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***Abstract**:*

International politics and economics are not independent. Often, countries face economic sanctions or deteriorated economic prospects because of adverse political developments. Foreign trade (exports and imports of goods), capital flow in form of foreign direct investments (FDI) or cross-border capital investments have frequently been studied to understand political relationships between countries. On one hand, we have quantitative macroeconomic indicators, and on the other we face qualitative multilevel political relations and events. To better understand the intertwined nature of economics and politics, we use the digitized massive archival news data, the Global Database of Events, Language, and Tone (GDELT) to model and systematically quantify global political processes. We then apply statistical and machine learning methods to analyze these political events correlations with global economies and societies. We categorize countries in four groups, based on the World Bank's income classification, and find that international relations have strong correlation with economic parameters, highly dependent on countries' income levels.

***Keywords**: Trade, FDI, International Relations, Data Science, GDELT, World Bank's income classification.*

***ACM Classification Keywords**: Information systems → Information systems applications → Data mining*

Introduction and related work

Trade and capital flows are important factors shaping international relations between countries because they affect broad economic developments that include resource transfer, job creation, and knowledge transfer [1]. Although most international trade and capital flows are carried out by the private sector, political leaders have a significant stake in directing their national trade and international capital flows. Sanctions, which are targeted, to specific variables, could limit or restrict the flow of goods and private investments. Powerful states have a long tradition of economic statecraft. Widely reported incidents suggest that governments continue to manipulate trade in response to political disputes [6]. In 2014, for example, the United States and the EU announced a range of economic penalties to punish Russian intervention in Ukraine, and Russia retaliated with its own boycotts of agricultural products from Europe. Politically-motivated trade disruptions, however, are not limited to formal declarations of economic sanctions about a use of force.

Evolutions of political processes are highly convoluted, appearing at times to have significant momentum and to follow well-planned paths, yet at other times they deviate substantially from desired routes [2]. Investigating the relations between political events and economic trends is challenging task that inspires many researchers to search for patterns, and attempt to forecast future developments.

For example, in [3] the authors present a study about the effect of trade, and financial integration on the relationship between growth and volatility. The complex interaction between trade and politics is analyzed for Japan and China using Granger causality approach. Results show that the economic relationship underpins and constrains the political relationship between Japan and China while an increase in positive political news and a decrease in negative political news promote trade to some degree [4].

In the past, most of the analysis has been based on trade and FDI datasets. The correlation between economic indicators and political relations was studied mainly on a country by country basis, or it was centered on limited datasets with a partial list of political events. In this study, we use a publicly available dataset, the Global Database of

Events, Language, and Tone (GDELT)[1] that contains more than 400 million events and offers an opportunity to investigate the correlations between countries economic and political relationship on a global level. Because of its worldwide coverage and high granularity, the GDELT dataset is used in various fields of research. For example, authors in [6] examine the effects of foreign relations on bilateral trade through state ownership of firms, which is an important form of government control. The study focuses on China and India and the analysis is based on bilateral trade data by firm ownership type, bilateral political relations based on diplomatic events and UN voting as well as GDELT data to estimate, the effect of political relations on import and export flows. The results show that imports controlled by state-owned enterprises exhibit stronger responsiveness to political ties than imports controlled by private firms. The authors in [8] analyze the effect of political motivations for economic integration. Using the GDELT dataset on political events and data from [9] on economic integration agreements the paper confirms the impact of political motivations for economic integration agreements. Additionally, based on GDELT dataset, the author proposes two indices: bilateral political importance and mood, which can be used to describe the state of political relations between two countries. The GDELT dataset is also used for predicting social unrest events [10]. The authors conduct empirical testing with data from five countries in Southeast Asia to demonstrate the effectiveness of their framework. They conclude that GDELT dataset does reflect some useful precursor indicators that reveal the causes or development of future events. The GDELT dataset together with data from World Values Survey, World Bank, Freedom House, and Transparency International is used in [11] to examine the contradictory claims of the Modernization theory and World-systems analysis regarding the modern social change. The study presented in [12] uses GDELT dataset and data from Crimson Hexagon Buzz Monitor, to analyze Chinese public diplomacy. Yuan [13] uses the GDELT to model the image of China in mass media, specifically, how China relates to the rest of the world, and how these relations have evolved over time, based on an autoregressive integrated moving

[1] http://www.gdeltproject.org/

average (ARIMA) model. In [14] authors have used the GDELT dataset to explore the connections between crude oil prices and political relations of major oil-exporting and oil-importing countries.

