9012303087565512, 0, 48, {'1%': -3.5745892596209488, '5%': -2.9239543084490744, '10%': -2.6000391840277777},
-372.69685597079206)
9
(-0.45165162154852845, 0.9011110846958867, 2, 46, {'1%': -3.5812576580093696, '5%': -2.9267849124681518, '10%': -2.6015409829867675},
-357.3279378500401)
10
(-0.041782162350891425, 0.9549372860786824, 0, 48, {'1%': -3.5745892596209488, '5%': -2.9239543084490744, '10%': -2.6000391840277777},
-349.14022219766997)
```

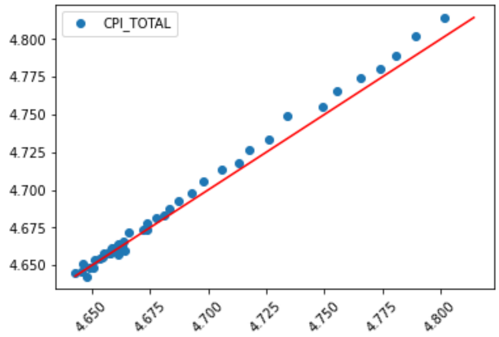
Regarding the time series of our fourth indicator, interest rate, we record that the t-value of the coefficient is lower critical value. In that case, we cannot reject the null hypothesis a unit root remains present in the time series which means that the time series is not stationary at lag 10.

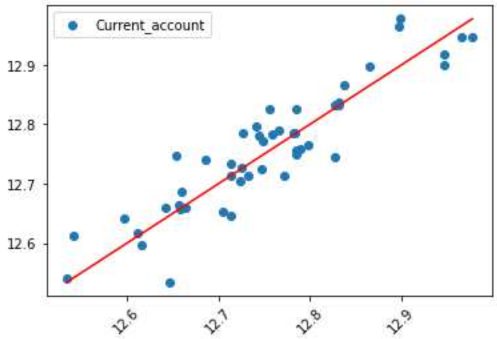
ADF test for unemployment:

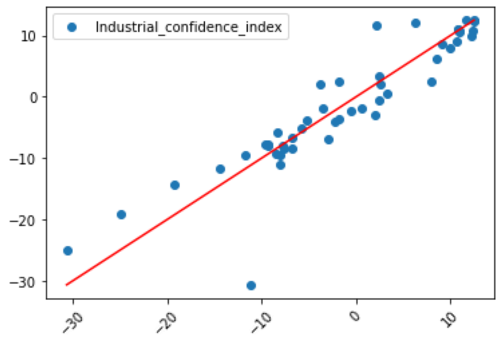
```
Unemployment
1
(-3.1086987405034634, 0.02591610442317844, 2, 46, {'1%': -3.5812576580093696, '5%': -2.9267849124681518, '10%': -2.6015409829867675},
513.4316256948417)
```

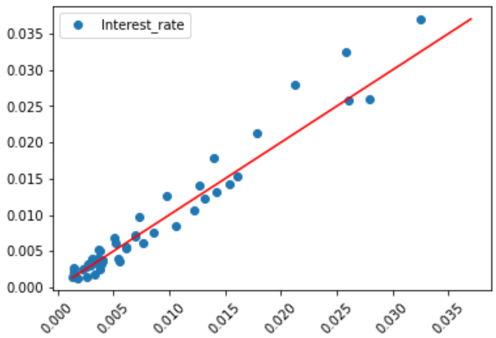
Regarding the time series of our fifth indicator, unemployment, we record that the p-value of the coefficient is less than 5% in all cases (0.0259 <0.05). In that case, we can reject the null hypothesis no unit root remains present in the time series which means that the time series is stationary at lag 1.

