INVESTIGATION OF THE IMPACT OF COVID-19 ON FREIGHT VOLUME: A CASE OF TANZANIA - RWANDA TRANSIT TRADE

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ABSTRACT

Cross-border trade in goods and services has expanded steadily over the past six decades due to increase of globalization and liberalization. Nonetheless, the current outbreak of the COVID-19 pandemic has posed unprecedented impediments to freight volume of transit trade across various international borders. This study analyses the effect of COVID-19 on cross-border trade between Tanzania and Rwanda. The analysis is carried by Multiple Linear Regression Model to explore the impact of explanatory variables on responsive variable, freight volume of full container loads (FCLs). The results reveal that the freight volume of transit trade between Rwanda and Tanzania varies linearly with the explanatory variables. More specifically, the freight volume varies positively with the number of trucks deployed and transit time days whereas the freight volume varies negatively with the number of port calls and logistics transit cost in dollars. The findings call both partner states to take corrective policy actions.

KEYWORDS

Cross-border trade, COVID-19, Freight Volume, Transit Trade, Multiple Regression Model.

1. INTRODUCTION

Cross-border trade (CBT) in goods and services has expanded steadily over the past six decades due to decrease in shipping and communication costs, globally negotiated reductions in government trade barriers, the widespread outsourcing of production activities, and a greater awareness of foreign cultures and products [1]. The CBT plays an important role in every country's economy as it drives a country's evaluation of its gross domestic product (GDP). The cross-border trade represents one of the mega business opportunities available to trading partners globally. The cross-border market has grown from $401 Billion in 2016 to $994 Billion in 2020 [2]. The CBT offers mutual benefits to trading partners since it allows a country to export goods whose production makes optimal use of resources that are locally abundant while importing goods whose production makes optimal use of resources that are locally scarce. In cross-border trade, goods have to undergo more than one border formality, one in the exporting country and another in the importing country. Trade facilitation is therefore the collective responsibility of all countries involved in the freight supply chain.

One of the most prominent cross-border trades is transit trade. The transit trade entails the transportation of goods under customs control that is not cleared while in transit. The international transit may involve one border crossing, in which case goods are transported directly from the origin to the destination country (e.g. from China to Rwanda via Tanzania). The international transit may also involve several border crossings, in which case transport takes place through at least two intermediate countries (e.g. from China to Zimbabwe through Tanzania, and Zambia). More specifically, goods in transit refers to goods that are moved from an origin country across international borders to another country overland.

Tanzania is one of the countries that benefits significantly from transit trade as this kind of trade is a potential driver of economic growth and job creation. The direct benefits to Tanzania from transit trade come from port charges (e.g. stevedoring charges, port storage charges etc), clearing and forwarding charges, fuel levies etc. On the other hand, indirect benefits to Tanzania from transit trade emanate from accommodation, restaurant and repair services. In addition, in the locations through which transit trade stops (either for customs procedure or park and rest), transit operations generate considerable spatial development opportunities that contribute to local economic development. It is worth noting that the volume of transit trade for Tanzania has grown enormously over time. For instance, the cost, insurance and freight (CIF) value of transit trade increased five-fold from about $3 Billion in 2007 to about $15 Billion in 2015 [3].

Tanzania and Rwanda have been for many years having great trade relations that accelerated economic growth between the two countries. For instance, Rwanda imports from Tanzania were $224.54 Million while Rwanda exports to Tanzania were $5.1 Million in the year 2019[4]. In addition to the export and import trade between the two countries, Rwanda uses Tanzania as the entry and exit point for most of its imports and exports. Thus, the Central Corridor is key to Rwanda as it covers a shorter distance to the Dar es Salaam sea port compared to Mombasa port on the Northern Corridor.

Nonetheless, the COVID-19 outbreak has contributed to tremendous global decline in trade flows [5]. Measures like border closure and international travel restrictions have hindered global trade flows by increasing trade costs and delaying or entirely prohibiting border clearance [6]. More specifically, the intrusion of COVID-19 pandemic has resulted in an economic shock globally which in turn impacts GDP of various countries and generated an economic downturn, with a negative effect on cross-border trade. Transit trade between Tanzania and Rwanda is no exception. After the World Health Organization (WHO) declared COVID-19 as a global pandemic, uncoordinated stringent measures were implemented to contain the spread of the virus. The initial lack of coordination in implementation and cohesive administrative actions among partner states was an achilles heel [7]. For instance, lack of harmonized testing protocols on the COVID-19 pandemic resulted in the truck drivers' test results taking long and, in some cases, rejected by partner states.

In this study, we present new evidence on the impact of COVID-19 pandemic on transit trade between Tanzania and Rwanda. The paper is structured as described hereafter. Section 2 provides an overview of the current literature on the impact of COVID-19 on cross-border trade as well as previous studies on the application of multiple linear regression models. Section 3 presents the proposed multiple linear regression model (MLRM). Section 4 offers the application of the MLRM as well as delivers our main findings. In section 5, we draw some conclusions and propose recommendations for Tanzania and Rwanda to build resilience and protect their trade against future shocks.