The authors in [16] use similar approach to analyze the interdependence of trade and conflict. The main empirical result in the paper is that exports and imports have opposite effects on conflict. While exports lead to a lower conflict against the destination, imports increase conflict against the origin. The authors conclude that the opposite effects of imports and exports may partially cancel out if, as is often the case, trade exists in both directions within a dyad. They also show that a highly unbalanced bilateral trade could create conflict pressures in the country where the deficit occurs. The study focuses on analysis of correlations between trade and militarized conflict, while in reality, all conflict types and all collaboration types have a direct or indirect impact on economic relationships between countries.

In this paper, we analyze countries based on their income level and investigate the relations between trade and FDI on one hand and and political relations on the other. To create a succinct global representation and obtain more general conclusions of our study, we organize similar countries in groups. There are many different methods to group countries, based on their development, political systems, or geographic relations; however, one of the most widely used classification that relates to macroeconomic indicators, is the World Bank's income classification, where countries are classified in four groups, low-income (LI), lower middle-income (LMI), upper middle-income (UMI), and high-income (HI), based on the countries' gross national income (GNI) per capita in current prices. For the current 2017 fiscal year, low-income economies are defined as those with a GNI per capita, calculated using the World Bank Atlas method, of $1,025 or less in 2015; lower middle-income economies are those with a GNI per capita between $1,026 and $4,035; upper middle-income economies are those with a GNI per capita between $4,036 and $12,475; and high-income economies are those with a GNI per capita of $12,476 or more[1]. In this research, we utilize GDELT a digitized massive archival news data, which gives us the opportunity to

[1] https://blogs.worldbank.org/opendata/new-country-classifications-2016

model and systematically analyze the political processes and their correlations to economy and society.

Data and Methodology

In scientific discovery, the first three paradigms were experimental, theoretical and the most recent, computational science. But the world of science is changing. An unprecedented amount of data is being generated at increasingly rapid rates in many disciplines. Because of this, new techniques and technologies for data-driven science have emerged [15]. They belong to the field of data science and are different enough to distinguish them as a new, forth paradigm for scientific exploration [20].
Today, a number of datasets, related to international relations exist, offering an immense opportunity to apply data science in this field. Our study is based on three massive datasets GDELT, UN COMTRADE, and UN UNCTAD, covering economic and political relations among almost all countries in the world.

Data

We use GDELT [21] a machine-coded event data to analyze bilateral political relations among countries. The GDELT Project currently consists of over a 400 million event records in more than 300 categories covering the entire world from 1979 to present, connecting news and events in a large network of key persons, organizations, locations, and themes. Organized into a single massive network that captures important worldwide economic, political, and alike events, GDELT offers a context of major worldwide events, the relations between “actors” of such events, as well as the worldwide sentiments about such events on daily basis. GDELT event records are represented using the dyadic Conflict and Mediation Event Observation (CAMEO) [22] format, capturing two actors, and the action performed by Actor1 upon Actor2. A wide array of variables that are added to the CAMEO actor codes facilitates the data interpretation. For each event, the Goldstein ranking score is provided, complemented by the average tone score of the event, additional indicators of importance, as well as a special array of geo-referencing fields, to enable estimated landmark-centroid-level geographic positioning of both actors and the location of the action.

To complement the GDELT dataset with global macroeconomic data, we additionally collected more than 3 million rows of data. The first dataset (2.9 million rows) contains trade data between countries from 1990 up until 2015. This data was obtained by crawling the UN trade data API[1]. The data consists of two countries for which the trade value was reported, the year in which the trade was effected, the trade rg_code (1-import or 2-export, 3-re-Import or 4-re-export), the trade value in millions US Dollars and the trade type.

The second dataset (210 thousand rows) contains Foreign Direct Investments (FDI) data for countries obtained from the UN Conference on Trade and Development[2]. One row of this data set consists of two countries (host economy and investor), year in which the investment was made, the investment value (in millions of US dollars) and the investment type.