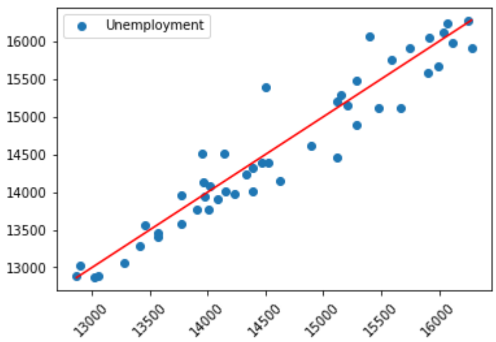
Now we apply the corresponding difference to our data we obtain:









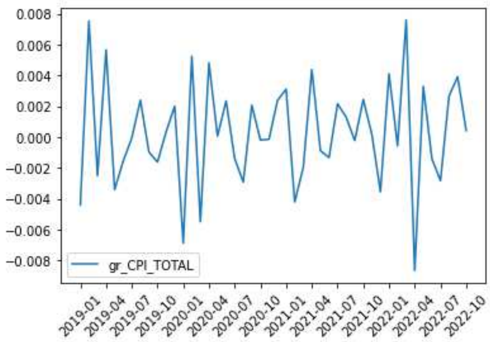


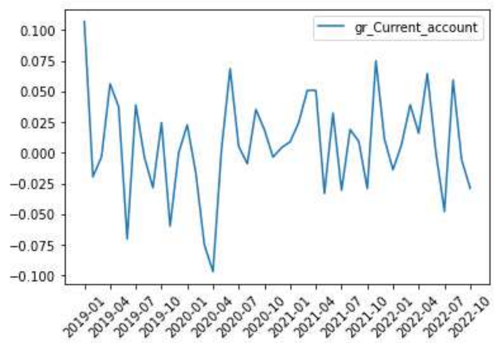
We transform our data into growth rate and logarithm and then we retest for stationarity. By a simple line of code- Stationarity df - the system will choose the series with the least number of lags for which the time series is stationary. And with differentiated dfs the system will choose the differentiated series with the least numbers of lags for which the times series is stationary.

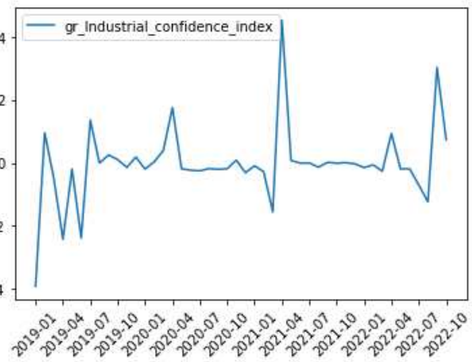
We define global df as the data frame that contains the time series with the least number of lags for which the times series is stationary. We notice that all of the time series are stationary at the level when transformed into growth except for the consumer price index which is stationary at the level.

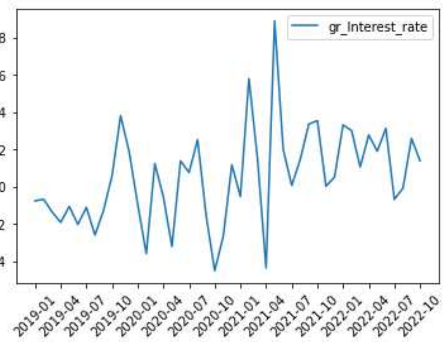
Index	Column	Order
0	gr_CPI_TOTAL	1
1	gr_Current_account	0
2	gr_Industrial_confidence_index	0
3	gr_Interest_rate	0
4	gr_Unemployment	0

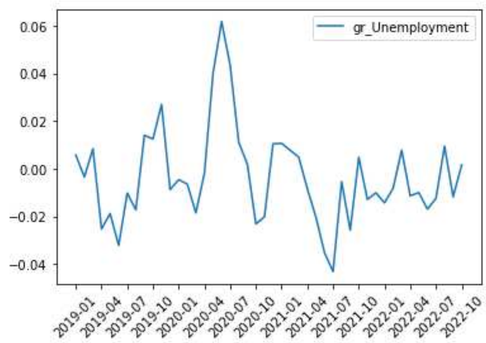
We plot our data after applying the transfiormation to our time series to see how the transformation affceted our data . We notice that theres no deterministic nor cyclucal trend left for any of the time series.











Correlation Matrix

Now we draw the correlation matrix to understand if there exists a relationship (correlation) between the variables. The further away the correlation coefficient is from zero the stronger is the relationship between the two variables

Index	gr CPI TOTAL	Current accou	strial confiden	gr Interest rate	Unemployme
gr_CPI_TOTAL	1	-0.0030681	0.238262	-0.184214	0.0378187
gr_Current_account	-0.0030681	1	-0.225678	-0.128443	0.155684
gr_Industrial_confidence_index	0.238262	-0.225678	1	-0.0111582	-0.0414578
gr_Interest_rate	-0.184214	-0.128443	-0.0111582	1	0.0349721
gr_Unemployment	0.0378187	0.155684	-0.0414578	0.0349721	1

Each cell in the matric shows us the correlation level between two different variables. A correlation level = 1 means that the variables are highly positively correlated. A correlation value close to 0 means that there no correlation between the two variables and a correlation value close or equal to -1 means that there exists a negative correlation between the two variables.

