The effect of Eurasian Economic Union on the trade volume of its member states in the dynamics social network

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Abstract. After the collapse of the Soviet Union, the former states have been supporting active relations and recently formed a new union between the 5 countries. Eurasian Economic Union (EAEU) united Russia, Belarus, Kazakhstan and later on brought Kyrgyz Republic and Armenia. EAEU was created with the purpose of promoting free trade flows between the member states and increase the level of cooperation both politically and economically. The research specifically looks at the total trade volume between the member states and compares dynamics in the trade network of EAEU to the rest of the world 2 years prior to the formation of the union and 7 years after. The paper presents a unique study that utilizes Social Network Analysis as a method of analyzing dynamic relationships between the actors in the network and further integrates it into a regression model, utilizing attribute data.

Keywords: Eurasian Economic Union· Social Network Analysis· Dynamic Social Network· Actors· Nodes· Attributes · Ordinary Least Squares ·

1 Introduction

Founded in 2010, the Eurasian Economic Union was initially meant to be an integration platform for the Post-Soviet Union countries, presenting both economic and political importance to the region. In other words, a “cohesive economic entity” that promotes free trade within its member states [1]. It was founded by Russian Federation, Belarus and Kazakhstan, promptly joined by Kyrgyzstan and Armenia in 2015. The union has a geographical advantage for its states. It supplies natural resources within the union. EAEU brought major mutual novelties such as common import tariff and customs code. It is important to note that each of the countries had their own reasons prior to joining the union specifically Russia. The customs union presents rather a political and strategic importance to the dominant country in the face of Russia on top of the economic advantages from the trade.

The main purpose of the research is to compare the trends in the total volume of trade within the 5 member states relative to the total volume of trade of the five member states with the rest of the world over time. The research horizon spans from 2008, two years before the union was founded until 2017, two years after the two final members states joined EAEU. The main assumption made in the paper is that the level of trade between the members states has increased as the countries entered a mutual economic platform. Assuming that Russia is believed to be the most influential member, we expect its influence would increase over time. In order to answer these questions, the research integrates two kinds of data- relational and attribute. Relational data is taken in order to define relationships between pairs of countries (dyads) and plots them in the Social Network Analysis. Taking the research one step further, the study takes into account actor attribute data and portrays the relationships between the Social Network Analysis generated metrics and attribute data in the regression analysis to further enhance the research.

2 Literature Review

Exploring the dynamics of the relations between the members of EAEU may reveal interesting findings. Based on the past analysis, Russia's role in the union has mostly political meaning. Strengthening ties within the CIS countries in order to "counter-act" third power countries' economic expansion in the region is, presumably, one of the main goals of Russia [2]. However, having established this union, Russia seems to be no longer interested in integrating further as it has already achieved its initial goal. Integrating further would require sacrificing some flexibility, which is not in the best interest of the country. The remaining EAEU countries view this economic integration as a potential to enrich their economies yet remain cautious about Russian dominance. Smaller countries such as Kyrgyz Republic, Belarus and Armenia are hoping to better off economically from Russia, which is not in the best interest of the dominant power. The initial goal in 2011- 2012 was to begin a rapid process of integration, allowing businesses to freely move within its members states. That way, the companies would find more tax friendly countries to operate it, which seems to be failing thus far [3]. To sum up, the country's potential integration within the union remains huge and is prognosed to be fully integrated by 2020 [2].

In order to analyze this phenomenon, we seek to deploy Social Network Analysis. There is a number of literature applying Social Network Analysis studies in international trade of various forms that inspired the current study. Zhou et al., in their work *Structure and formation of top networks in international trade,* used Social Network Analysis to analyze the global trade networks [4]. The nodes are presented as individual countries. Interestingly, they treat import and export networks as separate networks. This is done in order to observe pure dynamics in each of the groups. Iaparde and Tajoli in their *Emerging countries and trade regionalization* article discuss the trade on both regional and global levels, which is consistent with the current study [5].
SNA is a very useful tool, however often times it gets limited when analyzed just by itself. As the previous literature recommends, it is common to combine both relational analysis with attribute data. William Simpson in his work uses SNA and Ordinary Least Squares analysis to analyze network in International Relations. In case if the data is binary, he recommends to use Logistic Regression. The main software used in the paper is UCINET [6].