2. Scrutiny of Relevant Studies

There are numerous recent studies which explore the effects of COVID-19 on cross-border trade. Hayakawa and Mukunoki [8] apply the gravity equation to investigate the effects of COVID-19 on international trade. The findings found significantly negative effects of COVID-19 on the international trade of both exporting and importing countries. Li and Lin [9] use China's trade data from- January to April 2020 to calibrate the influence level parameters and then simulate the trade effects of COVID-19 in China, the EU, the US, and the world. The simulation results found that all countries' trade and exports will be significantly hurt by the pandemic. Hobbs [10] considers the short, medium, and potential long-term implications of COVID-19 for food supply chains. The findings offer lessons for the food industry in proactively identifying and addressing points of vulnerability within supply chains. Brakman *et al.* [11] apply insights from international economics and economic geography to examine how the current COVID-19 crisis may structurally change the international economy. The findings reveal that the current crisis will change key economic actors' risk appetite. Sanabria-Diaz *et al.* [12] present a literature review of the most up-to-date studies on the impacts of the COVID-19 global pandemic in European Union countries and the joint actions taken to fight the pandemic. Nchinji *et al.* [13] use survey data collected from nine countries in Central, Eastern, and Southern Africa to understand the immediate impact of COVID-19 on production, distribution, and consumption of common beans, and possible food security implications. The findings reveal that the production and distribution challenges negatively impact on frequency and patterns of food consumption in household in Africa. Uğur and Akbryrk [14] present a study on the reactions of travellers during COVID-19 pandemic by adopting text mining techniques. The results reveal that the tourism sector is easily affected by global crises. Yang *et al.* [15] explore the dynamic impacts of COVID-19 on the intra-provincial and inter-provincial express parcel flows. The findings show that the temporal fluctuation of inter-provincial express logistics flows affected by COVID-19 is stronger than that of intra-provincial flows. Mtimet *et al.* [16] present a study that quantified the economic losses associated with the current partial livestock ban on Somali imports and the added impacts associated with COVID-19. The results reveal that the additional losses imposed by the COVID-19 pandemic are estimated at $ 42 million. Loske [17] examines the impact of COVID-19 on German food retail logistics. The results indicate that transport volume does not depend on the duration of the COVID-19 pandemic but on the strength quantified through the total number of new infections per day. Li [18] discusses the situation of China's air cargo sector facing the COVID-19 pandemic. The findings suggest strategies for China's air cargo suppliers to adapt to the pandemic. Tisdall *et al.* [19] present experiences of the aviation sector in Australia amid the COVID-19 crisis. The findings suggest that there has been a lack of applied learning by policy makers in the past, and that generic support on offer now does not address the long-term resilience of the sector. Coopmans *et al.* [20] assess the resilience of Flemish food supply chain actors to COVID-19 by focusing on impacts and resilience actions. The findings suggest that flexibility and diversity, despite their tendency to diminish price optimums, increase resilience capacities, which may be more beneficial to systems for thriving in turbulent and uncertain environments. Chowdhury *et al.* [21] systematically review existing research on the COVID-19 pandemic supply chain disciplines. The findings reveal that four broad themes recur in the published work, impacts of the COVID-19 pandemic, resilience strategies for managing impacts and recovery, the role of technology in implementing resilience strategies, and supply chain sustainability in the light of the pandemic. Lashitew and Socrates [22] use a product-by-country data for the one-year period from July 1, 2019 to June 30, 2020 to analyse how Kenya's import and export was affected by lockdown policies during the COVID-19 outbreak. They found that the strength of lockdown policies had an asymmetric effect between import and export trade. Szabo *et al.* [5] propose a study on the impacts of COVID-19 public measures on country-level trade flows. The findings reveal that COVID-19 outbreak has contributed to tremendous global decline in trade flows. Banga *et al.* [6] present a study on the effect of COVID-19 on Africa trade with a focus on supply chain. The analysis show that lockdown policies imposed by governments have impeded trade flows at local, regional and international levels. UNCTAD [23] propose a study on the impact of COVID-19 pandemic on trade and development. The results reveal that the COVID-19 pandemic has gravely wounded the world economy with serious consequences impacting all communities and individuals. Khorana *et al.* [24] examine the effect of COVID-19 pandemic on global and intra-Commonwealth trade flows. This study finds that the incidence of

COVID-19 in both exporting and importing countries has impacted on Commonwealth trade flows and that the extent of the effect varies with the development level of trading partners. Wei *et al*. [25] use a cross-country data spanning from January 2020 to December 2020 to empirically investigate the impact of COVID-19 pandemic on exports and imports in China, Japan, and South Korea. The findings reveal that there is heterogeneity in the impact of the epidemic on imports and exports in China, Japan, and South Korea. Lakatos [26] provides a summary of the impact of COVID-19 across the world's economies, and the mechanisms through which the pandemic has affected them. The findings reveal that the COVID-19 pandemic has caused massive disruptions to international trade and global value chains (GVCs). Pan and Yue [27] analyse the multidimensional effects of COVID-19 on the economy by gathering primary data from eleven countries. The results reveal that all sectors of the economy including trade are negatively affected except the environment which is positively affected.

In this study, we apply Multiple Linear Regression Model (MLRM) to explore the impact of COVID-19 on freight volume of transit trade. The MLRM has been applied extensively to analyse the relationship between explanatory and response variables for tackling numerous research problems. For instance, Fumo *et al*. [28] propose a multiple regression analysis with parameters or independent variables that are a function of the physical driving forces for energy performance. The results show that the proposed approach is as accurate as the Bayesian approach. Thiangchanta and Chaichana [29] use the MLRM to develop a heat load model of an air-conditioned room. The results show that this model gave a good prediction of the heat load with an error of 0.15%. Schon *et al*. [30] apply the MLRM to quantitatively extract a number of micro structural characteristics of SAC207 and SAC307 alloys. The MLRM results well represent the ultimate tensile strength of both alloys. Maaouane *et al*. [31] propose the MLRM based on five macro-economic independent variables for accurate prediction of the future industry energy demand. This model produces results comparable to those of the International Energy Agency. Vilsen and Stroe [32] use the MLRM to reduce the amount of data which needs to be transmitted by the extraction of descriptive features of the voltage. The results reveal that the mean absolute percentage error (MAPE) calculated on the validation set, never exceeded 5% for the proposed methods. Olsen *et al*. [33] apply the MLRM as a data analysis in pharmacy education. The findings reveal the usefulness of the model to better understand variables that may predict specific outcomes such as student achievement or program retention. Zhang *et al*. [34] propose two multiple regression models to predict the concentration of bromoform (TBM) and dibromochloro methane (DBCM) in full-scale ballast water. The results verify that the two models possess excellent reproducibility and high accuracy. Zsuzsanna and Marian [35] apply multiple regression model to analyse the performance indicators in the case of an enterprise that produces technical ceramic products in Romania. The results show significant correlations between the analysed indicators. Uyanik and Güler [36] apply multilinear regression model for measurement and evaluation of Sakarya University Education Faculty student's lesson. The findings validate the usefulness of the regression model. Yu [37] uses the MLRM to explore ways of improving English reading ability by analyzing the influencing factors. The results validate the usefulness of the model.

On the one hand, researchers and practitioners apply the MLRM to evaluate the spread of COVID-19 based on established factors. For instance, Kubota *et al*. [38] apply multiple regression to evaluate COVID-19 spread based on climate, international mobility and region-specific conditions. The findings demonstrate the effectiveness of the model. Ogundokun *et al*. [39] use multiple linear regression model to measure the impact of travelling history and contacts on the spread of COVID-19 in Nigeria. The findings validate the usefulness of the model. Rath *et al*. [40] use the MLRM to predict new active cases of COVID-19 pandemic in Odisha and India.
On the other hand, very few researchers and practitioners apply the MLRM to evaluate the impact of COVID-19 on trade. For instance, Flor *et al*. [41] use multiple linear regression

analysis to predict average statewide mobility during COVID-19 based on the factors of daily cases, daily deaths, and imposed governmental restrictions. Farzanegan *et al*. [42] use multiple linear regression model to examine the relationship between international tourism and COVID-19 cases and associated deaths in more than 90 nations.