We notice that there is no high correlation between any of the variables, but we notice that some variables are weakly negatively or positively correlated.

For example there is a weakly positive correlation between the consumer price index and industrial confidence (0,238262), this can be explained in economic terms because the industrial confidence index reflects the trust of investor ,if there confidence in business is low they will invest less and this means that investments will fall , and if investment will fall , producers will produce less , supply of goods is not highly available which will lead to a change in prices and hence a change in the cpi.

For the current account and growth industrial confidence there is a weakly negative correlation (-0.2256).

Structural break:

To test the effect of the war on the previous five variable we use the structural break method. This method shows an unexpected change in time series due to an event that happened in a certain point of time. This change can lead to a change in the mean and other factors in the series and can lead to changes in forecasting and models.

We set the structural break to be at the month of the invasion which is February 2022. And then we define the pre-event period to be before the invasion of Russia and the post event to be after the invasion of Russia in February 2022.

Key	Type	Size	Value
gr_CPI_TOTAL	float64	1	1.8539821367014042e-07
gr_Current_account	float64	1	1.887379141862766e-15
gr_Industrial_confidence_index	float64	1	1.5210055437364645e-14
gr_Interest_rate	float64	1	1.1102230246251565e-16
gr_Unemployment	float64	1	1.1102230246251565e-16

We perform a Chow-Test on each column of the dataset. As describe above, the p-values which are stored in the Value column above are all much lesser than 0.05, because of this the null hypothesis can be rejected and it can be concluded that there is a significant difference between the full and reduced models, indicating a structural break in the data. This means that the coefficients in the regression model are not the same across the different subsamples of the data and that there is a significant change in the relationships between the variables before and after February 2022.

Testing for Cointegration:

Given that the presence of a unit root is observed within all series, we continue by testing for cointegration between the three series. The presence of cointegration between the time series indicates the possibility of correlation in the long term. We test for cointegration between the variable pre-event.

Key	Type	Size	Value
('gr_CPI_TOTAL', 'gr_Current_account')	tuple	2	(-6.152556866949391, 7.554736923698569e-07)
('gr_CPI_TOTAL', 'gr_Industrial_confidence_index')	tuple	2	(-11.007741282405203, 7.978030639336528e-19)
('gr_CPI_TOTAL', 'gr_Interest_rate')	tuple	2	(-11.455263575452786, 6.860458138537235e-20)
('gr_CPI_TOTAL', 'gr_Unemployment')	tuple	2	(-6.221358073303894, 5.326207698059964e-07)
('gr_Current_account', 'gr_Industrial_confidence_index')	tuple	2	(-6.763565069349066, 3.0995059856482026e-08)
('gr_Current_account', 'gr_Interest_rate')	tuple	2	(-6.299282955165262, 3.5732451720030095e-07)
('gr_Current_account', 'gr_Unemployment')	tuple	2	(-6.558174699957321, 9.2645464573192e-08)
('gr_Industrial_confidence_index', 'gr_Interest_rate')	tuple	2	(-8.146398826115552, 1.2933918808058508e-11)
('gr_Industrial_confidence_index', 'gr_Unemployment')	tuple	2	(-8.428424621082295, 2.4976616987745306e-12)