3 Methodology

Despite an abundance of literature on the application of SNA in international trade there are no recent studies conducted within the framework of the EAEU. In fact, this paper presents a unique analysis of the trade dynamics of the 5 members states before and after joining the Eurasian Economic Union, integrating both relational and attribute data to conduct a more thorough analysis. The main two components of the analysis are Social Network Analysis (SNA) and a Pooled Ordinary Least Squares (OLS) analysis.

Social Network Analysis

In this study, we will be focusing on the directional network, where each individual node is an individual country and a relation that connects the two countries are the import and export percentage as a partner share correspondingly. Thus, if Russia exports a certain amount to Kazakhstan, then the direction of the arrow stems from Russia towards Kazakhstan. The opposite direction of the arrow will be going in case of imports into Russia from Kazakhstan. The data is taken for 9 years, from 2008 to 2017 excluding 2014 due to the absence of data for Kyrgyz Republic. Each year is treated as a separate network and every single one of them will be analyzed to track dynamic changes occurring over the course of time. This research however scrutinizes only a partial network, where the five countries are presented as the key players and their interactions with the rest of the world as well as with each other are being presented in the network. In case of a fully connected network, every single country would have been connected dyadically based upon the amount of trade connecting one country to another.

There are multiple centrality measures to detect whether an individual actor or node has a high degree of power, influence and importance. The first measure we consider is betweenness centrality. In simple terms, this measure detects how well a node is connected to all other nodes, without which the network would have been much weaker, i.e. less interconnected. Such node lies in between other nodes and without which it becomes hard for other nodes to connect. Having identified an actor with a high betweenness centrality will help give a clear idea of the influence of an actor in the network, without which the entire network would not have been as connected. Another measure of centrality is indegree and outdegree. Indegree measures the amount of relations towards the actor of interest. On the other hand, outdegree centrality measures the amount of links moving outward from the actor of interest. Thus, an actor with a high indegree centrality presents a high interest for other nodes in the network and the actor with high outdegree is said to be have an easy reach to other actors. The third measure of the interest is eigenvector centrality. Imagine an actor who is connected to those actors that are highly connected to other nodes. Therefore, looking at these particular measures would be a useful way to identify the most influential actors and specifically the dynamic changes over time.

Ordinary Least Squares

The study takes a step further by combining both relational and attribute data in Linear Regression Analysis. Having identified the dynamics in the trade networks over time, we are now interested in identifying the key correlates of the macroeconomic data and the dependent variable of our interest. Since the main question of the study is to identify whether the trade volume within the 5 member states has increased over time, we will be looking at the total trade between Russia, Belarus, Kazakhstan, Armenia and Kyrgyz Republic measured by the sum of total imports and exports in dollar value as a percentage of the total trade volume of the 5 countries with the rest of the world. In this case, the calculations are performed from the perspective of each of the 5 countries following the formula below, where country A is one of the countries of the Eurasian Economic Union:

Percentage trade, country A= (Total trade b/w country A and 4 remaining members) / Total trade b/w country A & the world .

Moving on to the independent variables, we still remember the metrics used in the Social Network Analysis which we will deploy in the baseline model. The main variable of interest in the model is the number of years the country has been a member of the union. The control variables include metrics derived from the Social Network Analysis such as betweenness centrality and indegree, as well as macroeconomic variables, namely unemployment rate, GDP and economic openness. All variables are taken on a country level, particularly for the 5 member states over the course of 9 years. The model below summarizes the baseline model for the Pooled OLS:

Percentage trade=b0+b1*unionyrs + b2*unemp + b3*lngdp + b5*econopen + b5*indeg + b6*betwcen + e .

4 DATA

The main source of the data is World Bank's World Integrated Solution (WITS) platform that contains bilateral data that is perfect for building a social network [7,8]. Regarding the attribute data, as mentioned, we take major macro-economic indicators such as GDP, Population, Economic Openness and Unemployment rate for each of the member countries for the same period of time. The table below provides a list of variables with a description, source and a time period. The variable of interested in marked with an asterisk.