Indices

The analysis of political relations between countries is based on the Goldstein Index (GSi) that is defined in the GDELT dataset. GSi or Goldstein Scale has values between -10 and +10 and describes the potential theoretical impact that a type of event couldl have on the stability of countries involved in the event. Goldstein Scale score of -10 indicates intense conflict, and a score of +10 means active cooperation between countries. Because Goldstein Scale score is strongly related to the type of event, two different events (of different scale and with different impact) of the same type receive the same Goldstein score. Thus, an aggregation of Goldstein Scale score is needed to be able to yield an approximation of the stability of a location or country over time. If we take into consideration only the average of the Goldstein Index, we will be giving the same weight to all events, while not all events are equally important. To solve this problem, we need to take into consideration the number of mentions an event has, the number of

[1] https://comtrade.un.org/data/doc/api/

[2] http://unctad.org/en/Pages/DIAE/FDI%20Statistics/FDI-Statistics-Bilateral.aspx

articles that were written about the event and the number of sources reporting on the event. Therefore, we define Average weighted Goldstein Index, by multiplying the Goldstein Index with the number of mentions/articles/sources, and then we divide it by the total sum of the number of mentions/articles/sources. To see which one of these variables is giving most dispersed values, we analyze the standard deviation of all of them and we find that a number of articles is creating the most dispersed variable, hence, we select it as the most relevant. The modified Goldstein Index is then defined as:

$$mGSi=Sum(GSi*NumberArticles)/Sum(NumberArticles) \tag{1}$$

The trade intensity index (T) is used to determine whether the value of trade between two countries is greater or smaller than would be expected based on their importance in world trade [18]. It is defined as the share of one country's exports going to a partner divided by the share of world exports going to the partner. It is calculated as:

$$T_{ij} = (x_{ij}/X_{it})/(x_{wj}/X_{wt}) \tag{2}$$

Where x_{ij} and x_{wj} are the values of country i's exports and world exports to country j respectively; X_{it} and X_{wt} are country i total exports and total world exports respectively. It is interpreted in much the same way as an export share. It does not suffer from any 'size' bias, so we can compare the statistic across regions, and over time when exports are growing rapidly. An index of more than one indicates a bilateral trade flow that is larger than expected, rendering the source country as more important partner with a stronger positive relationship. Values smaller than 1 indicate a 'mild' trade relationship from source to destination, meaning that the destination is not such an important partner, and thus we can interpret this as a negative relationship.

To have a comparable value to the Goldstein Index that is used to quantify the events in CAMEO scale, we modify the definition (2) taking logarithm of T, to obtain positive numbers for values of T greater than one, and negative numbers for values of T smaller than one. The adjusted Trade Intensity Index T' is defined as:

$$T'_{ij}=\log(T_{ij}) \tag{3}$$

Similar to Trade Intensity index we can define FDI Intensity index [19] as:

$$FDI_{ij} = (f_{ij}/F_{it})/(f_{wj}/F_{wt}) \tag{4}$$

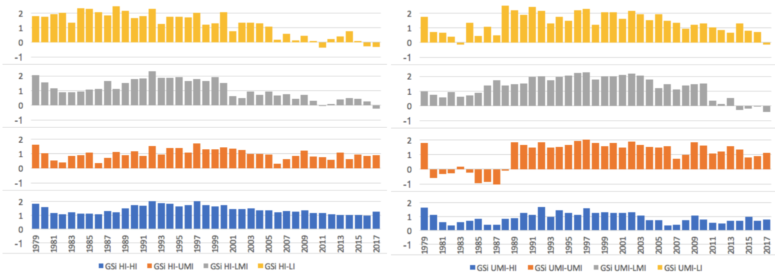
Where f_{ij} and f_{wj} are the values of country i's FDI and world FDI to country j; F_{it} and F_{wt} are country i total FDI and total world's FDI respectively. And for the same reasons as for Modified Trade Intensity Index we define Adjusted FDI Intensity index as:

$$FDI'_{ij}=\log(FDI_{ij}) \tag{5}$$

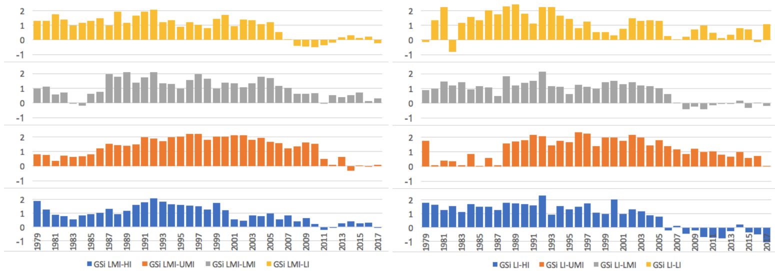
Tools

GDELT's dataset is publicly available on Google's BigQuery platform which provides SQL query interface. We used BigQuery platform to obtain the required data for our analysis. We imported the downloaded data into R, RapidMiner and Microsoft Excel, and proceeded with our analyses using these tools.

