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Pakistan's Position in the Global Trade Network and Its Connection to Default Risk: A Machine Learning Approach

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Abstract

Pakistan is one of the main beneficiaries of China's One Belt, One Road initiative. However, the benefits do not seem to accrue rather, the country seems to be converging to default. This study focuses on the impact of Pakistan's network centrality in the trade network of countries on the probability of default, a measure of debt sustainability. This study implies machine learning technique to predict probabilities of default, it further implies regression analysis in order to understand the relation between default probabilities and trade network probabilities. The results show that a country's trade network increase has a negative and significant impact on its probability of default. The study provides evidence that Pakistan's network position has improved, and therefore, its integration into the "One Belt-One Road" initiative of China is integral to improving its debt sustainability.

Keywords: Trade network centrality, Machine learning, Probability of default, Economic growth.

INTRODUCTION

The term trade network centrality is often used in literature to understand the importance of a specific country in a global trade network. A country is perceived to be more central to the trade network if it has a higher number of trade links with other countries. A higher number of trade links are sometimes linked to

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the geographical position of a country in the world. For example, Singapore and Hong Kong are not very big countries in terms of production and GDP compared to other countries, but their geographical position makes them important while defining most trade-central countries. Countries like the USA have fewer trade routes than Hong Kong or Singapore, but their share in Global gross domestic product is much higher than in these countries. So, the importance of a certain country while defining its position in the global trade network centre can be done by using both the number of links and its share in the global gross domestic product (Richmond, 2019).

Vidya and Prabheesh (2020) found that trade connections between countries had been severely affected during and after COVID-19. Countries like the UK, USA, France, etc., were severely affected from 2018 to 2020Q1 in terms of their trade connectedness due to COVID-19. They also found that China's position in trade connectedness during this period was not affected much.

The trade volume and trade connections between two countries also depend upon the relationship between them. A good relationship between these countries will result in more trade and more links. However, a bad relationship will lead to less trade and fewer trade networks (Antonietti et al., 2022).

More central countries also enjoy other benefits like lower interest rates and currency risk premiums. Richmond (2019) argues that the consumption growth of the countries which are more central in global trade networks is more connected to global consumption growth shocks. This results in the appreciation of the currency of these countries during shocks, lower interest rates, and currency risk premiums.

Ying (2023) found that idiosyncratic sovereign risk (ISR) increases during periods with low oil prices and decreases during periods with high oil prices. He also found that ISR becomes a systematic sovereign risk during oil price booms and that idiosyncratic contagion occurs during oil price busts.

The probability of default is the term described as the chances of a country being unable to fulfill its debt obligations within a specified period. It is one of the key instruments credit institutions use as a measure of risk assessment to decide whether to enter into further debt agreements in future or not. The probability of default is affected by many factors, such as financial health, economic conditions, country risk, etc. Financial health includes many factors, such as a country's debt-to-income ratio and a specific country's credit history. Economic conditions include inflation rate, interest rates, etc. in a country, while the country's risk can be associated with its graphical locations, etc.

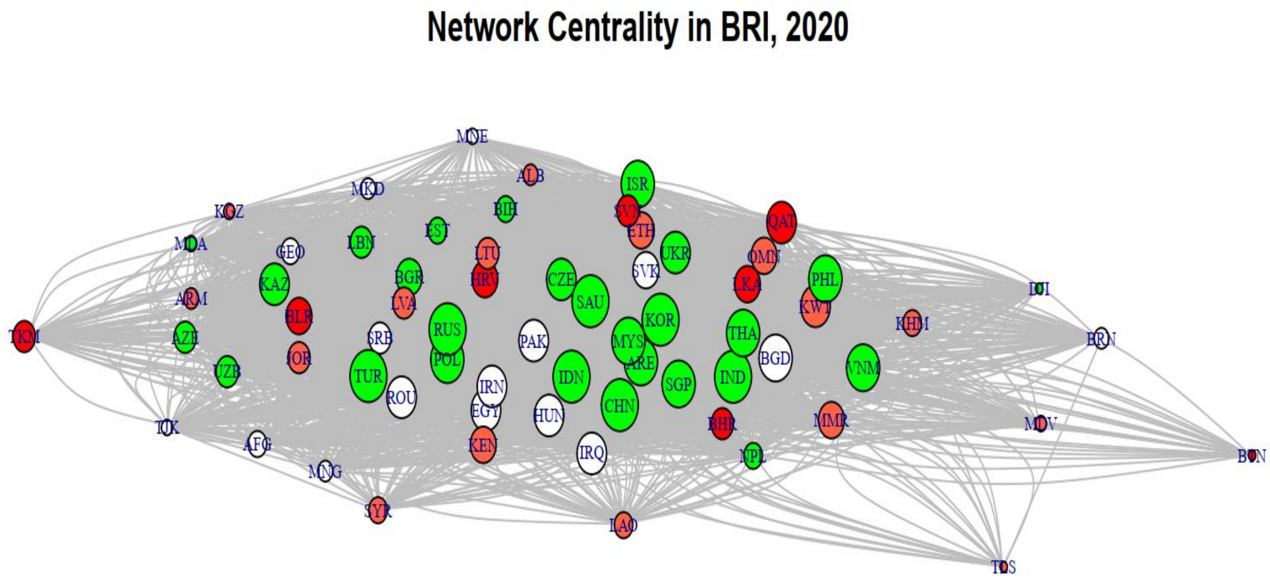
In most countries, the probability of default is linked with political risk; political risk is defined by many factors, such as political instability and change in governments, which results in changes in economic policies, making the financial environment difficult for investors and ultimately affecting the country's economic condition adversely. The probability of default is also linked to external factors such as wars and natural disasters. It can also be linked to Global economic shocks, which mostly affect developing countries more than that of developed countries (Chi & Li, 2017).