Table 1. Variable Description

Variable	Description	Source	Period
Trade as percentage from total	A ratio of the trade between union members to the trade of members with the rest of the world	WITS World Bank	2008-2017 (excl 2014)
Import/Export percentage as partner share	Percentage import/export, partner share	WITS World Bank	2008-2017 (excl 2014)
GDP	USD	World Bank	2008-2017 (excl 2014)
Total Population	Count	World Bank	2008-2017 (excl 2014)
Economic Openness	A score from 0 to 100, with 100 being the most open	The Heritage Foundation	2008-2017 (excl 2014)
Number* of years in the union	A number of years the member country has been in the union	Investopedia	2008-2017 (excl 2014)
Unemployment	Unemployment rate measure in %	World Bank	2008-2017 (excl 2014)

The figure below shows the plot of the dependent variable, namely percentage trade from the total as an average of all 5 member states. As we can see over time, the trade volume between member states seems to be increasing gradually at a slow pace with a steeper behavior starting from 2016.

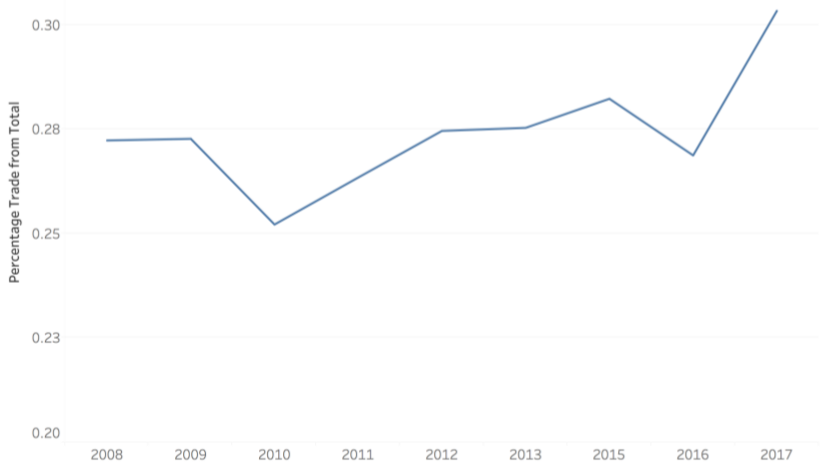


Fig. 1. Percentage trade between the 5 member countries as a ratio to the trade between the 5 countries and the rest of the world over time across all 5 countries.

Moving on from Figure 1 to Figure 2, we can see the dependent variable used in the linear regression in detail for each of the countries. The main takeaway from the graph is that Belarus and Kyrgyz Republic are the most dependent countries on the trade with the EAEU members. Belarus's trade within the union accounts for almost 50% of its total trade volume, whereas Russia appears all the way at the bottom with about 7% of its total trade volume within the boundaries of the union. As noted from the previous figure, all countries experience a sharp increase in trade starting from 2016.