The review of the literature reveal that few studies examine the relationship between COVID-19 and trade. To the best of our knowledge, there is currently no study that use the MLRM to explore the impact of COVID-19 on freight volume of transit trade between Tanzania and Rwanda. Thus, this study fills a gap in the literature and inform discussions of the impact of COVID-19 on freight volume of transit trade between Tanzania and Rwanda as well as propose recommendations for effective policy making.

3. Multiple Linear Regression Model

Multiple linear regression model (MLRM) is a statistical approach that uses several explanatory variables to predict the outcome of response variable. The goal of the MLRM is to model the linear relationship between the explanatory (independent) variables and a response (dependent) variable. The prime stages of the proposed MLRM are model construction, model fine-tuning, formulation of model assumptions, addressing significant modelling problems and model validation.

Stage 3.1. **Model Construction**

A prior knowledge is necessary to identify explanatory variables to be included in the model. Screening techniques can help analysts to find the best combination of variables that contribute to the response variable. Another approach is to adopt all-possible regression to check all subparts of significant explanatory variables, some numerical criteria are:

- *Coefficient of determination* (R^2) measures the proportion of variability in the response variable that can be explained by explanatory variables. R^2 can have values between 0 and 1, where 0 indicates that response variable cannot be predicted by any of the explanatory variables and value 1 reveals that the response variable can be predicted by the explanatory variables without errors.
- *Coefficient of non-determination* or *coefficient of alienation* $(1 - R^2)$ measures variability in the response variable that remains unexplained by the linear regression model.
- Adjusted R-squared $({R_c}^2)$, *variables having larger* ${R_c}^2$ *are better fit variables for the model*.
- *Predicted Sum of Squares* (PSS), the lesser the PSS, the more the predictive strengths of the model.

Using a given data set, we construct a multiple linear regression model to predict the freight volume for the Tanzania – Rwanda transit trade (y_j). The response variable (i.e. freight volume) is modelled as a function of explanatory variables (x_{ij}) as given by equation (1).

$$y_j = \mu_0 + \mu_1 x_{1j} + \mu_2 x_{2j} + \cdots + \mu_k x_{kj} + \delta_j \tag{1}$$

Where

$j \in \{1,2, \dots N\}$ stands for observations

y_j stands for a response variable j

x_k stands for explanatory variable k

μ_0 stands for the y-intercept (constant term)
μ_k stands for the coefficient (slope) of explanatory variable k
δ_j stands for model's error term (i.e. residuals)

A predicted value of the response variable (i.e. the least squares prediction equation) is given by equation (2).

$$\hat{y}_j = \hat{\mu}_0 + \hat{\mu}_1 x_{1j} + \hat{\mu}_2 x_{2j} + \cdots + \hat{\mu}_k x_{kj} \qquad (2)$$

Where $\hat{\mu}_k$ are sample estimates of μ_k which minimize the sum of squared errors. The $\hat{\mu}_k$ values are deduced from statistical software (i.e. SPSS) whereas the x_{kj} values are specified by the modeller. $\hat{\mu}_i, i \in \{1, 2, \cdots k\}$ represents a change in $\hat{y}_j$ caused by a unit change in x_{ij}, $i \in \{1, 2, \cdots k\}$ when x_{ij}, $i \neq k$ are held constant. $\hat{\mu}_0$ represents $\hat{y}_j$ when $x_{ij} = 0$, $i \in \{1, 2, \cdots k\}$.

The difference between an actual and a predicted value (i.e. estimated value) is a residual term (i.e. error term) and is given by equation (3).

$$\delta_j = y_j - \hat{y}_j \qquad (3)$$

Stage 3.2. Model Fine-tuning

The following criteria are used to determine the significance and if necessary improve the model:

- *Global F-test* is deployed to test the significance of explanatory variables to predict the response variable.
- R^2 and R_c^2 are measures that show how well the prediction equation fits the data. The greater the value of R_c^2, the better fit of variables for the model.
- The estimated standard deviation of the random error (SDRE). The interval $\pm 2SDRE$ reveals the accuracy of explanatory variables in predicting a response variable.
- Coefficient of variation (CV). Models with CV values of 10% or smaller usually lead to accurate predictions.

Stage 3.3: Formulating Model Assumptions

The proposed MLRM is based on the following assumptions:

- Explanatory variables and a response variable are linearly related. *The best way to identify the linearity, is to draw a Scatter diagram .and then inspect. for linearity*. If the non-linearity is revealed in the Scatter diagram, then non-linear regression modelling is appropriate.
- The explanatory variables are not highly correlated with each other (i.e. there is no multicollinearity in the data). When the explanatory variables demonstrate multicollinearity, it would be cumbersome to identify the variable that makes the variance in the response variable. This assumption is generally tested by a *Variance Inflation Factor (VIF)* method. If $VIF = 1$, the explanatory variables are not correlated; If $1 < VIF < 5$, the explanatory variables are moderately correlated; If $VIF > 5$, the explanatory variables are highly correlated.

- The response variables (y_j) are both independently and randomly selected from the population. Consequently, *residuals values are independent of one another*.
- It is assumed that the amount of errors in the residuals is same at each point of the MLRM model (i.e. *homoscedasticity*). While examining the data, standard residuals should be plotted against predicted values in order to determine whether the points are currently distributed over all the values of explanatory variables. To test this assumption, *Scatter diagrams can be used*.
- Multivariate normality. When the residuals (or errors) are normally distributed, then the multivariate normality occurs. To test the multivariate normality, histograms with a superimposed normal curve or the normal probability plot may be used.

Stage 3.4: Addressing Significant Modelling Problems

If one of the assumptions of the model is violated, the analyst should fix or minimize the problem that is against the assumptions as explained hereafter.

- If the data is *heteroscedastic*, the response variable can be transformed.
- If the residuals are non-normal due to the presence of large outliers, remove the outliers to correct the non-linearity in residuals.
- If explanatory variables are highly correlated in the model (i.e. Correlation coefficient is close to 1 or -1), remove one of the correlated explanatory variables in the model.
- If a model has missing and/or invalid data values, treat the data or use dummy variables in the model to account for the missing data values.