Various researchers are now using machine learning (ML) methods to measure the probability of default. Coenen et al. (2022) studied various estimation methods to predict the probability of default. They studied different ranking techniques, classification techniques, and regression methods to estimate the probability of default. Their main focus was on the short-term probability of default. They studied the risk of default with the connection to the due date of an invoice. The three ML methods they used resulted in the regression technique being the best predictor to estimate future profits and the probability that an invoice will default.

Jian (2022) argues that ML, while used for default predictions, faces many drawbacks, such as multicollinearity in the data, small sample size, etc. He introduced the muddling label technique to counter these problems and argues that this labelling technique replicates the same results when different data sets are used. This mentioned technique also resulted in better results than results produced by ML techniques.

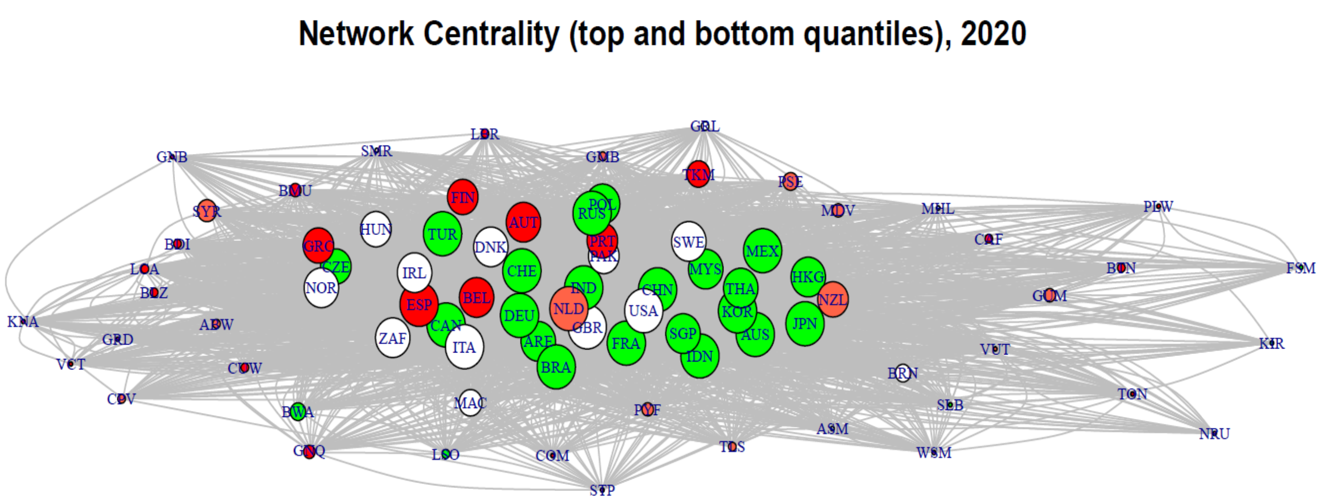
Breeden (2021) argues that ML is now finally being used widely as a measure of credit risk; now, most of the research is being done to find out the optimal use of ML in order to predict the best credit risk related to transitions. ML methods are now easily outperforming linear predicting methods; however, there is still a need for improvement, and there is still a need to improve ML methods to predict credit risk more precisely and accurately.

