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An Analysis of Cross-Border Freight Mode Choice Using Logistic Regression: A Case Study

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ABSTRACT

To increase exports, the activity of cross-border trade should be government attention, especially in Indonesia. Export trade is influenced by several factors, including accessibility to the market area in neighboring countries. It is primarily determined by the transportation system, specifically cross-border freight, that emphasizes a disaggregated approach, focusing on the roles and behavior of logistical decision-makers. This paper outlines the choice of transportation modes as one of the most important aspects of transport and logistics analysis. This case was analyzed using the ordinal logistic regression method with STATA analysis software. The data consists of daily records of 2,017 export transport vehicle trips carrying marine commodities from the Province of West Kalimantan in Indonesia to Kuching City in Malaysia from 2016 to 2018. The result shows that the stereotype logistic regression model is the most appropriate mode of transportation. However, an analysis is needed to determine the characteristics of cross-border transport and help in policymaking.

Key words: Cross-border, disaggregate, freight mode choice, ordinal logistic regression.

1. INTRODUCTION

Cross-border trade occurs due to the availability of sellers and buyers between countries and involves transactions and movements through an inter-country road. Therefore, this trade is influenced by the distance and accessibility to the market areas in neighboring countries since it is carried out across national borders [1]. According to [2], cross-border trade was the flow of goods and services across international land borders within reach of a defined area.

Cross-border trade can be divided into two parts, including trade, carried out around the border, and the movement of commodities across national borders, from the hinterland to market areas that could have been away from the border. In the business to consumer (B2C) framework, it is estimated that the global market for cross-border trade is around 2.3 percent [3].

In the transport sector, especially on goods, analysis of the type of freight vehicle chosen is supposed to be used in essential stages. For instance, in the conventional method of the four-step model, the choice of mode is the third step [4]. It becomes a vital factor in the analysis of goods transportation because of its close relationship with transportation system policies that determines the level of efficiency safety and congestion [5].

In modelling transport demand, the discrete choice model is commonly used in analysis since it has a response variable with an exclusive alternative set. The assumption that the environment forming individual behavior is random and specific for each situation is also critical. These two characteristics make it possible to separate and personalize the actor's behavior to understand preferences according to their motives and characteristics [6]. In its development, a discrete choice model was developed in coordination with econometrics. Modelling travel demand decisions should be carried out with a view of maximizing the utility of the multi-attribute travel choice [7], [8].

2. LITERATURE REVIEW

Mode choice analysis has long been carried out by comparing several modes. For instance, outstanding studies include the choices between road, rail [9], [10], rail and maritime [11], road, rail, and sea [12] or road, rail, water, air [8]. The most widely used method is binary and multinomial logit [8], [9], [13]–[17].

The basis of mode choice between available alternatives is often based on several parameters, including cost, delivery distance, delivery time, transit time, quality, the weight of the shipment, and service frequency [11], [18]–[20]. According to [21], the components of deterministic functions can be distinguished from utility functions into three groups. These include utilities (i) associated with alternative attributes, (ii) related to the characteristics of decision-makers, and (iii) based on the interaction between alternative attributes and decision-maker characteristics. Limited studies have been conducted on the choice of transportation mode based on the characteristics of decision-makers. This study combines alternative attributes, including type, weight, and value of commodities transported, as well as the characteristics of decision-makers, such as the type or scale of the exporting company.

From the initial analysis, the mode choice model is based on the random utility maximization principle. This principle is derived from econometric theory [22], [23]. The method commonly used in previous studies is multinomial logit (MNL). This approach is used because the selection of transportation modes includes more than two options that cannot be ranked (e.g., public transport, bicycles, walking). However, in cross-border freight transportation, the modes of transportation chosen are typically the same, such as pickup and truck. The only distinction between the two is on the carrying capacity. In this paper, freight vehicles can accommodate small, medium, and large capacity goods. Data variables with different characteristics require a different approach, which is mainly ordinal logistic regression. The application of unordered models, such as multinomial logit, cannot be used to prevent loss of efficiency [24] (Figure 1). This paper examines the model in an ordinal logistic regression framework.