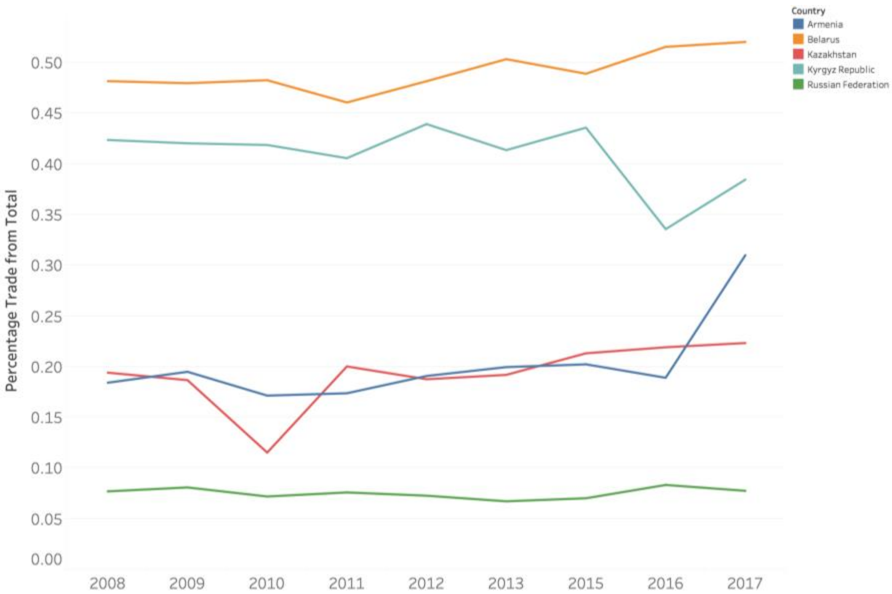
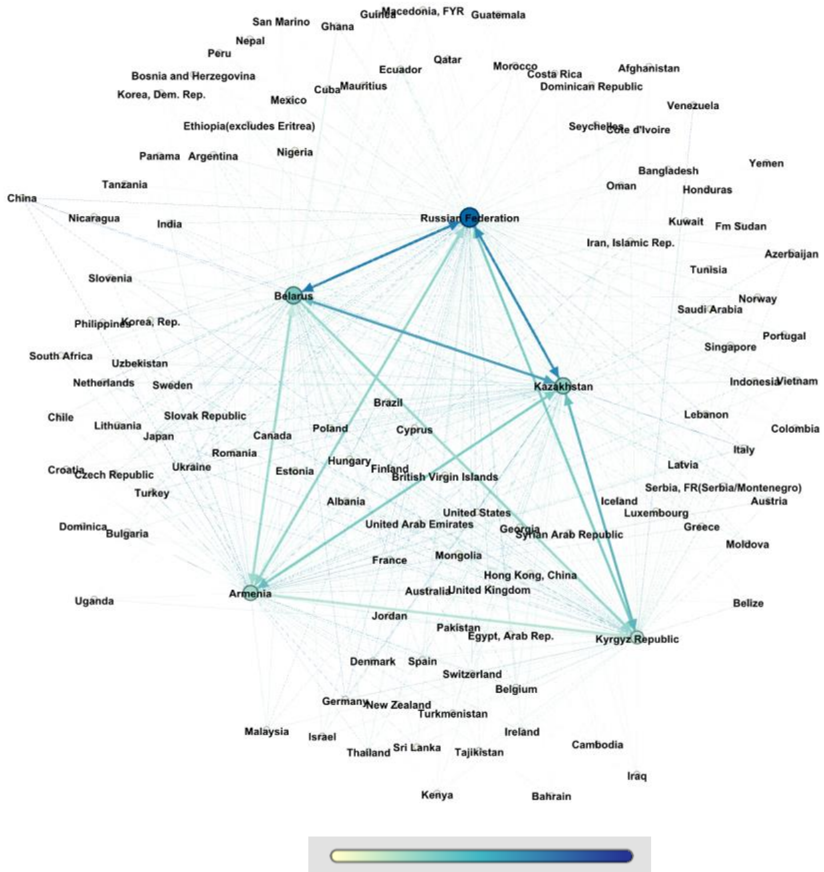


Fig. 2. Percentage trade between the 5 member countries as a ratio to the trade between the 5 countries and the rest of the world over time for each member country.

5 RESULTS

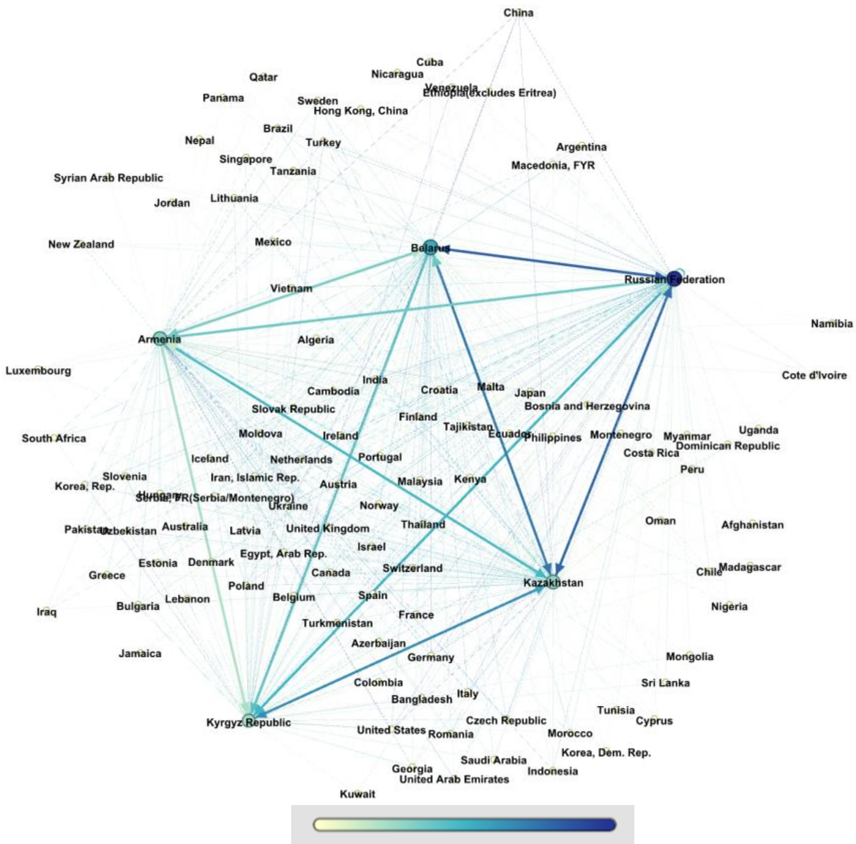
The figures below present graphs of social networks. For the sake of time, we will only focus on three time periods, 2008, 2015 and 2017. The first time period presents 2 years before the creation of the union. 2015 is the year when two more countries joined the union followed by 2017, when all 5 members were in the union, which is the latest year with available data. Each of the individual nodes (circles in the graph) depicts a single country of the world. In each of the graphs, the network is build based upon the interaction of the 5 key countries, namely Russia, Kazakhstan, Belarus, Kyrgyz Republic and Armenia with the rest of the world. Every node has a distinct size and a color code. The size of the node indicates its degree i.e. the amount of links that a node has in total. The color indicates betweenness centrality, where the darker color indicates higher betweenness centrality. The darker edge color indicates a higher value traded between two actors. The edge thickness is determined by the weight ranking.