Results and discussion

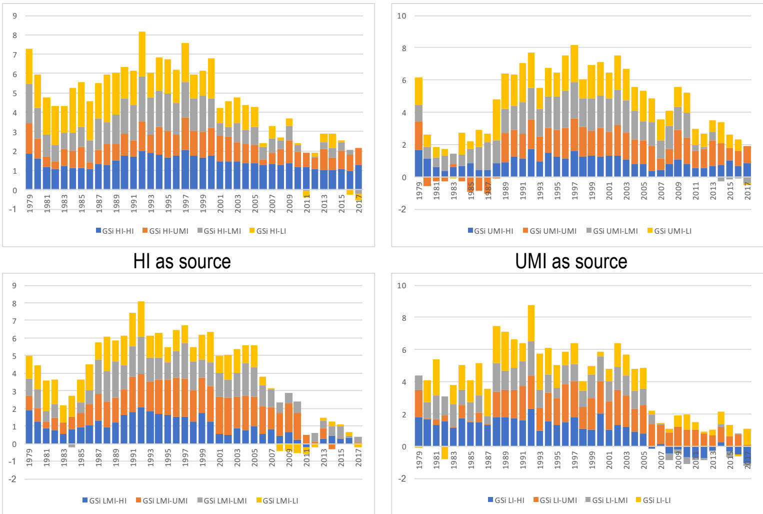


HI as source UMI as source



LMI as source LI as source

Figure 1 Average Goldstein Index between different income groups in the period from 1979 to 2017

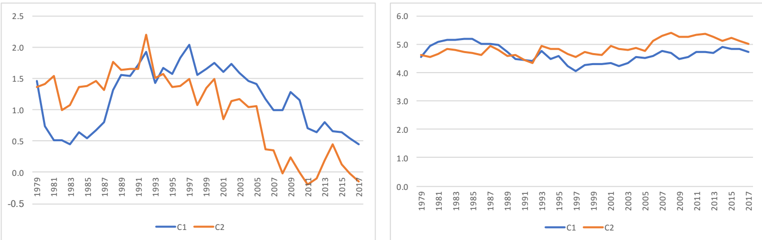


LMI as source LI as source

Figure 2 Stacked Average Goldstein Index between different income groups in the period from 1979 to 2017

The average Goldstein index on a yearly basis between different income groups starting from 1979 to 2017 is shown in Figure 1 as a bar chart and on Figure 2 as stacked bar chart. It is interesting to note that the HI-HI relationship is the most stable (average stdev=4.3) and most positive one, and LI-LI most volatile (average stdev=5.00). The most negative relationship is LI-LMI and the second lowest is LI-HI relationship. From the stacked bar chart, we notice that the political relations are worsening in the last two decades. In this period, there are only six pairs out of 16 that are positive (HI-HI, HI-UMI, UMI-UMI, UMI-HI, UMI-LI, and LI-UMI) and all other relationship pairs are negative or close to zero. This is an interesting observation showing that conflict dominates collaboration in the last two decades, especially in political relations where LI and LMI countries are involved.

To further analyze political relation, we apply k-means clustering to create two clusters. In the first, we have the following relation pairs: HI-HI, HI-UMI, UMI-HI, UMI-UMI, UMI-LMI, UMI-LI, LMI-UMI, LMI-LMI, and LI-UMI. The second cluster is composed of HI-LMI, HI-LI, LMI-HI, LMI-LI, LI-HI, LI-LMI, and LI-LI. It is interesting to note that C1 consists of the pair HI-HI, all six pairs of the Upper-middle-income group and LMI-LMI pair.