3. METHOD

This research uses ordinal logistic regression, a model that is rarely applied in the freight mode choice analysis. It is used to investigate the relationship between independent variables, such as attributes of alternatives, with the dependent variable, specifically the freight vehicle capacity. It is a case study on cross-border freight in the corridor between the West Kalimantan provinces and Sarawak, Malaysia.
Logistic regression analysis in this research using STATA software. STATA is a comprehensive statistical package that involves data management. It is a widely-used package and mainly available in economic literature. Also, it requires the use of ordinal logistic regression with an analysis of proportional odds. This underlying assumption emphasizes that the relationship between each pair of outcomes groups is equal. In cases where the dependent variable can be ordered, the distance between the categories is unknown. It includes a survey question that divides responses to categories, including strongly agree, agree, disagree, and strongly disagree. Therefore, it cannot be assumed that the distance between strongly agreeing and agreeing is the same as between agreeing and disagreeing [24].

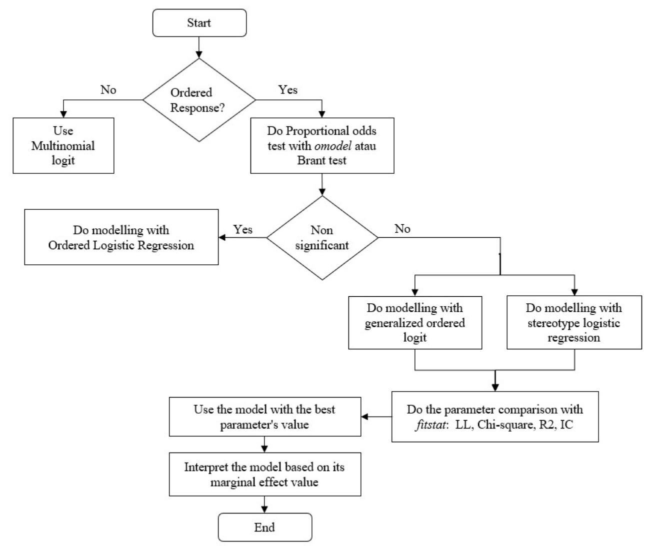

Figure 1: Flow chart of the logistic regression model choice process

3.1 Ordered Logistic Regression

Although many alternatives responses in the transportation sector are unordered, there are quite a lot of ordered opinions on new transportation policy, including disagree, neutral, and agree or about the severity of an accident such as property damage-only crashes, injury crashes, and fatal crashes. As explained previously, there can be a loss of efficiency in the case ordered alternatives are modelled with an unordered model. STATA is statistical software that can be used to analyze the ordinal logistic regression model with a routine called *ologit*.

According to [25], the ordinal logistic regression model an be stated in the logit form as follows:

$$\ln(Y1') = \text{logit}[\pi(x)] = \ln((\pi j\,(x)) / (1-\pi j\,(x))) = \alpha 1 + (-\beta 1\,X1 - \beta 2\,X1 - \ldots - \beta p\,Xp) \quad (1)$$

Where $\pi j\ (x) = \pi(Y \leq j\ |x1, x1, ..., xp\ )$, is the probability of being at or below category j given a set of predictors, j = 1, 2, …., J − 1. αj is the cut points, and $\beta 1, \beta 2, ..., \beta p$ are the logit coefficients.

For example, at all three levels outcome variable, such as the type of freight mode based on capacity, 1 = small, 2 medium, 3 = large;

$$p(Y\leq 3) = p(Y = 1) + p(Y = 2) + p(Y = 3) = 1 \qquad (2)$$
$$p(Y\leq 2) = p(Y = 1) + p(Y = 2) \qquad (3)$$
$$p(Y\leq 1) = p(Y = 1) \qquad (4)$$

The probability, p(Y > 1) = p(2) + p(3), is the sum of the probabilities when Y = 2, 3:

$$\text{Odds}\ (Y \leq 1) = (p(Y \leq 1))/(1-p(Y \leq 1)) = (p(1))/(p(2)+p(3)) \qquad (5)$$

Odds (Y ≤ 2) is equal to the probability ratio of being at category 2 or below it until the probability is above this category. Because $p(Y \leq 2) = p(1) + p(2)$, and $p(Y > 2) = p(3) + p(4)$, odds of being at or below category 2 can be expressed as follows:

$$Odds\ (Y \leq 2) = (p(Y \leq 2))/(1-p(Y \leq 2)) = (p(1)+p(2))/p(3)) \qquad (6)$$

3.2 Generalized Ordered Logistic Model

In case the above test shows a significant result, or proportional odds assumption is violated, the model runs as a generalized ordered logistic model. It uses the gologit2 command, which estimates generalized logistic regression models for ordinal dependent variables [26]. The strength of gologit2 lies in its ability to estimate the partial proportional odds model to predict models with less restrictive than the proportional odds/parallel lines, where assumptions are often violated [26].