Looking at 2008 we can immediately tell that Russia is the most influential actor. Its degree centrality judged by the node size is the largest in the entire partial network as well as the betweenness centrality. The next central player is Belarus, whose betweenness and degree centrality is the second largest in the network. Clearly the third most influential actor judged by the degree and betweenness centrality is Kazakhstan, followed by Armenia and Kyrgyz Republic, not necessarily in that order. The main takeaway from this graph is that the 5 member countries have a high volume of trade with each other, yet there is a number of other important trade partners that are not within the scope of this study. Namely, China appears to be an important actor that has high trade volumes with all 5 countries judging by the edge color.



Node- Betweenness Centrality
Edge- Value
Node size- Degree

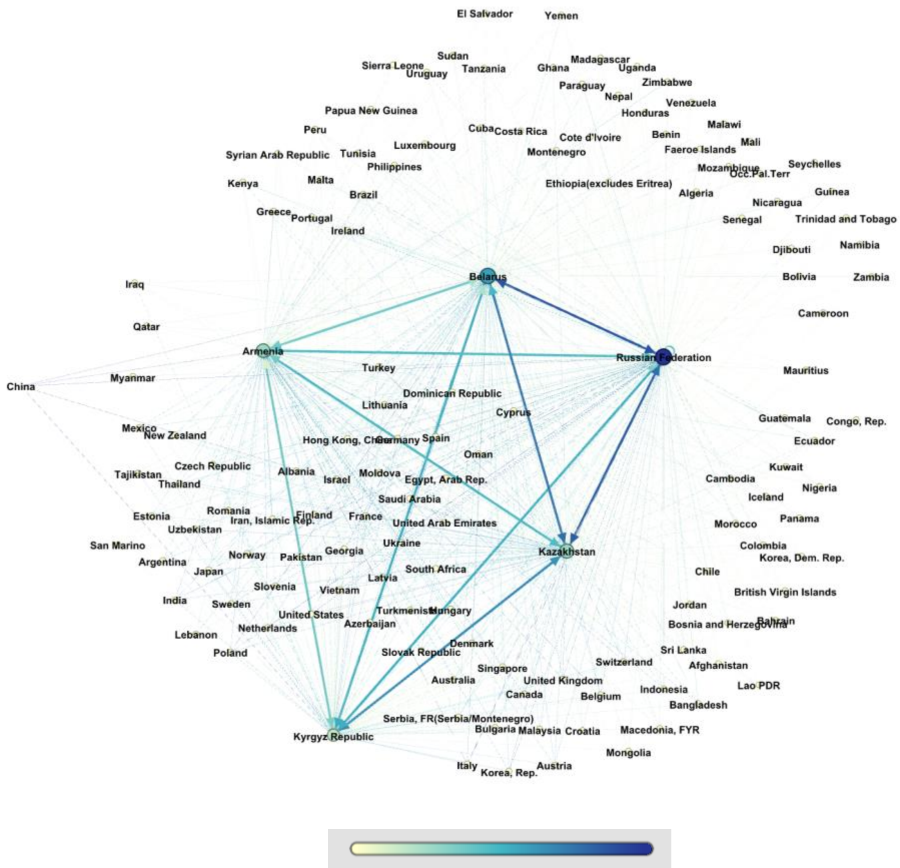
Fig. 3. 2008 Social Network of the 5 member states