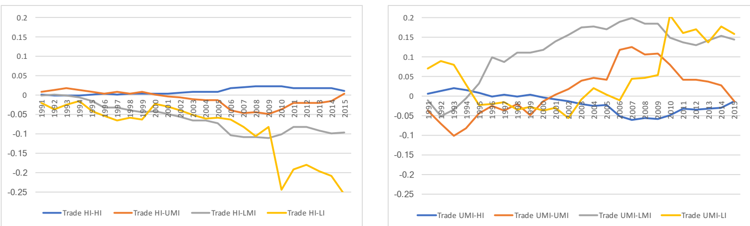


a) Clustering based on average Goldstein index

b) Clustering based on average Standard Deviation of Goldstein index

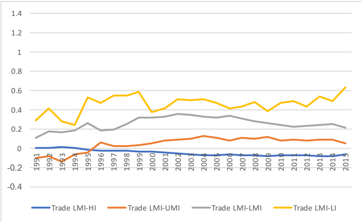
Figure 3 The line plot of cluster's centers through years

The line plot of cluster's centers through the years is shown in Figure 3. Cluster C1 has lower average Goldstein index than C2 from 1979 until 1993, when the situation changes and the group pairs that are part of C1 have better international relationships.

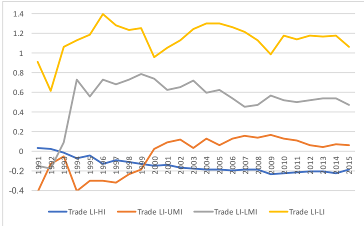


HI as source

UMI as source



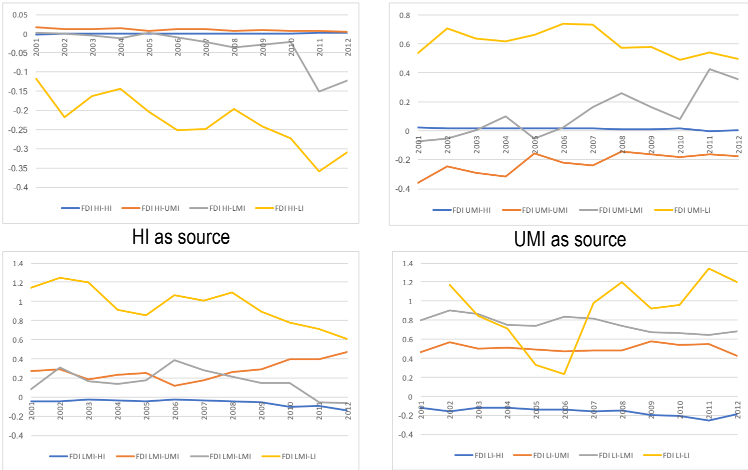
LMI as source



LI as source

Figure 4 Adjusted Trade Intensity Index between different income groups in the period from 1991 to 2015

In Figure 4 we show the adjusted trade intensity between different income groups in the period from 1991 to 2015. Analyzing the index when HI countries are the source of the trade we can see that HI has mainly negative adjusted trade intensity index with all others groups, which means that they are trading (exporting) with them less than it would be expected. HI group has positive adjusted trade intensity index only whit the HI countries, meaning that HI countries prefer to trade among themselves more than it is expected. The UMI countries have a negative index with HI, so they do not export as expected to HI countries. The relationship with countries in the same group is oscillating, so while they tend to have negative index values until 2000, their collaboration changes and it is positive reaching the maximum around 2008, when the index starts declining again achieving negative values in 2015. This movement is entirely opposite of the trade relations with HI countries. This can be interpreted as follows: improvement in trade relations with the HI group results in worsening of the relations with UMI group and vice-versa.
The relations with LMI are positive and constant over time, while the relations with LI have significantly improved in the last decade.
LMI and LI have similar values and arrangements for adjusted trade intensity index, with the main characteristic being that they are more constant over the analyzed period compared to HI and UMI group indices. The LMI and LI groups have positive trade (export) relations with LI, LMI and UMI and negative trade relations with HI.



HI as source UMI as source

LMI as source LI as source

Figure 5 Adjusted FDI Intensity Index between different income groups in the period from 2001 to 2012

In Figure 5, we show the adjusted FDI Intensity Index between different income groups in the period from 2001 to 2012. From the first chart where HI are sources of FDI (meaning they are investors), we can see that HI have an adjusted FDI intensity index that is near zero when the target countries are in the same group, meaning that their FDI in the HI group is almost ideal. HI countries have a positive index when UMI are a destination, meaning that they are investing more that it is expected, and the index for LMI and LI is negative showing that the HI countries do not have appropriate FDI in the poorest countries' groups.