Figure 1



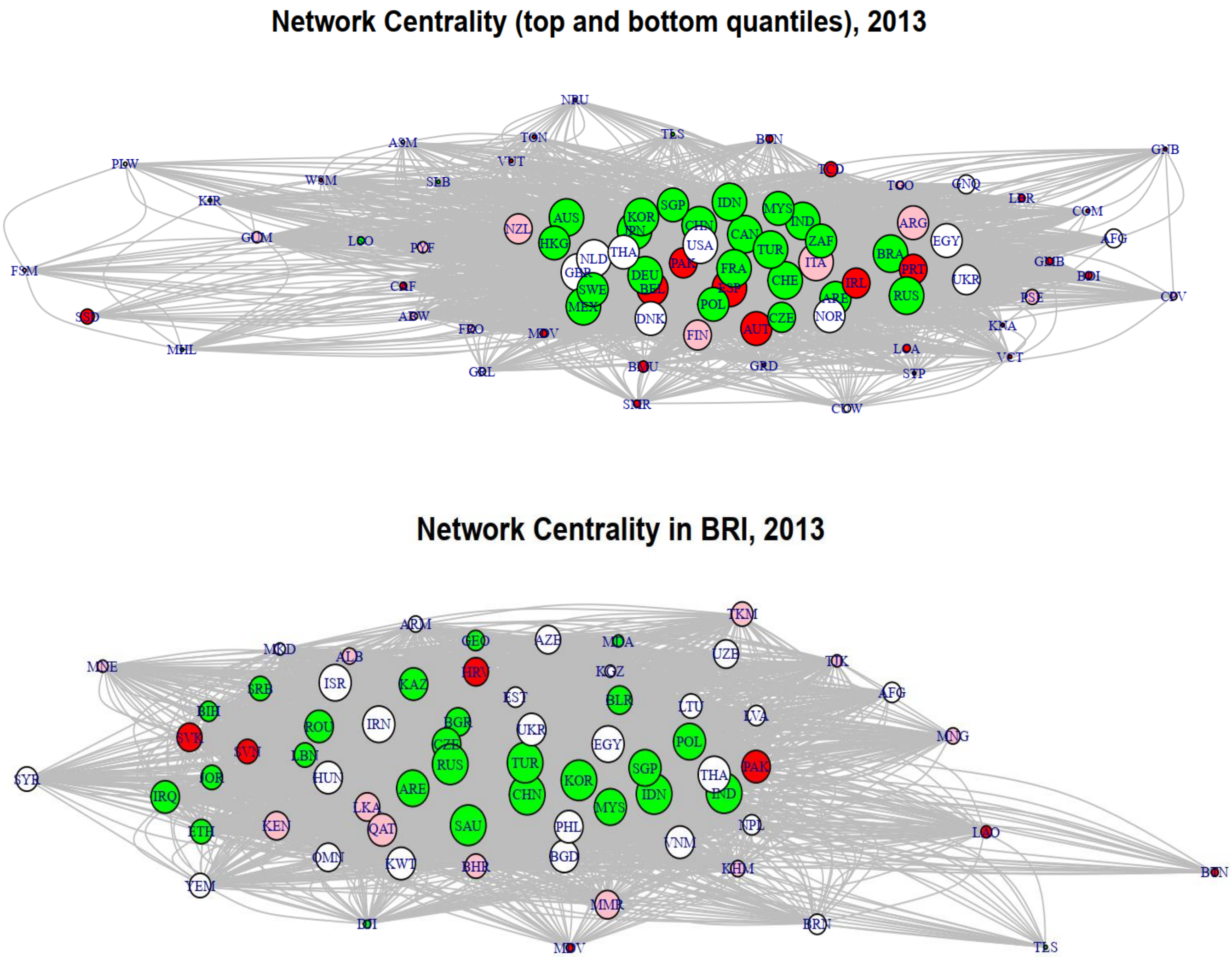
This figure depicts country links as measured by bilateral trade intensity—pairwise total trade normalized by pairwise total GDP. Circle position corresponds to trade network centrality, and circle size corresponds to GDP. Trade data are from the IMF Direction of Trade Statistics, and GDP data are from the World Bank, both in dollars. The red circles represent countries with a high probability of default in the next five years, and the green colours represent the lowest probabilities of default. The ISO3 country codes are from https://wits.worldbank.org/wits/wits/witshelp/content/codes/country_codes.htm.