Node- Betweenness Centrality
Edge- Value
Node size- Degree

Fig. 4. 2015 Social Network of the 5 member states

Figure 4 shows the social network for 2015, when all Kyrgyz Republic and Armenia joined the union. Russia still remains the most influential actor in the network judged by the two criteria. There seem to be no significant changes in the trade volume between the countries as well as with the rest of the world based on this graph.



Node- Betweenness Centrality
Edge- Value
Node size- Degree

Fig. 5. 2017 Social Network of the 5 member states

The final figure presents the most recent year, where again, Russia's position confirms to be stable across the time. There is not a lot of variation compared to the two previous graphs, which suggest that the dynamic changes are not quite obvious for certain reasons to be discussed later in the paper.

Figure 6 below presents the trends of betweenness centrality for each of the 5 member countries across the time. Based on the graph it is clear that Russia has the highest degree centrality which was clearly demonstrated in the SNA graphs. It is interesting to note that Kazakhstan and Armenia experience gradual increases in the betweenness centrality, meaning that over time, these two countries start playing a more important role of lying on geodesic distances between other countries in the network. There is an interesting reverse relationship between Russia`s betweenness centrality and Belarus's in 2015, exactly the year when the two more countries joined the union. This reverse relationship is followed by the further divergence in this centrality measure between the two largest states, indicating the rising role of Russia and a declining influence or Belarus.

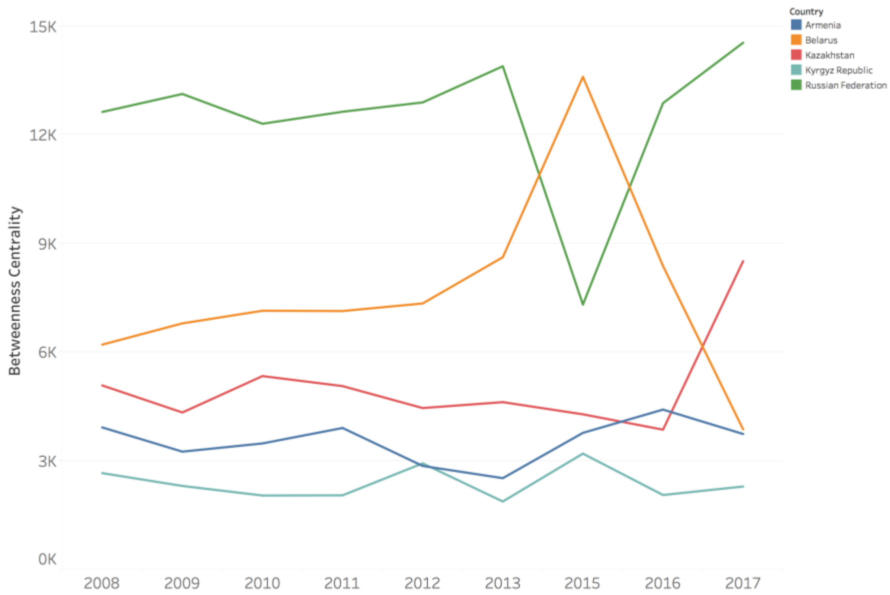


Fig. 6. Betweenness Centrality of the 5 member states over time.

Ordinary Least Squares

The table 2 below provides the summary statistics for each of the variables considered in the linear regression model after the data has been normalized. Given the fact that all data has been given in different units of measurements, it has been normalized based on the minimum and maximum position of each variable, so the end result would range from 0 to 1. Due to the fact that GDP is positively skewed, we take a natural log of the variable and further use it in the regression. The main inference we can draw from the descriptive statistics is the high variation in data. Given that, we have to conduct a test for heteroscedasticity. As we know from OLS assumptions, the presence of heteroscedasticity does not make the model biased, however the estimator is no longer efficient.