From the chart where UMI is the source, we can conclude that UMI group is having balanced FDI relations with HI, and positive index with LMI and LI. It is interesting to note that FDI relations between countries in the UMI group are the worst, which means that UMI countries do not have FDI in similar countries as expected. The last two groups LMI and LI have a negative adjusted FDI intensity index with HI countries, meaning that there is no adequate level of FDI from these countries to HI countries as expected. LMI and LI have positive indices with the other three groups.

	Trade HI-HI	Trade HI-UMI	Trade HI-LMI	Trade HI-LI	Trade UMI-HI	Trade UMI-UMI	Trade UMI-LMI	Trade UMI-LI	Trade LMI-HI	Trade LMI-UMI	Trade LMI-LMI	Trade LMI-LI	Trade LI-HI	Trade LI-UMI	Trade LI-LMI	Trade LI-LI
GSi HI-HI	-0.846	0.696	0.874	0.775	0.781	-0.727	-0.721	-0.572	0.884	-0.706	-0.339	-0.337	0.822	-0.729	-0.172	-0.245
GSi HI-UMI	-0.656	0.620	0.613	0.472	0.652	-0.621	-0.432	-0.500	0.512	-0.339	-0.102	0.063	0.466	-0.505	0.167	-0.257
GSi HI-LMI	-0.837	0.728	0.862	0.693	0.798	-0.765	-0.773	-0.482	0.896	-0.777	-0.403	-0.285	0.857	-0.812	-0.235	-0.244
GSi HI-LI	-0.848	0.725	0.835	0.734	0.777	-0.697	-0.627	-0.569	0.746	-0.570	-0.209	-0.239	0.740	-0.695	-0.112	-0.214
GSi UMI-HI	-0.768	0.729	0.744	0.524	0.767	-0.736	-0.606	-0.454	0.692	-0.540	-0.259	-0.072	0.648	-0.645	-0.032	-0.388
GSi UMI-UMI	-0.493	0.391	0.500	0.490	0.444	-0.373	-0.295	-0.490	0.402	-0.215	-0.023	-0.086	0.314	-0.417	0.162	-0.023
GSi UMI-LMI	-0.630	0.371	0.623	0.832	0.477	-0.354	-0.344	-0.773	0.604	-0.340	0.087	-0.265	0.551	-0.464	0.060	-0.040
GSi UMI-LI	-0.664	0.488	0.625	0.690	0.544	-0.428	-0.364	-0.598	0.548	-0.320	-0.029	-0.214	0.538	-0.521	-0.059	-0.097
GSi LMI-HI	-0.816	0.683	0.846	0.730	0.761	-0.723	-0.753	-0.485	0.878	-0.759	-0.384	-0.340	0.857	-0.773	-0.284	-0.231
GSi LMI-UMI	-0.612	0.341	0.593	0.843	0.448	-0.319	-0.305	-0.794	0.573	-0.303	0.116	-0.266	0.521	-0.432	0.075	-0.007
GSi LMI-LMI	-0.711	0.527	0.653	0.721	0.570	-0.452	-0.411	-0.586	0.613	-0.407	-0.109	-0.203	0.637	-0.491	-0.182	-0.103
GSi LMI-LI	-0.889	0.769	0.821	0.749	0.801	-0.698	-0.584	-0.581	0.712	-0.555	-0.090	-0.257	0.726	-0.576	-0.182	-0.239
GSi LI-HI	-0.884	0.745	0.837	0.785	0.795	-0.696	-0.590	-0.645	0.743	-0.543	-0.130	-0.238	0.735	-0.645	-0.091	-0.247
GSi LI-UMI	-0.759	0.568	0.714	0.792	0.632	-0.507	-0.411	-0.718	0.621	-0.363	-0.011	-0.214	0.590	-0.573	0.017	-0.062
GSi LI-LMI	-0.866	0.714	0.805	0.798	0.759	-0.646	-0.534	-0.638	0.685	-0.489	-0.019	-0.261	0.687	-0.514	-0.138	-0.223
GSi LI-LI	-0.638	0.603	0.683	0.411	0.642	-0.632	-0.670	-0.108	0.627	-0.619	-0.324	-0.289	0.631	-0.374	-0.394	-0.314