Stage 3.5: Model Validation

The regression model can be validated by the following methods:

- Check the predicted values by picking new data and test it against values of the response variable that are predicted by the model.
- Cross-validate of the values of the response variable by splitting the sample data into two parts with one part (i.e. first-half) used to estimate the model parameters and the other part (i.e. other half) used to validate the predictions.
- Coefficient of determination (R^2) by showing the total variance that is explained with the relationship between explanatory variables and a response variable. The best fit variables for the model possess larger R^2.

4. Application of MLRM to Determine the Impact of Covid-19 on Freight Volume of Transit Trade

After a comprehensive review of the data set considering the relevance, quality and adequacy of data, we found that the number of port calls, number of trucks deployed for transit trade, transit time from Dar es Salaam Port to Kigali, and logistics transit cost influence the freight volume of FCLs in the central corridor transit trade. The data values of these variables collected from January 2020 to December 2020 are analysed by SPSS as represented in table 1.

Table 1. Time series data of response and explanatory variables of the model for the year 2020.

	Input Y	Input X			
Months	Freight Volume (00" TEUs)	Number of Port Calls (Frequency)	Number of Trucks Deployed (00")	Transit Time (Days)	Logistics Transit Cost (USD)
Jan	33.76	31.00	33.50	14.00	0.00
Feb	36.18	38.00	35.00	14.00	0.00
Mar	43.35	31.00	40.50	25.00	0.00
Apr	38.39	28.00	38.00	25.00	100.00
May	28.41	42.00	28.50	35.00	100.00
Jun	26.76	37.00	26.50	35.00	100.00
Jul	35.68	33.00	35.60	35.00	100.00
Aug	53.56	38.00	53.50	25.00	100.00
Sep	42.07	35.00	41.00	20.00	50.00
Oct	41.90	37.00	41.50	14.00	50.00
Nov	38.23	25.00	38.00	10.00	0.00
Dec	40.05	41.00	39.50	10.00	0.00

4.1. Testing the MLRM Assumptions

4.1.1. Computation of the correlation matrix

In order to determine the degree of relationship between variables, a cross-correlation analysis/Pearson correlation was conducted by using the performance analytics package in R. The interconnectedness of all available variables is illustrated in table 2.

Table 2. Pearson correlation coefficients of model variables.

	Freight Volume (00" TEUs)	Number of Port Calls (Frequency)	Number of Trucks Deployed (00")	Transit Time (Days)	Logistics Transit Cost (USD)
Freight Volume (00" TEUs)	1	-0.08	0.99	-0.34	-0.12
Number of Port Calls (Frequency)	-0.08	1	-0.06	0.19	0.22
Number of Trucks Deployed (00")	0.99	-0.06	1	-0.33	-0.06
Transit Time (Days)	-0.34	0.19	-0.33	1	0.81
Logistics Transit Cost (USD)	-0.12	0.22	-0.06	0.81	1

From table 2, the Pearson correlation measures the strength and direction of the linear relationship between the two variables in terms of the correlation coefficients. The correlation coefficients range from -1 to +1, with -1 indicating the perfect negative correlation and +1 indicating perfect positive correlation and 0 indicating no correlation at all. The pair of variables in the table that show significant correlation are freight volume and number of trucks deployed as well as logistics transit cost and transit time. The rest of the pairs of variables show moderate correlation (i.e. relationship) with each other.

4.1.2. Testing for Multicollinearity of Variables

Table 3. Multicollinearity of the explanatory variables.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	$\hat{\mu}$	$y_j - \hat{y}_j$	μ			Tolerance	VIF
(Constant)	-2.18	1.86		-1.17	0.28		
Number of Port Calls (Frequency)	-0.01	0.03	-0.01	-0.21	0.84	0.95	1.05
Number of Trucks Deployed (00")	1.05	0.03	1.03	36.50	0.00	0.76	1.32
Transit Time (Days)	0.10	0.04	0.14	2.88	0.02	0.26	3.86
Logistics Transit Cost (USD)	-0.02	0.01	-0.17	-3.64	0.01	0.29	3.50

Table 3 presents the *Variance Inflation Factor* (VIF) given by SPSS. $VIF = 1.05$, indicates that the number of port calls is approximately not correlated with other explanatory variables of the model; $VIF = 1.32$, illustrates that the number of trucks deployed is lowly correlated with other explanatory variables; $VIF = 3.86$, reveals that transit time (days) is moderately correlated with other explanatory variables; and $VIF = 3.50$, depicts that the logistics transit cost (USD) is moderately correlated with other explanatory variables**.**

4.2. Significance Testing for Explanatory Variables

The MLRM uses two tests to test whether the model and the estimated coefficients can be found in the general population from which the sample was drawn. Firstly, the *F-test* tests the overall model. The null hypothesis is that the explanatory variables have no influence on the response variable. In other words, the F-tests of the MLRM tests whether the $R^2 = 0$ Secondly, *t-tests* analyse the significance of each individual coefficient and the intercept. The t-test has the null hypothesis that the coefficient/intercept is zero. More specifically, to determine whether the association between the response variable and each term in the model is statistically significant, we compare the p-value for the term with the significance level. The null hypothesis is that the term's coefficient is equal to zero, which indicates that there is no association between the term (i.e. coefficient) and the response variable. Usually, a significance level (denoted as α) of 0.05 works well. A significance level (α = 0.05) indicates a 5% risk of concluding that an association exists when there is no actual association. Generally, if $p - value \leq \alpha$, there is statistically significant association between the response variable and the term.

The table 4 shows the results of the multiple regression model at $p - value = 0.05$ for determining the association of the variables, whereby explanatory variables namely the number of trucks deployed, transit time and logistics transit cost are statistically significant, which implies that their term’s coefficients are not equal to zero, while the explanatory variable, the number of port calls is not statistically significant, as the coefficient of its term is approximately equal to zero.