('gr_Interest_rate', 'gr_Unemployment')	tuple	2	(-5.195685801697617, 7.076915793327106e-05)

H0: there are no cointegration

H1: there are cointegration

- The columns gr_CPI_TOTAL et gr_Current_account are not cointegrated (p-value = 0.5015)
- The columns gr_CPI_TOTAL et gr_Industrial_confidence_index is cointegrated (p-value = 0.0000)
- The columns gr_CPI_TOTAL et gr_Interest_rate is cointegrated (p-value = 0.0000)
- The columns gr_CPI_TOTAL et gr_Unemployment are cointegrated (p-value = 0.0000)
- The columns gr_Current_account et gr_Industrial_confidence_index is cointegrated (p-value = 0.0000)
- The columns gr_Current_account et gr_Interest_rate is cointegrated (p-value = 0.0000)
- The columns gr_Current_account et gr_Unemployment are cointegrated (p-value = 0.0000)
- The columns gr_Industrial_confidence_index et gr_Interest_rate is cointegrated (p-value = 0.0000)
- The columns gr_Industrial_confidence_index et gr_Unemployment are cointegrated (p-value = 0.0000)
- The columns gr_Interest_rate et gr_Unemployment are cointegrated (p-value = 0.0000)

Building the Vector Error Correction Model (VECM)

Det. terms outside the coint. relation & lagged endog. parameters for equation gr_CPI_TOTAL

	coef	std err	z	P>|z|	[0.025	0.975]
L1.gr_CPI_TOTAL	-0.0385	0.152	-0.254	0.799	-0.336	0.259
L1.gr_Current_account	-0.0128	0.008	-1.644	0.100	-0.028	0.002
L1.gr_Industrial_confidence_index	0.0004	0.000	1.573	0.116	-0.000	0.001
L1.gr_Interest_rate	-0.0022	0.001	-1.605	0.108	-0.005	0.000
L1.gr_Unemployment	0.0715	0.023	3.163	0.002	0.027	0.116

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-1.4061	0.246	-5.706	0.000	-1.889	-0.923

Loading coefficients (alpha) for equation gr_Current_account

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	3.6051	4.178	0.863	0.388	-4.584	11.794

Loading coefficients (alpha) for equation gr_Industrial_confidence_index

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-449.6622	95.726	-4.697	0.000	-637.281	-262.043

Loading coefficients (alpha) for equation gr_Interest_rate

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	91.6514	28.143	3.257	0.001	36.492	146.811

Loading coefficients (alpha) for equation gr_Unemployment

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	0.9990	1.917	0.521	0.602	-2.758	4.756

Cointegration relations for loading-coefficients-column 1

	coef	std err	z	P>|z|	[0.025	0.975]
beta.1	1.0000	0	0	0.000	1.000	1.000
beta.2	-0.0087	0.008	-1.154	0.248	-0.024	0.006
beta.3	0.0007	0.000	2.440	0.015	0.000	0.001
beta.4	-0.0016	0.001	-1.653	0.098	-0.004	0.000

Growth CPI is our dependent variables , while the four other variables are the independent variables. Therefore, through interpretation, we take the first equation alone.

ECT in the VECM model represents long run it should be negative and significant. In our case the ECT is negative and significant only for the CPI and industrial confidence index. Therefore we can say that there is a long run association or causality moving from CPI to industrial confidence index. But we can not say the sale thing for all other variables . Because the ECT coefficient is positive so the disequilibrium cannot be corrected to equilibrium in the long run.

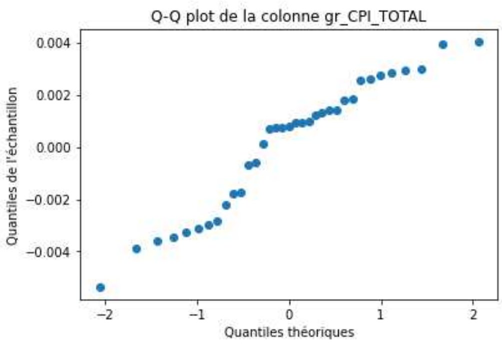
Granger Causality Testing:

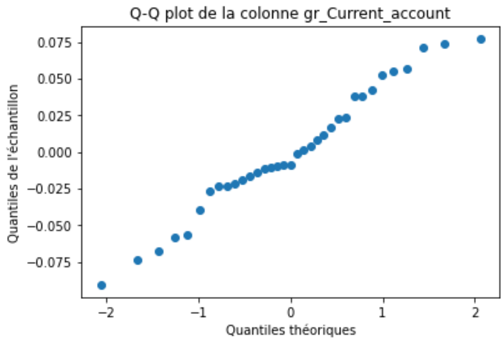
We continue with Granger causality testing for the five series:

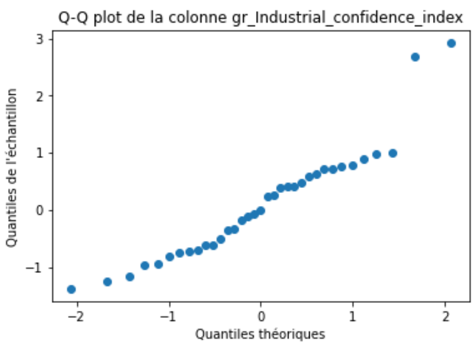