Figure 2



This figure depicts country links as measured by bilateral trade intensity, but only shows data for top and bottom quantiles. The country codes are from **https://wits.worldbank.org/wits/wits/witshelp/content/codes/country_codes.htm**.

Fig 3



Those in the centre are highly connected institutions and exhibit a high probability of default. However, in this figure, the default probability cannot be absolutely attributed to the trade connectedness of countries. The peripheral countries are not only far away from the centre or less connected to the rest of the world, but also they have small economies and a high probability of default. This pattern shows a relationship between trade network centrality and the probability of default for countries. We measured the variables as below.

Trade Network Centrality: Two countries are connected if they trade with each other. The connection weight depends on the bilateral trade intensity as defined above.

Probability of Default: It is obtained using a feed-forward network model of machine learning. The features include economic variables, the list of which is given in Refinitive's Starlink probability of default measure.

Right now, the value is as follows.

1. We investigate the relationship between two different variables that has not been investigated before.
2. We provide a new machine-learning-based probability of default measure.

LITERATURE REVIEW

The literature on trade networks is scattered across multiple streams of knowledge. Some scholars have focused on the context of "trade and global economy", where major part of conversation focuses on the flow of goods, services, and investments between nations and how global markets operate. It explores trade policies, economic growth, global value chains, and international competition. It also considers how trade impacts profitability and economic development, making it a key element of globalization and financial forecasting (Okere et al., 2022; Song & Zhou, 2020). While some scholar has discussed this topic with the lens of "supply chain and industrial networks", where they discuss the logistics and processes involved in moving goods and services from suppliers to consumers. It includes the study of supply chain management, industrial and industry chains, and the resilience of supply chains to disruptions. Complex networks and input-output analysis help optimize operations, lower costs, and reduce vulnerabilities (Gereffi et al., 2021; Verschuur et al., 2022).

Another group of authors have studied trade networds with the relation of "energy and environmental impact", where scholarly conversation has been focused on the relationship between energy production, consumption, and its effects on the environment. Topics include carbon emissions, sustainability, energy markets, and emission control. It explores how global economies adapt to environmental challenges and the role of sustainable development in mitigating climate change (Halder and Sethi, 2022; Khan et al., 2020). "Technology and Innovation" has also been the focus of some academicians as they discuss trade network with the lens of the impact of technologies like machine learning, deep learning, and blockchain on various industries. It explores how optimization, neural networks, and complex algorithms enhance innovation, problem-solving, and decision-making. The use of advanced numerical models and programming techniques contributes to technological breakthroughs (Ascani et al., 2020; Asghar et al., 2024).

"Economics and decision making" is another area of discussion for scholars where the discussion is on the study of economics and the factors that influence decision-making in markets. It covers the efficiency of resource allocation, risk assessment, financial markets, and economic growth. It also analyzes price dynamics, economic development, and the social impacts of economic policies (Moktadir et al., 2020; Nurhayati et al., 2020).

Regional and country specific studies have also been the center of discussion in literature that focuses on specific countries and regions (e.g., China, the European Union, the United States) and their roles in global economics, trade, and innovation. It looks at how developing countries navigate economic growth and global value chains, as well as the geopolitical dynamics influencing international trade (Ascani et al., 2020; Wang et al., 2020).

Social networks and analysis is one of the emerging trends in the literature of trade networks that explores the structure and dynamics of social networks—whether they are physical, digital, or theoretical. It uses network analysis to study relationships between individuals, organizations, or entities and how these connections impact behaviors, economic trends, and societal changes. Social network analysis is crucial in understanding information flow and influence in a connected world (Camacho et al., 2020; Sun et al., 2020). Some scholars also discussed trade networds with the context of COVID-19 and its effects, which examines the impact of the COVID-19 pandemic on the global economy, trade relations, and societal resilience. It focuses on the pandemic's economic and social effects, how businesses and supply chains have adapted, and the long-term changes in global economies. Resilience and crisis management are critical subtopics (Antonietti, 2022; Kiyota, 2022). This article discusses regional aspect of pakistan its position in trade network and its relation with economic growth.