Table 4. The coefficients for the MLRM, t-values and levels of significance.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	$\hat{\mu}$	$y_j - \hat{y}_j$	μ		
(Constant)	-2.18	1.86		-1.17	0.28
Number of Port Calls (Frequency)	-0.01	0.03	-0.01	-0.21	0.84
Number of Trucks Deployed (00")	1.05	0.03	1.03	36.50	0.00
Transit Time (Days)	0.10	0.04	0.14	2.88	0.02
Logistics Transit Cost (USD)	-0.02	0.01	-0.17	-3.64	0.01

Table 4 gives the coefficients of the MLRM and consequently our estimated (i.e. predicted) multiple linear regression model is given by equation (4).

$$\hat{y}_j = -2.18 - 0.01x_{1_j} + 1.05\, x_{2_j} + 0.1x_{3_j} - 0.02x_{4_j} \tag{4}$$

Where: x_{1j} = number of port calls (Frequency), x_{2j} = number of trucks deployed (00"), x_{3j} = Transit time (Days), x_{4j} = Logistics Transit Cost (USD).

Equation (4) reveals that if the Dar es Salaam Port receives 1 more port call, the freight volume decreases by 0.01 TEUs; if 1 more truck is deployed for transit trade, the freight volume increases by 1.05 TEUs; if the transit time increases by 1 day, the freight volume increases by 0.1 TEUs; if the logistics transit cost increases by 1 dollar, the freight volume decreases by 0.02 TEUs; and if the number of port calls, number of trucks deployed, transit time and logistics transit cost are all zero, the freight volume decreases by 2.18 TEUs.

Table 5. Model summary for the estimation of the standard deviation.

R	R Squared	Adjusted R Squared	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	Df_1	Df_2	Sig. F Change
0.998[a]	0.996	0.993	0.5768	0.996	412.614	4	7	0.000

Table 5 gives the coefficient of determination, denoted as R^2 (R -squared) whose value is 0.996 which indicates that 99.6% of the variability in the response variable is explained by the explanatory variables. Both R-squared value of 0.996 and an adjusted R-squared (R_c^2) value of 0.993 proves that COVID-19 has a significant impact on freight volume of FCLs passing through the Rusumo border. Consequently, $R^2 = 0.996$ and $R_c{}^2 = 0.993$ validate the model i.e. MLRM and confirm the efficiency in model fitness respectively.

We conduct the analysis of variance for the MLRM and obtain the results indicated in table 6.

Table 6. Analysis of variance – ANOVA·

	Sum of Squares	df	Mean Square	F	Sig.
Regression	549.11	4	137.28	412.61	0.00[b]
Residual	2.33	7	0.33		
Total	551.44	11			

Table 6 reveals that most of the total variance is generated by the regression equation at the p-value less than α =0.05 which implies that the model/equation is statistically significant. To *analyse the significance of explanatory variable* of the MLRM, we test whether all the explanatory variables have regression coefficients equal to zero, or whether the explanatory variables have at least one regression coefficient not zero. The regression coefficients of the model are tested by the null hypothesis (H_o) and alternative hypothesis (H_a) [43].
The null hypothesis: All model coefficients are equal to zero

$$H_O : \mu_1 = \mu_2 = \mu_3 = \mu_4 = 0$$

The alternative hypothesis: All model coefficients are not equal to zero

$$H_a : \mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4 \neq 0$$

4.2.1. F-Test

To test the null hypothesis, we turn to F- test that requires an analysis of the variance identified in table 6. *F-statistic* or *F-value* (F_{ca}) is the value that is calculated from the data set whereas *F-critical value* (F_{cr}) is a specific value in the F-table. If the value of F-statistic (F_{ca}) is equal to or very close to 1, the results are in favour of the null hypothesis and we fail to reject it. An F-statistic greater than F-critical is equivalent to a p-value less than alpha (α). If F-value is larger than F-critical value i.e. $F_{ca} > F_{cr}$, the null hypothesis is rejected. Thus, the sample data provide sufficient evidence to conclude that the regression model fits the data better than the model with no explanatory variables. From table 06 the value of the calculated F is 412.61. The critical value of F, at the significance level of 0.05 with 4 degrees of freedom in the numerator and 7 degrees of freedom in the denominator is 4.12. Since 412.61 > 4.12, the null hypothesis is rejected and thus, we accept the alternative hypothesis which implies that not all regression coefficients are equal to zero. This means that the model is significant i.e. Explanatory variables have influence on the response variable (i.e. freight volume).

4.2.2. Student's T-Test

To know exactly which variable or variables have a linear association with the response variable, we perform a student's t- test to test the null and alternative hypothesis. The null hypothesis states that the coefficients, μ_k are equal to zero, and the alternative hypothesis states that the coefficients, μ_k are different from zero [43].
We therefore use a two tailed student's t-test with n-(k+1) degrees of freedom where n=sample size and k=number of explanatory variables [43]. The t-regression coefficients (μ_k) from table 04 are 0.21 for number of port calls, 36.50 for number of trucks deployed, 2.88 for transit time in days and -3.64 for logistics transit cost in dollars.

To define the decision rule concerning the null hypothesis, the calculated t -values (t_{ca}) are compared with the critical value (t_{cr}) of t at a significance level of 0.05 (i.e. each side of the distribution is cut at 0.025), with 12- (4+1) = 7 degrees of freedom. This value is $t_{cr} = \pm 1.895$. Therefore, null hypothesis is rejected whenever $|t_{ca}| > t_{cr}$ i.e. $|t_{ca}| < 1.895$. The comparison analysis of the t-values gives the following results:

- For the number of port calls: the calculated t -value, $-0.21 \in \{t|-1.895 < t < 1.895\}$. Therefore, the null hypothesis is accepted, that is the coefficient $\mu_1$is equal to zero. The statement is confirmed by $p - value = 0.84 > 0.05$. Thus, the number of port calls does not show significant linear relationship with the freight volume of transit trade.
- For the number of trucks deployed at Rusumo border: the calculated t-value, $36.50 \notin \{t|-1.895 < t < 1.895\}$. Therefore, the alternative hypothesis is accepted, that is the coefficient μ_2 is different from zero. The statement is confirmed by $p - value = 0.00 < 0.05$. Thus, the number of trucks deployed exhibit significant linear relationship with the freight volume of transit trade.
- For the number of transit time: the calculated t-value, $2.88 \notin \{t|-1.895 < t < 1.895\}$. Therefore, the alternative hypothesis is accepted, that is the coefficient μ_3 is different from zero. The statement is confirmed by $p - value = 0.02 < 0.05$ Thus, the transit time show significant linear relationship with the freight volume of transit trade.
- For the logistics transit cost: the calculated t-value, $-3.64 \notin \{t|-1.895 < t < 1.895\}$. Therefore, the alternative hypothesis is accepted, that is the coefficient μ_4 is different from

zero. The statement is confirmed by $p - value = 0.01 < 0.05$ Thus, the logistics transit cost exhibit significant linear relationship with the freight volume of transit trade.