In order to check the heteroscedasticity, we conduct a Breusch-Pagan test to check whether heteroscedasticity is present in the model. The outputs of the tests for each one of the models are included in Appendix. Based on the results, all four models show the presence of heteroscedasticity, which means that we have to use robust standard errors in the model.

Table 2. Summary Statistics

Variable Name	Observations	Mean	Standard Deviation	Min	Max
Percentage trade from total	45	0.46	0.35	0	1
Union years	45	0.30	0.34	0	1
Unemployment	45	0.27	0.33	0	1
Economic Openness	45	0.56	0.30	0	1
Log GDP	45	0.42	0.33	0	1
Indegree	45	0.54	0.27	0	1
Betweenness Centrality	45	0.34	0.31	0	1
Eigenvector Centrality	45	0.63	0.28	0	1

The table 3 below summarizes the output results for 4 different models. Model number one (left) is a baseline model that includes all macroeconomic variables, however, does not include betweenness centrality. As we can see, in the first model, our variable of interest is insignificant. Adding to the model betweenness centrality slightly changes the coefficient of union years, however still shows its insignificance. In the mean time, all other variables, except for betweenness centrality are significant in the model. The third model includes all variables considered in this study, adding eigenvector centrality. As we can see, the goodness of fit of the model increases even more, however, the variable of interest remains insignificant.

Judging by the goodness of fit, we may conclude that the best model so far is the Model 3, however the Variance Inflation Factor (VIF) will help us eliminate the multicollinearity issue. The outputs for VIF are demonstrated in the Appendix section. Based on that, the variables with the VIF of 10 or higher are Log GDP and Eigenvector Centrality. Dropping those variables gives us Model 4, which shows that our variable of interest is significant at a 99% confidence level.

Based on the conducted tests, we choose Model 4 as the best performing and robust model. The main takeaway of the regression is that the number of years being a part of the EAEU is positively correlated with the dependent variable. Economic openness suggests that a higher level of economic openness leads to a lower level of trade between the 5 member states. Interestingly, the indegree is also negatively correlated with the dependent variable. This suggests that given a high level of incoming trade links from other countries of the world, the trade volume between the 5 member states declines which intuitively makes sense. Betweenness centrality appears to be significant at a 95% confidence level and is negatively correlated with the dependent variable. The higher is the importance of a country in the network in terms of being a bridge to between other countries, the lower is the trade between the member countries. This is an interesting inference, which might be intuitively explained by the fact that a more powerful country within the union belongs to other number of economic unions besides EAEU, therefore has a lower share of trade with the countries of given union.

Table 3. OLS Regression Models Outputs

	Dependent variable			
	Percent Trade from Total			
	(1)	(2)	(3)	(4)
Union years	0.096	0.085	0.054	0.374***
	(0.077)	(0.079)	(0.090)	
(0.12603)				
Unemployment	-0.527***	-0.562***	-0.550***	0.325**
	(0.134)	(0.142)	(0.144)	
(0.11572)				
Economic openness	-0.596*** (0.092)	-0.551*** (0.111)	-0.569*** (0.114)	-0.992*** (0.22914)
Log GDP	-1.500***	-1.575***	-1.539***	
	(0.177)	(0.205)	(0.212)	
Indegree	0.430**	0.432**	0.602*	-0.827***
	(0.202)	(0.203)	(0.307)	(0.21181)
Betweenness centrality		0.099 (0.132)	0.084 (0.135)	-0.407** (0.16299)
Eigenvector centrality			-0.188 (0.252)	
Constant	1.298***	1.282***	1.314***	1.400***
	(0.063)	(0.066)	(0.079)	(0.12603)
Observations	45	45	45	45
R2	0.894	0.896	0.898	0.734
Adjusted R2	0.881	0.880	0.878	0.700
Residual SE	0.119 (df = 39)	0.120 (df = 38)	0.121 (df = 37)	0.190 (df = 39)
F Statistic	66.125***	54.570***	46.305***	21.506***
	(df = 5; 39)	(df = 6; 38)	(df = 7; 37).	(df = 5; 39)

*p<0.1; **p<0.05; ***p<0.01

6 CONCLUSION

The main purpose of the Eurasian Economic Union was to build a mutual platform for economic and political integration. That implies common tariffs and the increase in the level of trade between the member nations. There is a number of studies and discussions about the impact of the union on the member states. At this point, the literature seems to have different routes, one of which suggests that the effect is not visible due to the political reasons or self-interest, where the most powerful states such as Russia are not interested in supporting high level of trade and boosting economies of the remaining countries. On the other hand, there has been a little time since the union came into effect to observe any visible changes on its member economies. Specifically, one source mentioned above suggested that the effect will not be explicit until 2020.