METHODOLOGY AND RESULTS

Table 1 presents the results for descriptive statistics, M2 stands for probability of default of a country in next two years, M3 stands for probability of the default of a country in next three years and M5 stands for probability of the country in five years.
The average value for M2 is 0.0089, for M3 it's 0.087 and for M5 it's 0.02. TNC stands for trade network centrality. It's value ranges from 30 to 383 with high value representing country with more rate network connections. For control variables: imports, Inflation, FDI, urban population and CO2 emissions are used.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
M2	5,794	0.00897	0.000787	0.007432	0.012751
M3	5,794	0.087753	0.006546	0.077659	0.159228
M5	5,794	0.020027	0.025454	0.003516	0.200825
TNC	5,794	191.4265	94.65678	30	383
Imports	4,955	8.63E+10	2.54E+11	1849551	3.41E+12
GDP Growth	5,536	3.310227	6.396185	-64.0471	149.973
Inflation	5,016	23.95374	370.505	-16.8597	23773.13
FDI	4,763	2.08e+10	2.08E+10	-3.45e+11	2.18E+11
Urban	5,794	56.54673	23.54259	5.491	100
Co2	5,234	4.321647	5.503848	0	47.65696

Table 2 presents the results for correlation matrices. It can be observed that correlation between independent variables is not that high which indicates that chances of Presence of multicollinearity Are quite low. It can be observed that TNC has positive correlation with M2 while it has negative correlation with M3 and M5.

Table 2: Correlation

	M2	M3	M5	TNC	imports	gdp	CPI	FDI	Urban	co2
M2	1									
M3	-0.4381	1								
M5	0.1708	0.2889	1							
TNC	0.1766	-0.4668	-0.239	1						
Imports	0.2923	-0.2887	-0.1415	0.4998	1					
Gdp growth	0.0472	0.0293	-0.1061	-0.0563	-0.0578	1				
Inflation pi	0.0653	-0.0615	-0.0252	0.0069	-0.0317	-0.0821	1			
Fdi	0.064	0.01	0.0085	0.0146	-0.001	-0.0757	-0.0025	1		
Urban	-0.3931	-0.0787	-0.1737	0.4811	0.2697	-0.126	0.0075	0.0566	1	
co2	-0.2429	0.1503	-0.0996	0.4434	0.3307	-0.0797	-0.0262	0.0597	0.6384	1

Table 3 presents the results for fixed effects regression. It can be observed that TNC has a negative impact on M2, M3 and M5. Which indicates that when a country has higher number of connections in their trade networks, their probability of default decreases. However, this impact is only significant for the case of M2 and M5. GDP Growth has significant impact on probability of default for all cases. Further, urban population also has negative and significant impact on M2,M3 and M5. These results further validate our hypothesis that increase in trade networks centrality of a country decreases their probability of default.

Table 3: Fixed effects regression Results

	(1)	(2)	(3)
VARIABLES	**M2**	**M3**	**M5**
TNC	-1.51e-06***	-1.36e-06	-3.95e-05*
	(3.22e-07)	(2.51e-06)	(2.20e-05)
Imports	0.000	0.000*	0.000**
	(0.000)	(0.000)	(0.000)
Gdp growth	-4.36e-06***	4.34e-05***	-0.000451***
	(1.00e-06)	(7.78e-06)	(6.82e-05)
Inflation cpi	3.92e-07***	-1.37e-06***	-4.15e-06
	(4.92e-08)	(3.83e-07)	(3.35e-06)
Fdi	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
Urban	-3.05e-05***	-7.00e-05***	-0.000596***
	(1.25e-06)	(9.72e-06)	(8.52e-05)
Co2	-2.50e-05***	-7.50e-05**	0.000130
	(4.90e-06)	(3.81e-05)	(0.000334)
Constant	0.0112***	0.0912***	0.0617***
	(9.76e-05)	(0.000759)	(0.00666)
Observations	3,732	3,732	3,732
R-squared	0.205	0.032	0.025
Number of country1	162	162	162

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

CONCLUSION

This research aimed to investigate whether or not a higher number of trade networks for a country impacts their probability of default. The countries' probability of default is calculated using machine learning techniques. The fixed effects regression technique is used to test the hypothesis after calculating probabilities for two years, three and five years. The regression result shows that a country's trade network increase has a negative and significant impact on its probability of default.

In economics, trade networks are often seen as a factor of national concern. Multiple trading partners can create different sources of income, increase exports and offer different types of products and services. From a theoretical point of view, countries with large trade networks are better protected against economic shocks in certain sectors or with their trading partners. This supports the idea that chain growth can reduce the risk of failure. Machine learning can capture complex relationships between economic variables that traditional economic models may miss. Taking into account various economic, financial and political factors, these models provide a quick and easy assessment of a country's vulnerability. This means that the probabilities used in regression analysis may be more accurate and reflect the true nature of the situation. A large trade network makes countries more competitive; i.e., Risk diversification and economic development.

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