In order to ensure that there is no violation in regression modelling assumptions, other statistical tests are conducted, including the normal probability plot of the residuals as illustrated in figure 1 and normal predicted probability (P-P) as illustrated in figure 2.

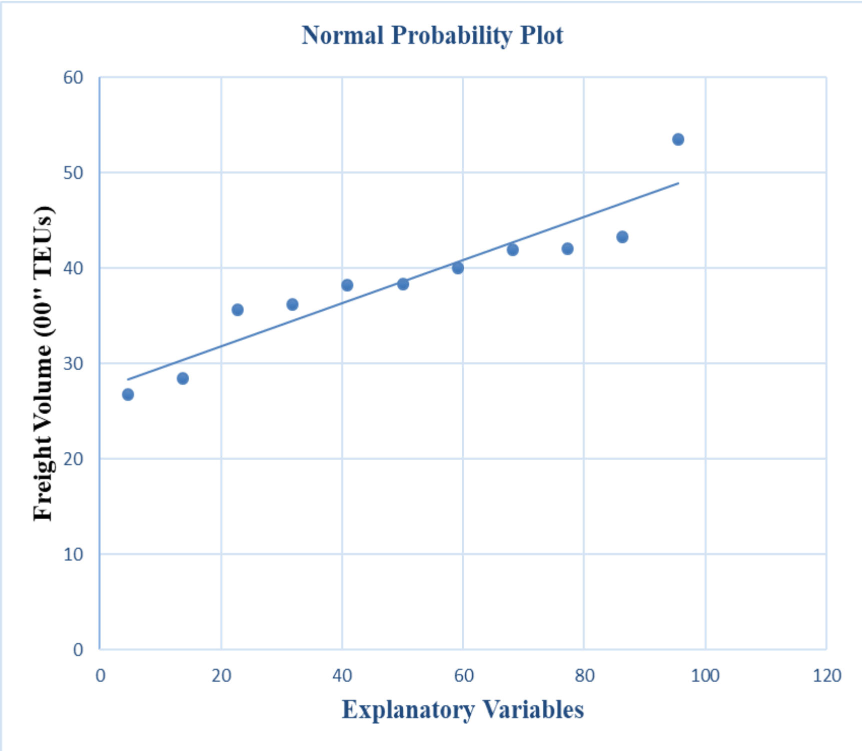

Figure 1. Normal probability plot of residuals

Since figure 1 is approximately linear, the error terms (i.e. residuals) are normally distributed. More specifically, the scatter plot of the residuals in figure 2 are normally distributed since there are no drastic deviations of the data points from the best fitting line.

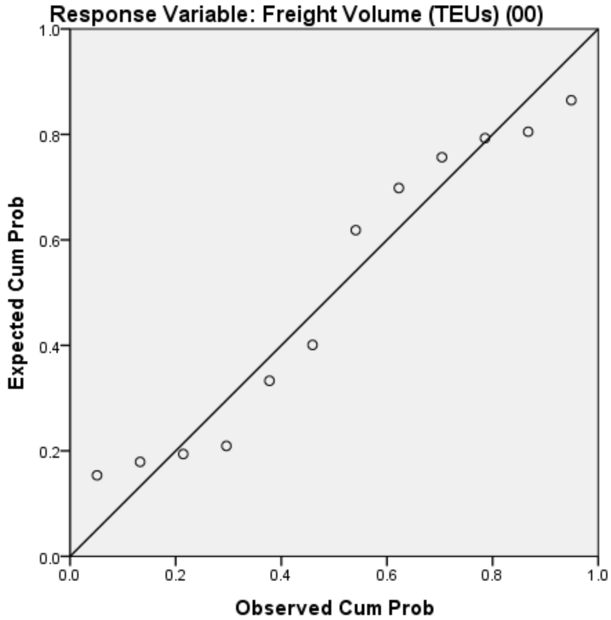

Figure 2. Normal P-P of regression standardised residuals

4.3. Relationship Between Freight Volume and the Explanatory Variables

This section presents a comprehensive discussion on the findings of the proposed study. The analysis of the MLRM reveals a strong linear relationship between freight volume and most of the explanatory variables as discussed in the next section.

4.3.1. Freight Volume and the Number of Port Calls

Table 3 shows that the number of port calls varies negatively with the freight volume at Rusumo border. The calculated coefficient, $\hat{\mu}_1 = -0.01 \approx 0$ for the number of port calls at the Dar es salaam port, at a calculated t – value (t_{ca}) = -0.21. Thus, the t-value reveals insignificant relationship between freight volume and the number of port calls as illustrated in figure 3. More specifically, any unit increase in the number of port calls impacts insignificantly on the freight volume at Rusumo border. Although the number of port calls was impacted globally due to lockdown measures, this study has identified that passenger/cruises vessels were the mostly affected while other types of vessels continued to call and transport globally commodities such as medicines, foodstuff etc. Moreover, the findings could imply that vessels visiting Dar es Salaam Port offloaded less FCLs during the period under consideration.

The findings of the study are in line with the study done by the International Transport Workers Federation [44] on impact of COVID-19 on transport industry which states that during the pandemic, shipping industry has largely proved resilient to the COVID-19 outbreak. Despite the current difficult times, a vast majority of ports have succeeded to stay open to cargo operations. However, most of them remain closed to passenger traffic. Despite the disruptions at ports and to crew changes the shipping industry has largely continued to operate around the world, facilitating the movement of essential supplies and medicines that are needed to keep countries running and to deal with the global public health crisis.