Figure 6 Correlation matrix between adjusted trade intensity index and Goldstein index

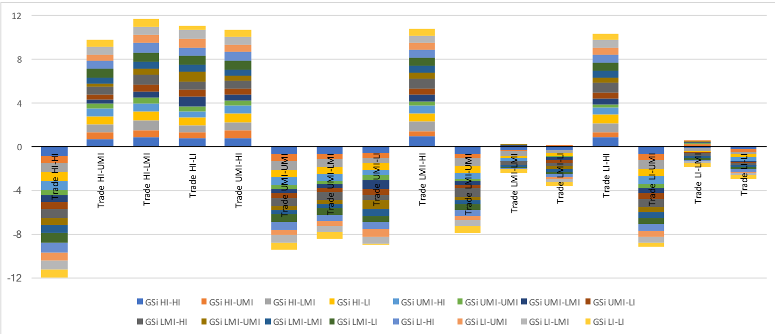


Figure 7 Stacked bar chart of correlation matrix between adjusted trade intensity index and Goldstein index

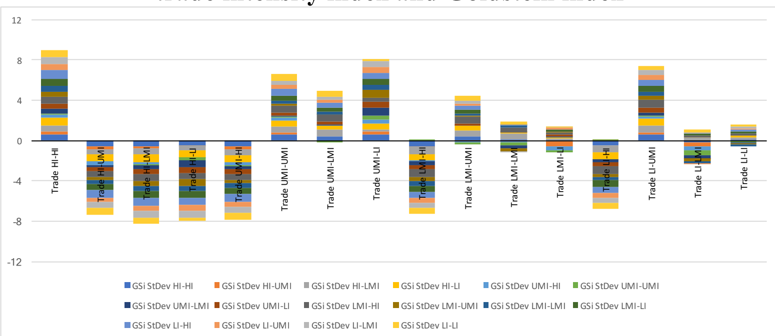


Figure 8 Stacked bar chart of correlation matrix between adjusted trade intensity index and the standard deviation of Goldstein index

To investigate the interdependence and correlations between political and economic relations we calculate the correlation matrix between adjusted trade intensity index and Goldstein index (Figure 6). From the matrix, we can see that there are groups of correlations that are mainly negative and another group that is primarily with positive correlations. To better represent the relations between the trade and FDI indices with the Goldstein index, we show the correlation matrix as a stacked bar chart. On the x-axis, we place the columns of the matrix and based on the values of the correlations, the corresponding stacked bars are plotted, with a different color for each matrix row (shown in the legend).

With this type of visualization, in Figure 7, we show the stacked graph of the correlation matrix between adjusted trade intensity index and Goldstein Index for all four countries' income groups. The main feature we observe is a different pattern of correlations related to HI countries compared to the correlations shown in all other groups. The correlations between trade and political relations, when HI countries are the source and destination of trade, are negative, and the trade originating from HI, when destinations are all other groups, has positive correlations with political relations. This simply suggests that the HI countries increase their trade with other groups when political relations are improving, and decrease the trade when there is worsening of the relations. In contrast, the trade of HI countries within the group has opposite pattern, which means that when there is worsening of international relations, the HI countries increase the trade among themselves, and when there are improvements in the international relations, they start trading with other countries. The other countries belonging to UMI, LMI and LI groups have opposite patterns regarding the correlation of their trade and international relations. We can summarize these patterns as follows: the HI countries adjust their trade with other groups based on their political relations with these groups, and all other countries do the same in relation to HI.

To understand how fluctuations in international relations are correlated with the trade, we further analyze adjusted trade intensity index and the standard deviation of Goldstein index, and the results from this analysis are shown in Figure 8. From this analysis, we can see that the correlations are significant, but opposite from the correlations in the previous case. This means that when fluctuations of the international relations increase (that there are more extreme events) the HI countries tend to trade with themselves and when fluctuation of international relations decrease (there are a smaller number of extreme events) then HI start to increase their trade with other income groups.