Index	gr_CPI_TOTAL	Current accou	rial confide	Interest ra	Unemploym
gr_Current_account	0.365574	nan	0.364973	1.00512	1.25001
gr_Industrial_confidence_index	0.0799336	0.495963	nan	0.498467	1.40383
gr_Interest_rate	0.0903296	6.06381	0.826043	nan	0.360839
gr_Unemployment	0.364835	0.733034	2.14904	2.14591	nan
gr_CPI_TOTAL	nan	0.00828673	0.896339	0.727045	1.24085

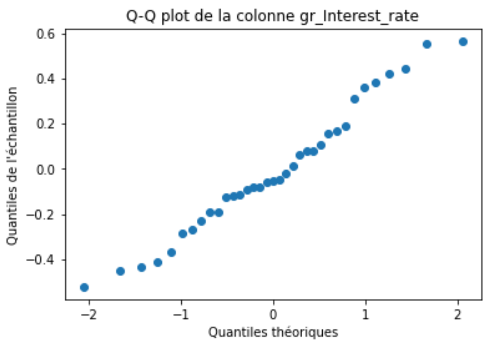
The null hypothesis is that the one variable does not granger cause the other:

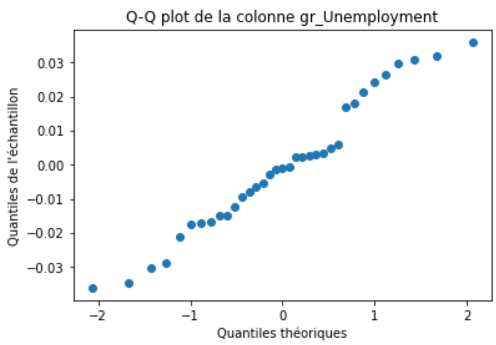
We can conclude that only the CPI TOTAL granger cause the current (p value < 5% -> we can reject the null hypothesis)











A Q-Q plot is a graphical tool that compares the distribution of a dataset to a theoretical distribution. To create a Q-Q plot, we plot the quantiles of the sample data on the horizontal axis and the quantiles of the theoretical distribution on the vertical axis. If the sample data come from a population with the same distribution as the theoretical distribution, the points on the Q-Q plot will follow a straight line. However, if there are deviations from this line, it may indicate that the sample data come from a population with a different distribution.

This is important because ideally, when building a model, the residuals should be randomly distributed and follow a normal distribution.

On the plots above we observe that the points are not completely aligned which shows the residuals do not completely follow a normal distribution, however this is not terrible either and we assume that this is due to the lack of points we use.

Now we move from the post event period to see the effect of the war on our variables:

We start by doing a cointegration test, we find the following ,

- The columns gr_CPI_TOTAL et gr_Current_account are cointegrated (p-value = 0.0122)
- The columns gr_CPI_TOTAL et gr_Industrial_confidence_index are cointegrated (p-value = 0.0002)
- The columns gr_CPI_TOTAL et gr_Interest_rate are cointegrated (p-value = 0.0012)
- The columns gr_CPI_TOTAL et gr_Unemployment are not cointegrated (p-value = 0.9390)
- The columns gr_Current_account et gr_Industrial_confidence_index are cointegrated (p-value = 0.0000)
- The columns gr_Current_account et gr_Interest_rate are cointegrated (p-value = 0.0000)
- The columns gr_Current_account et gr_Unemployment are cointegrated (p-value = 0.0001)
- The columns gr_Industrial_confidence_index et gr_Interest_rate are not cointegrated (p-value = 0.2335)
- The columns gr_Industrial_confidence_index et gr_Unemployment are not cointegrated (p-value = 0.5307)
- The columns gr_Interest_rate et gr_Unemployment are not cointegrated (p-value = 0.1977)

  We notice that the cointegration between two variables has changed for example pre-event CPI Total and current were not cointegrated after the event these two variables are cointegrated . The opposite thing is true for CPI toral andunemployment , industrial confidence and interest and unemployment and finally after the invasion interest rate and unemployment are not cointegrated

  We run now the VECM for the post event period:

	coef	std err	z	P>|z|	[0.025	0.975]
L1.gr_CPI_TOTAL	3.48e+06	1.58e+05	-0.469	0.000	3.17e+06	3.79e+06
L1.gr_Current_account	-1.468e+04	4.77e+04	0.469	0.000	-1.08e+05	7.87e+04
L1.gr_Industrial_confidence_index	3.97e+04	3024.490	-0.469	0.000	3.38e+04	4.56e+04
L1.gr_Interest_rate	-9.91e+04	6.52e+03	0.469	0.000	-1.12e+05	-8.63e+04
L1.gr_Unemployment	-5.66e+06	3.42e+05	0.469	0.000	-6.33e+06	-4.99e+06