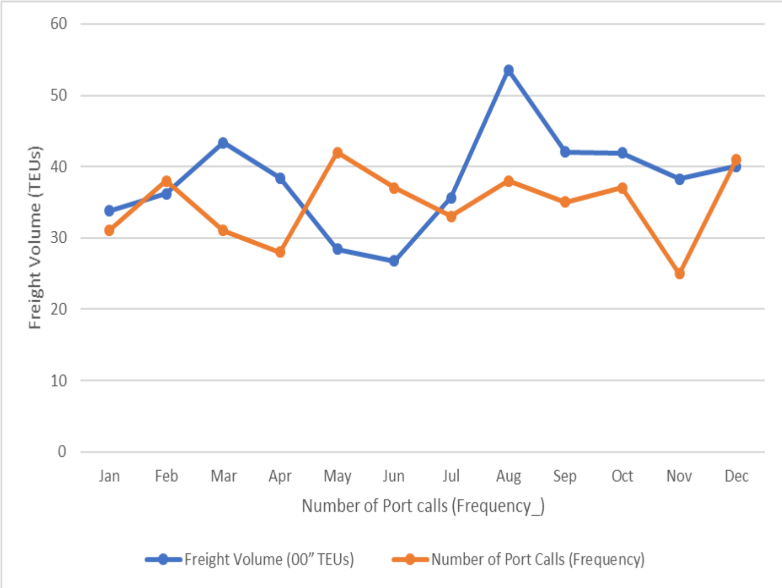

Figure 3. Relationship between freight volume and number of port calls

4.3.2. Freight Volume and Number of Trucks Deployed at Rusumo Border

From table 3 the calculated coefficient, $\mu_2 = 1.05 \neq 0$ for the number of trucks deployed at Dar es salaam port, at a calculated t – value (t_{ca}) =36.50. Thus, the number of trucks deployed increases with freight volume at Rusumo border, whereby for any unit increase/decrease in the freight volume to Rwanda there is a corresponding increase/decrease in the number of trucks deployed as depicted in figure 4.

The study has also found that the fear of the COVID-19 slowed down the movement of trucks in East Africa. Also, the country lockdown in Rwanda in March 2020 was mainly triggered by COVID-19 measures put in place by the government of Rwanda. These measures left trucks to Rusumo from the Dar es salaam Port stranded during peak times of the pandemic especially in early first and second quarter of 2020, as during that time drivers were withheld at Benaco few kilometres prior crossing to Rusumo border. With truck drivers seen as high-risk COVID-19 carriers after some cases were traced to them, the Kigali Government ordered that they turn over their vehicles to Rwandese drivers in a system of relay driving. The other option was to offload merchandise onto Rwandese trucks except for trucks carrying perishable goods and petroleum products destined to Rwanda. Other measures which slowed down the trucking capacity includes shunting of the trucks/swamping, re-testing of the drivers, and self-quarantine. The stiff measures put in place pushed more trucks to be held at one location, also it led the trucks operators to re-allocate the trucks to other destinations with smooth border crossing measures.
The findings of this study are in line with the study done by Dimakou *et al.* [45] who argue that several travel restrictions were applicable for the truck drivers and the containers which led to a significant factor of perilous hurdles for the carriers, and also resulted in a shortage and hindrance of operations in the industry. The findings are also related with the study done by Xu *et al.* [46] who conclude that the lockdown situation adversely affected the transport and logistics.

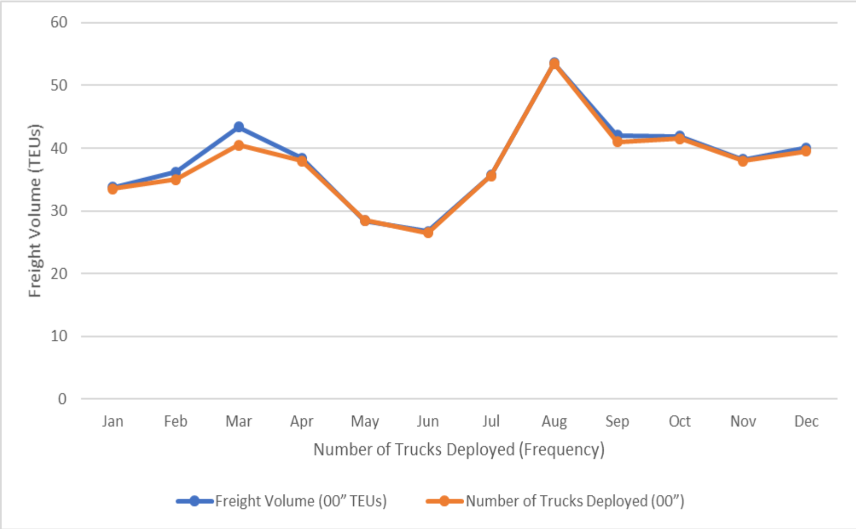

Figure 4. Relationship between freight volume and number of trucks deployed

4.3.3. Freight Volume and Transit Time from Dar Es Salaam Port to Kigali

From table 3 the calculated coefficient, $\mu_3 = 0.1 \neq 0$ for the transit time from Dar es salaam port to Kigali, at a calculated t – value (t_{ca}) =2.88. Thus, the transit time increases with freight volume.

The study has found a proportional relationship between freight volume at Rusumo and transit time as depicted in figure 5. The study reveals that the impact of the spread of COVID-19 in early December 2019, continued until the first quarter in 2020. The spread of the pandemic led to freight volume to increase with the transit time due to delay in border crossing of trucks as a result of increase in number of reported COVID-19 cases in Rwanda.

The figure also reveals that the introduction of the lockdown and border measures in early second quarter of 2020 led to decreased freight volume as a result of increased transit time. In the third quarter of 2020 the freight volume increased as a result of decreased transit time from Dar es Salaam Port to Kigali due to the removal of the lockdowns and the introduction of soft border crossing procedures.

The study has also found that due to the global lockdown policies, the supply of goods and services was limited for landlocked countries such as Rwanda due to experienced long queues of the vessels at the outer anchorage and berthing delays as vessels were allowed only when they have received green light for berthing from the local port. In some cases, vessels were delayed to berth due to the suspected infected crew members in the vessel which led to berthing delays or vessels not berthing at all.

The aforementioned delays led to the late finalization of the customs formalities at the border since paper works were discouraged during documentation process by the Rwanda Revenue Authority (RRA). In addition, the study has found that during the COVID-19 pandemic several offices/staff at customs, shipping agents, container terminal service providers were working remotely this also delayed the release process. Moreover, the high congestion of containers in the container yard at Dar es Salaam Port led to inefficient delivery of containers which exaggerated the transit time from Dar es Salaam Port to Kigali.

These findings are in line with the study done by Markit [47] who argue that long transit time, delays in transit, missed pickups and deliveries have been the most serious problems for shippers/carriers during COVID-19 pandemic as transit times are often extended more than normal.