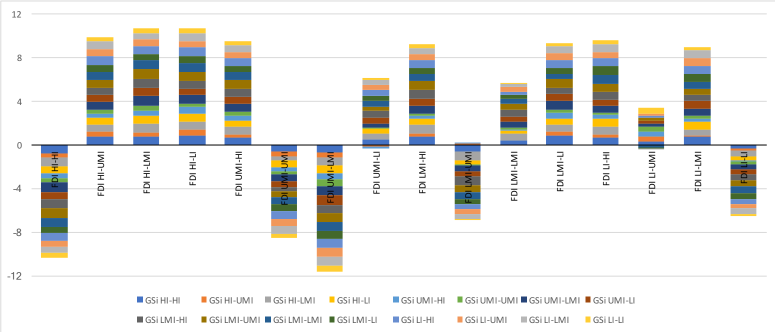


Figure 9 Stacked bar chart of correlation matrix between adjusted FDI intensity index and Goldstein index

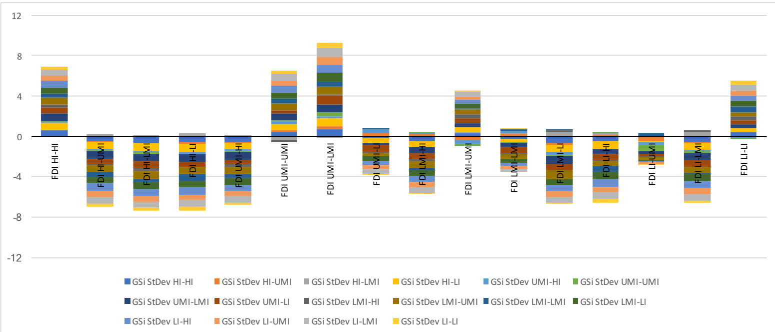


Figure 10 Stacked bar chart of correlation matrix between adjusted FDI intensity index and the standard deviation of Goldstein index

Another important global macroeconomic indicator is FDI. In Figure 9 we present the stacked bar chart of correlation matrix between adjusted FDI intensity index and Goldstein index. We observe that most of the correlations are positive, and in total there are more positive correlations than in the case of trade. This means that FDI is more positively correlated to political relations, meaning that if there is an improvement in international relations then the FDI will increase. The FDI from HI to HI, UMI to UMI, UMI to LMI, LMI to UMI, and LI to LI has negative correlations with international relations. This result leads to an interesting observation that generally when there is deterioration of international relations the countries tend to increase their FDI with countries from the same group (except for LMI to LMI).

Discussion

The primary focus of this paper is to use the data science paradigm to explore interdependence of global economy represented by the dataset on trade and FDI and political relations based on the dataset provided by the GDELT project. Goldstein index has values in the range of -10 to +10, while the trade and FDI intensity indices have values between 0 and +infinity.

To be able to compare trade, FDI, and international relations, we transformed the trade and FDI intensity indices into new measures, named adjusted trade and FDI intensity index, obtained as a logarithms of the trade and FDI intensity indices. With this transformation, we created comparable variables, which are interpreted in the same way, e.g. if the index is positive then the relations are good, while if the index is negative it indicates bad relationships.

Based on these transformations, we created a new set of feature variables that we used as input in our model. We conducted a series of analysis, and we showed that there are significant correlations between political and economic relations among countries.

Besides these general findings, one of the main results is that HI countries have an opposite correlation pattern between trade and international relations compared with all other income groups. This supports the findings from [6][7], and it is a consequence of the fact that powerful states are building economic statecrafts in response to political disputes. This effect is most pronounced for the UMI countries, which means that they are completely opposite from HI countries. This is yet another proof of the so-called Middle-Income Trap that refers to a group of countries that became middle-income some time ago, but have not been able to cross the high-income threshold yet [17][5].

Conclusion

In this paper, we present analysis of the interdependence of global economy, represented by the trade and FDI flows, and international relations.

The proposed model is centered on transformed, new feature variables, adjusted trade intensity index and adjusted FDI intensity index. Together with Goldstein index the transformed economic variables are the basis for the analysis. We study correlations, clustering, and employ a variety of visualization techniques to show our results.

The general conclusion is that there is a significant correlation between economic and political relations. The results suggest that relations with HI countries exhibit completely opposite patterns for economic-political correlations compared with the relations with all other countries. This can be interpreted as a possibility of high-income countries to adjust political relations in line with their economic goals. Another interesting finding is that the upper middle-income countries have the most opposite economic-political correlations compared to high-income countries, which is another proof of the existence of the middle-income trap.

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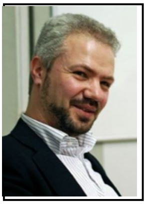

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