In case the proportional odds model in ordered logistic regression by STATA can be analyzed by gologit2, restriction to the Bk coefficients are similar for every dividing point k=1, …m-1. Reference [26] describes generalized ordered logit as follows:

$$\log [P(Y > k) / P(Y \leq k)] = XBk \qquad k = 1,\ldots, m-1 \qquad (7)$$

The partial proportional odds model (estimated only by the gologit2 via command the ***npl ()*** dan ***pl ()*** options) restricts some Bk coefficient to be similar for every dividing point while other coefficients vary (equation 7).

3.3 Stereotype Logistic Regression

Stereotype logistic that limits the PO postulations is used to determine the viability of the ordinal response based on the subjective judgment of the categories [21]. Stereotype logistic (SL) regression was developed by [27] and furthered by [28]. According to [25], the SL model can be treated as an extension of both multinomial logistic regression and the PO model. SL is regarded as an extension of the multinomial logistics model since they estimate the odds of being at a particular category based on the baseline.

The SL is similar to the PO model since it estimates the ordinal response rather than the nominal outcome when given a set of predictors. However, it does not assume the PO assumption and allows the effect of each predictor to vary in the ordinal category.

Reference [25] proposed Anderson's stereotype logistic regression model [27] in the following form:

$$\begin{aligned} logit\ [\pi(j,J)] &= \ln\left(\frac{\pi(Y=j\,|x_1,x_1,\ldots,x_p)}{\pi(Y=J\,|x_1,x_1,\ldots,x_p)}\right) \\ &= \alpha_j - \phi_j\,(\beta_1 X_1 + \beta_2 X_2 + \ldots \beta_p X_p) \end{aligned} \qquad (8)$$

4. STUDY LOCATION AND CONSTRUCTION DATA

This research is a study of cross-border freight involving exporting marine commodities in the corridors of West Kalimantan, Indonesia, and Sarawak, Malaysia (Figure 2). Primary data were obtained from the Indonesian Fish Quarantine Inspection Agency (BKIPM) under the authority of the Indonesian Ministry of the Maritime Affairs and Fisheries. The data includes daily trips of freight vehicles with marine commodities.

The hinterland area includes a fishing port and packaging-collection point spread across several districts and cities on the coast of West Kalimantan. The commodity market area is in the city of Kuching, Sarawak state, Malaysia.

The data obtained include:

1. Date and time of shipment
2. Type or scale of the exporter company (*ltdp*)
3. Classification of commodities (*comc*)
4. Weight of commodities (*comw*)
5. Value of commodities (*comv*)
6. Travel distance or Length of haul (*lgth*)
7. Type of freight vehicle (*tpfv*)

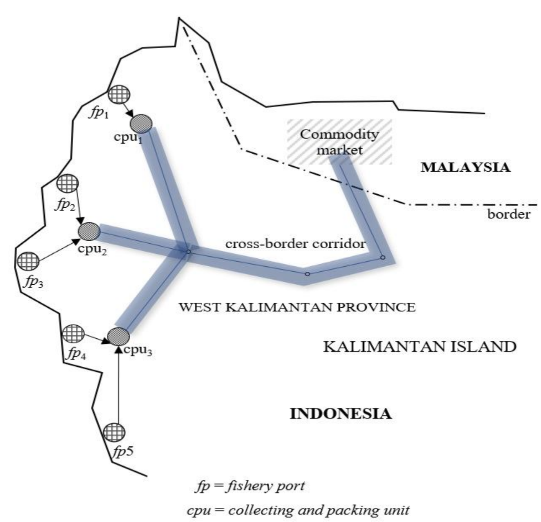

Figure 2: Map of truck trips on cross-border marine commodity exports from West Kalimantan, Indonesia to Kuching, Malaysia