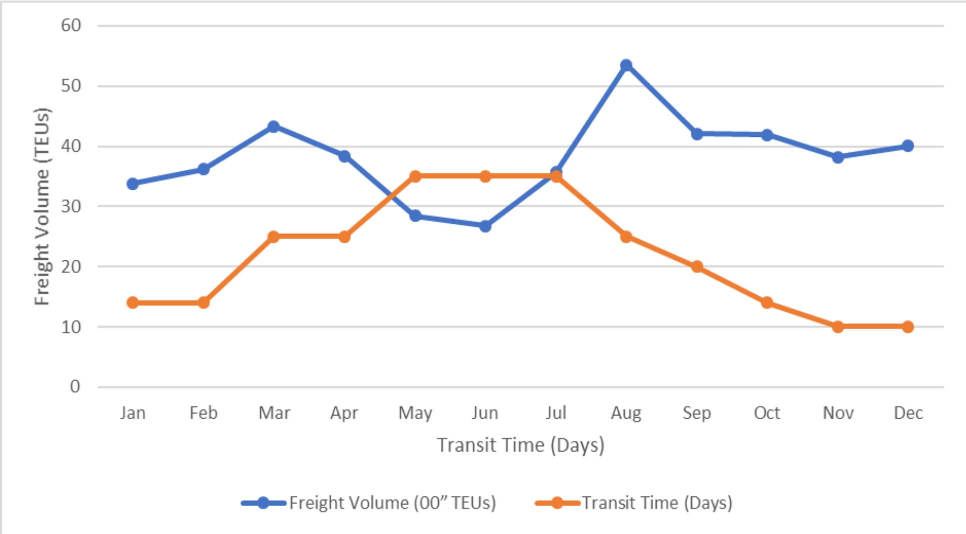

Figure 5. Relationship between freight volume and transit time

4.3.4. Freight Volume and Logistics Transit Cost from Dar Es Salaam Port to Kigali

From table 3 the calculated coefficient, $\mu_4 = -0.02 \neq 0$ for the logistics transit cost from Dar es salaam Port to Kigali, at a calculated t – value (t_{ca}) =-3.64. Thus, the logistics transit cost decreases with freight volume at Rusumo border.

Figure 6 reveals that as the logistics transit cost increased in the first quarter of 2020, the freight volume at Rusumo border decreased as a result of the introduction of the lockdown measures. These lockdown measures led to a decrease of freight volume in the second quarter as well. It is worth noting that the removal of lockdown and introduction of soft border crossing measures led to increase of freight volume at the decrease of logistics transit cost.

The study has found that COVID -19 has impacted the logistics transit cost from Dar es Salaam Port to Kigali. The study has found that the logistics transit cost increased by $ 100 from the beginning of the second quarter to the third quarter of 2020 while the logistics transit cost decreased at the average of $ 50 in September and October with a significant decrease in November and December 2020.

During the study it was also found that, the increased logistics transit cost was mainly triggered by the intrusion measures to combat the pandemic such as lockdown which had led to imposed surcharges such as COVID-19 facilitation fee, parking fee, COVID-19 testing fee, shunting fee. These charges were factored directly into the total logistics cost by the trucks operators to cover their additional operational cost. The findings of this study confirm that the outbreak of COVID-19 has created the inefficiency in global logistics systems as most Governments have imposed several regulations and have restricted the businesses to carry out the operations in this regard. The same argument is supported by Gasiorek *et al*. [48] who argue that the barriers cost the economies of the two nations (i.e. Tanzania and Rwanda) and extra-regional trade. For instance, the poor people in Tanzania could see their real income rise by almost 2.8% as a result of a reduction in transport and logistics costs.

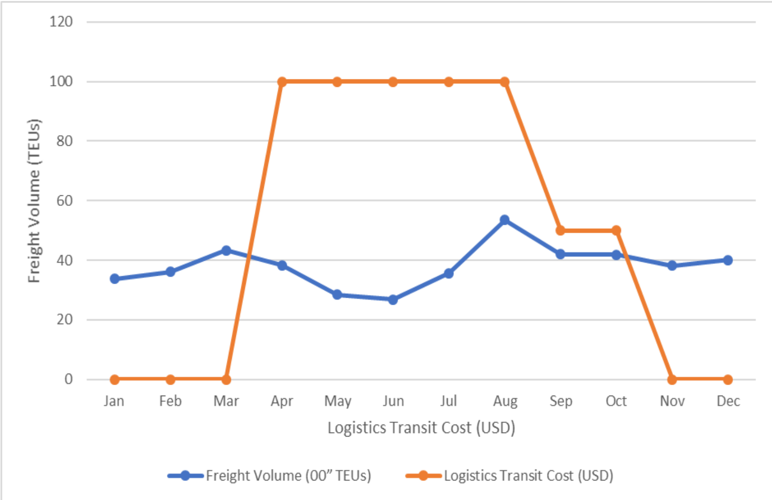

Figure 6. Relationship between freight volume and logistics transit cost

5. Conclusions

The spread of COVID-19 and the public measures implemented by governments to contain the pandemic have had serious ramifications to the world economy and transit trade. This study presents new evidence on the impact of COVID-19 pandemic on transit trade between Tanzania and Rwanda. The study provides a detailed multiple linear regression analysis of the transit trade amidst the pandemic based on determinants such number of port calls, number of trucks deployed, transit time and logistics transit cost. We use a time series data (monthly data) of FCLs from Dar es Salaam Port to Kigali from January 2020 to December 2020 and reveal that in contrast to the number of port calls which varies insignificantly with the freight volume, the other explanatory variables including the number of trucks deployed, truck transit time and logistics transit cost all vary linearly with goods in transit. Specifically, the lockdown measures implemented by the Rwandese government in March 2020 including swamping of trucks, re-testing of the drivers (i.e. refusal of Rwanda to accept COVID-19 test certificates from Tanzania), self-quarantine, Tanzanian truck drivers necessitated to offload containers at the Rusumo border, had serious consequences to the transit trade between Tanzania and Rwanda. In addition, the increased supply chain cost (e.g. logistics transit cost and transit time) along the central corridor and other corridors) if not well managed could adversely affect consumer welfare. More specifically, the escalation of supply chain costs could render businesses and the trading environment in these countries uncompetitive. The ongoing uncertainties about the pandemic's trajectory suggest that Tanzania and Rwanda are not out of the woods yet. This calls for the trading partners, whenever faced with a similar scenario, introduce a common electronic transit document, a unified border transit control and strengthen regional value chain, which reduces delays and trade costs. Moreover, the partner states are called to harmonize their health and trading policies in order to curb the ongoing and/or future pandemic. The findings also validate that the MLRM is one of the useful approaches that tracks the correlation between explanatory variables and determine the variation of the model and the relative contribution of each explanatory variable. Our future direction of this study could be the analysis of the impact of COVID-19 on Tanzanian export trade.

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