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-7.041e+05	2.59e+04	0.469	0.000	-7.55e+05	-6.53e+05

Loading coefficients (alpha) for equation gr_Current_account

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-1.717e+06	8.9e+05	-0.855	0.063	-3.46e+06	2.73e+04

Loading coefficients (alpha) for equation gr_Industrial_confidence_index

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-2.249e+07	1.84e+07	-1.071	0.032	-5.85e+07	1.36e+07

Loading coefficients (alpha) for equation gr_Interest_rate

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-2.5e+06	1.53e+06	-0.716	0.084	-5.5e+06	5.01e+05

Loading coefficients (alpha) for equation gr_Unemployment

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-1.002e+06	4.88e+04	-1.363	0.000	-1.1e+06	-9.06e+05

Cointegration relations for loading-coefficients-column 1

Our dependent variable is still CPI, but now we notice a negative significant ECT for all the variables which means that there is a long run association or causality moving from CPI to industrial confidence index, current account , unemployment and interest rates. Which is logic because an increase in CPI means and increase in prices, and an increase in prices can lead to changes in interest rates. It could affect the economic activity in the country which could affect unemployment, production and many other factors.
We couldn't perform the granger causality test nor the normality test on our variables after the event because the size of our data is very small.

To conclude , based on our study we can notice the change in the pre-event values and the post event values , we notice that after the war some variables were affected and we expect a long run relationship between these variables which makes economic sense because this war affected the economic activity in the EU which means it affected prices (CPI) , trade activity in the country (current account) there is less production (industrial activity) hence less investment and less production which leads toa higher level of unemployment .

PART 3: We study the impact of the war on the EU economies (using a diff in diff)

Now we would like to study how the war impacted the European economy. To do so we will use a diff in diff model to see how it impacted EU economies.

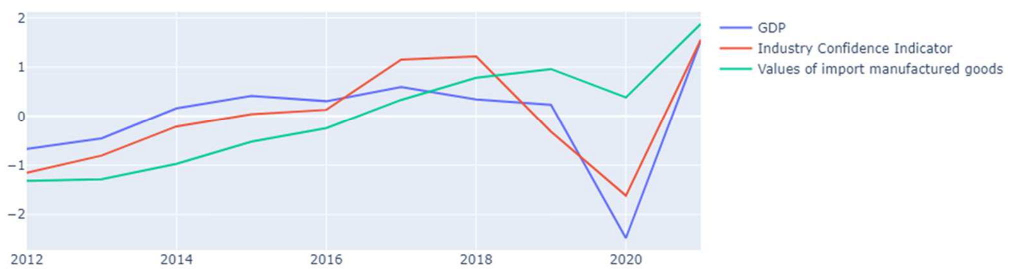
We're using a DID study to assess the differential effect of a treatment, here at the beginning of the war, on a treatment group versus a control group, in a natural experiment.

Here the treatment isn't randomly affected so that's why we will not go to an RCT analysis. The measure of the treatment is obtained by comparing: the average change over time in the outcome variable for the treatment group to the average change over time for the control group. By studying effects of a shock on time series variables, it requires to highlight the date when this shock happened. We decided to choose the beginning of the war on February 24th even if there were intuitions of a new conflict in the past weeks. This date is chosen because, before that, nobody could be sure that the invasion of Ukraine by Russians would happen. Once it becomes real, markets can fully react to what this context implies.

The DID analyses will also allow us to assess if the effects last over time. Having significant results on such analyses means that the effect of the treatment created a change over time for our series.