The purpose of this paper was to determine whether the level of overall trade between the member countries compared to the rest of the world increased during the period of 9 years. The Social Network Analysis did not reveal clear pattern of behavior, but rather confirmed the initial thought about influence of Russia in this trade network. There were no visible changes revealed in the level of trade between the member states given three main cut off in time (2008, 2015, 2017). However, based on the Exploratory Data Analysis, the average number of trade percentage across all 5 countries over 9 years showed a gradual increase in the level of trade.

The regression analysis suggested that there is a positive correlation between the number of years being a part of the Economic Union and the overall level of trade between the five countries given the total trade of the member states with the rest of the world. Interestingly, the regression found that the higher level of economic openness is associated with a lower level of trade between the member countries, which intuitively suggests that more open economies tend to trade more with other countries of the world, decreasing the trade level within the union. Another interesting finding was a negative relationship between indegree and the level of trade, just like in the case of economic openness: the more countries trade with the EAEU member country- the less is the level of trade of this country with other EAEU members. Finally, betweenness centrality is negatively correlated with the trade level. This can be explicitly seen in the case of Russia. As a member with a high betweenness centrality, Russia has a low percentage of trade with other members of the union given the total trade with the rest of the world. Russia is an economic giant relative to the 4 remaining countries and belongs to a number of other economic and trade unions. It has very strong trade and economic ties with China and EU, therefore the negative correlation makes intuitive sense. Based on all of the said above, we can conclude that there is some increase in the level of trade between the countries, however the effect is not pronounced given the time effect and other geo-political factors mentioned in the literature.

7 POLICY IMPLICATIONS

Russia remains the most influential and important actor in the network of trade between the 5 EAEU countries with the rest of the world. It`s power is stable over time which suggests that any significant change in the dynamics of the countries within the union will have to come from Russia`s side. In the meantime, Belarus and Kyrgyz Republic are the most union dependent countries with the total percentage trade of about 50 % from the total trade with the rest of the world.

As far as the volume of trade concerns, there are no major changes in the trade volume between the trade. This has to do with the short-term vs. long-term effect of the union on the trade volume of its member states. In order to see pronounced behavior, there needs to be an ongoing interaction between the member countries and an increased participation of all countries, including Russia. Only then, there will be clear positive effects.

8 Study Limitations

The biggest limitation of the study is the lack of data and controlled variables. This spans to the time span that could be expanded and the benchmarking economic union that would provide a better idea of the effects of EAEU of its members relative to other union`s effect on its participants. From the SNA perspective, the study only considered a partial network, which might create biased results. The further studies can take a look at a larger network, minimizing the bias. There is a number of tools that can be used in the study, including but not limited to time series and machine learning.

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8. The World Bank Group, statistics by country

10 Appendix

Table 3. VIF for each of the regression models

Model 1

Union years	Unemployment	Econ openness	LogGDP	Indegree
2.093135	6.185470	2.314187	10.493818	9.436617

Model 2

Union years	Unemployment	Econ openness	LogGDP	Indegree	Betwcen
2.165409	6.929079	3.297453	13.914310	9.437255	5.222913

Model 3

Unionyears	Unemp	Econ open	LogGDP	Indegree	Betwcen	Eigcen
2.728574	7.012745	3.452204	14.707368	21.220321	5.334898	14.847199

Model 4

Unionyears	Unemp	Econopen	Indeg	Betwcen
1.679101	2.394359	2.412456	3.335427	3.938988

Table 4. Breusch-Pagan test for Multicollinearity

Model 1
Non-constant Variance Score Test
Variance formula: ~ fitted.values
Chisquare = 0.3824677, Df = 1, p = 0.53629

Model 2
Non-constant Variance Score Test
Variance formula: ~ fitted.values
Chisquare = 0.1114751, Df = 1, p = 0.73847

Model 3
Non-constant Variance Score Test
Variance formula: ~ fitted.values
Chisquare = 0.03410661, Df = 1, p = 0.85348

Model 4
Non-constant Variance Score Test
Variance formula: ~ fitted.values
Chisquare = 0.3451912, Df = 1, p = 0.55685