Find data for control and treatment groups

Our goal is to use the DID methodology to analyse the impact of the war on the European economy. It is easy to think of using a country affected by the war as a control group and Europe as a treatment group. However, the scope of the war was global, so it is difficult to realize such a scenario. We therefore shifted our thinking and decided to find time series data within the EU that were relatively less affected by the war to use as a control group. And use some other more major data as a treatment group. The choice of the time series is mainly based on the means of technical analysis. Since the data on real GDP growth rate is only available until 2021, we cannot use it as a treatment group, but we can use it to find other correlated, monthly data with a time horizon extending to before and after the war.



PS. For all the data, we normalized the data in order to be able to keep them at the same scale level. Also, in order to be able to benchmark the annual data of GDP, we have averaged all other data on a monthly basis with a twelve-month window.

We first need to find a time series that can replace GDP and that series needs to be in months. We choose **the industrial confidence indicator**. The industrial confidence indicator is calculated as the arithmetic average of the balances (in percentage points) of responses on production expectations, the assessment of order books and stocks of finished products (the latter with inverted sign). This indicator is capable of reflecting industry's predictions of the level of economic development. The rationality of the choice can be observed in the graph, where the index and GDP have developed in essentially the same trend over the last decade.

At the same time, we need to find another time series that is also influenced by the overall economic development of the EU, but more independent from the effects of the war. The other time series we choose is **the value of EU imports of manufactured products**. The goods that have already been manufactured are mainly products marketed to EU consumers and therefore will be less involved in the production of the EU industrial chain. Again, the chart shows that imports of manufactured goods and GDP have followed essentially the same trend over the past decade.

We found that the industrial confidence indicator, the value of EU imports of manufactured products and the level of GDP development were basically in a uniform trend before the war, so we will continue our DID analysis using the first two data for the treatment and control groups, respectively.

We further looked at the difference between the treatment and control groups before and after the war on a monthly scale, and we found a clear change in the trend of the data after the outbreak of war. Next we will use the DID method to analyze the validity of their differences.

DID regression

The did regression is constructed such that the outcome Y is modelled by the equation

$$y_i = \beta_0 + \beta_1 * Time\_Period_i + \beta_2 * Treated_i + \beta_3 * (Time\_Period_i * Treated_i) + \epsilon_i$$

With *β_0* a constant

Time_Period_i : the dummy variable which takes the value 0 before the treatment date, and 1 after

Treated_i : the dummy variable which takes the value of 1 if the regression refers to the treatment group

*(Time_Period_i*Treated_i)* : the interaction term, the multiplication of the two dummy variables. The key part of the regression because It assesses the level of the differences due to the beginning of the war.

ϵ_i : the error term of the equation.

In order to use the DID method, we will set the dummy variables manually. We set the industrial confidence indicator data to treat (1) and the value of EU imports of manufactured products to treat (0). The breakpoint variable is also set. We set the time series data up to February 2022 to post (0) for both the control and treatment groups, and post (1) for data after this point in time. Finally, we multiply the treat variable of each time series with the post variable to generate dummy variables for the DID regression. We find that only the industrial confidence indicator is DID (1) for the time series after February 2022, while all other data are DID (0). Since the both time series are different in nature, the dependent variable in the DID regression is constructed directly through their difference.

DID variable	value of EU imports of manufactured products - treat（0）	industrial confidence indicator - treat（1）
before 2022/02 - post（0）	0	0
after 2022/02 - post（1）	0	1

```
                            OLS Regression Results

==============================================================================
=======
Dep. Variable:                      y   R-squared:                      0.154
Model:                            OLS   Adj. R-squared:                 0.147
Method:                 Least Squares   F-statistic:                    23.09
Date:                Fri, 30 Dec 2022   Prob (F-statistic):          4.29e-06
Time:                        20:10:57   Log-Likelihood                -163.85
No. Observations:                 129   AIC                             331.7
Df Residuals:                     127   BIC:                            337.4
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
=======
                coef    std err          t      P>|t|    [0.025   0.975]
------------------------------------------------------------------------------
-------
const         0.0880      0.079      1.119      0.265     -0.068     0.244
DID          -1.6220      0.338     -4.805      0.000     -2.290    -0.954
==============================================================================
=======
Omnibus:                       20.538   Durbin-Watson:                  0.513
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              24.695
Skew:                          -0.987   Prob(JB):                    4.34e-06
Kurtosis:                       3.836   Cond. No.                        4.43
==============================================================================
```

Finally, we obtained the reality of the results of the DID regression, and the DID variable was significant in terms of its effect on the change in trend for the control and treatment groups.

References

Commodity prices surge due to the war in Ukraine. (2022). Retrieved 30 December 2022, from https://blogs.worldbank.org/developmenttalk/commodity-prices-surge-due-war-ukraine

Cai Yang, Zibo Niu, Wang Gao, The time-varying effects of trade policy uncertainty and geopolitical risks shocks on the commodity market prices: Evidence from the TVP-VAR-SV approach, Resources Policy, Volume 76, 2022, 102600, ISSN 0301-4207, https://doi.org/10.1016/j.resourpol.2022.102600.

Imran Yousaf, Ritesh Patel, Larisa Yarovaya, The reaction of G20+ stock markets to the Russia–Ukraine conflict “black-swan” event: Evidence from event study approach, Journal of Behavioral and Experimental Finance, Volume 35, 2022, 100723, ISSN 2214-6350, https://doi.org/10.1016/j.jbef.2022.100723.

Marcel Prokopczuk, Andrei Stancu, Lazaros Symeonidis, The economic drivers of commodity market volatility, Journal of International Money and Finance, Volume 98, 2019, 102063, ISSN 0261-5606, https://doi.org/10.1016/j.jimonfin.2019.102063.

Muhammad Umar, Yasir Riaz, Imran Yousaf, Impact of Russian-Ukraine war on clean energy, conventional energy, and metal markets: Evidence from event study approach, Resources Policy, Volume 79, 2022, 102966, ISSN 0301-4207, https://doi.org/10.1016/j.resourpol.2022.102966.

Oluwasegun B. Adekoya, Johnson A. Oliyide, OlaOluwa S. Yaya, Mamdouh Abdulaziz Saleh Al-Faryan, Does oil connect differently with prominent assets during war? Analysis of intra-day data during the Russia-Ukraine saga, Resources Policy, Volume 77, 2022, 102728, ISSN 0301-4207, https://doi.org/10.1016/j.resourpol.2022.102728.

Reuters, 2022. Timeline: The events leading up to Russia's invasion of Ukraine, available at: https://www.reuters.com/world/europe/events-leading-up-russias-invasion-ukraine-2022-02-28/

Sabri Boubaker, John W. Goodell, Dharen Kumar Pandey, Vineeta Kumari, Heterogeneous impacts of wars on global equity markets: Evidence from the invasion of Ukraine, Finance Research Letters, Volume 48, 2022, 102934, ISSN 1544-6123, https://doi.org/10.1016/j.frl.2022.102934.

Yihan Wang, Elie Bouri, Zeeshan Fareed, Yuhui Dai, Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine, Finance Research Letters, Volume 49, 2022, 103066, ISSN 1544-6123, https://doi.org/10.1016/j.frl.2022.103066.

The Economic Costs of the RussiaUkraine Conflict. (2022, mars). National Institute of economic and social research. https://www.niesr.ac.uk/wp-content/uploads/2022/03/PP32-Economic-Costs-Russia-Ukraine.pdf

World Bank Group. (2022, 4 octobre). *Russian Invasion of Ukraine Impedes Post-Pandemic Economic Recovery in Emerging Europe and Central Asia*. World Bank. https://www.worldbank.org/en/news/press-release/2022/10/04/russian-invasion-of-ukraine-impedes-post-pandemic-economic-recovery-in-emerging-europe-and-central-asia

https://onlinelibrary.wiley.com/doi/epdf/10.1111/eufm.12386

Lloyd, N. (2022, 8 juin). *How has Europe's economy been affected by Russia's war in Ukraine ?* euronews. https://www.euronews.com/next/2022/06/08/how-has-europe-s-economy-been-affected-by-russia-s-war-in-ukraine

https://onlinelibrary.wiley.com/doi/10.1111/twec.13336

European Central Bank. (2022, 25 mai). *Russia-Ukraine war increases financial stability risks, ECB Financial Stability Review finds*. https://www.ecb.europa.eu/press/pr/date/2022/html/ecb.pr220525%7Efa1be4764d.en.html