The data collected was three consecutive years (2016-2018), with 2,017 shipments. Additional information was obtained from interviews with stakeholders, both from government agencies and the private sector. The scales of exporter companies are divided into two categories, including the sole proprietorship (small size) and limited partnership (larger scale)

Similarly, the freight vehicles are divided into small capacity freight vehicles, medium-capacity freight vehicles, and large capacity freight vehicles. Table 1 shows a classification of freight types that operate at a study location. The length of haul data is continuous in the form of distance from commodity collection and packaging point locations in West Kalimantan in Indonesia to inland ports in Malaysia. Classification of commodities consists of (i) shrimp and crab, (ii) fish, and (iii) combinations.

Table 1: The Type of Freight Transportation in the Study Location

Classification	Description of Freight Transportation
Type 1	Small Capacity Freight Vehicle
Type 2	Medium Capacity Freight Vehicle
Type 3	Large Capacity Freight Vehicle

Considering the high level of difficulty in collecting data at the disaggregated level, the characteristics of cross-border freight transportation from 2016 to 2018 between West Kalimantan and Sarawak is critical in the analysis.

5. MODEL ESTIMATION AND RESULT INTERPRETATION

The ordinal logit model was used to determine the relationships between the dependent variable and a set of independent variables [29]. Commodity weight uses continuous data obtained from the Indonesian Fish Quarantine Inspection Agency (BKIPM). The variables used in the ordinal logistic regression are shown in Table 2.

Table 2: Name and label variables in the logistic regression model

Parameter	Variable	Description
α	-	Regression constant
β_1	*ltdp*	Type or scale of the exporter company
$\beta 2$	*comv*	Value of commodity
$\beta 3$	*comc*	Classification of commodity
$\beta 4$	*lgth*	Length of haul
$\beta 5$	*comw*	Weight of commodity

The freight vehicles characteristics used at the study location is shown in Table 3. Medium capacity box trucks are the dominant type of vehicle in the cross-border freight transportation system, though it depends on the cargo being transported.

Considering the cost of transportation, the medium-capacity freight vehicle used is not from the reefer truck type with a cooler. The use of open type freight vehicles, such as pick up and large non-box trucks, affects the quality of the fresh marine freight vehicles. Apart from using a box (from polyethylene), it also utilizes ice cooler, as well as transportation at night, to reduce the impact of the air temperature.

Table 3: Tabulation of the type of freight vehicle

Type of freight vehicle	Freq.	Percent
Small Capacity Freight Veh.	77	3.82
Medium Capacity Freight Veh.	1,480	73.38
Large Capacity Freight Veh.	460	22.81
Total	2,107	100.00

Trucks are still the main choice when it comes to the transportation of goods, especially in cross-border corridors. It is because they offer relatively low operational costs, with door-to-door service, as well as the ease of loading and unloading. At the study location, transportation is carried out conventionally, using a land mode. Ordinal logistic regression analysis is implemented in STATA using the command *ologit*.

Table 4: The result from Ordered Logistic Regression Model

Model		LR chi2 (6)		1182.52
		Prob > chi2		0.0000
		Pseudo R2		0.4255
		Log-likelihood		-798.29428
			P > | z |	Odds Ratio
Coeff.	*ltdp*	-1.182508	0.000	0.3065
	comv	0.0028407	0.061	1.0028
	comc2	-1.038939	0.000	0.3538
	comc3	-0.4911379	0.019	0.6119
	lgth	0.0457288	0.000	1.0468
	comw	0.0028094	0.076	1.0028
	cut1	8.991664		
	cut2	16.81068		

From Table 4, the value Prob> chi2 (the probability of obtaining the chi-square statistic) proved that the null hypothesis is true. The p-value is 0.0000, and when compared to a critical value, 0.05, it shows the overall model is statistically significant. Furthermore, the test is carried out with the *omodel* command, which gives the following results.

Table 5: The result of proportional odds with *omodel*

Approximate likelihood-ratio test of proportional odds across response categories:	
Chi (5)	406.23
Prob > chi2	0.0000

Evaluation of proportional odds assumptions in Table 5 results in Prob > chi2 value at 0.0000. The results are significant, and therefore, the assumptions are violated. The next step involves running the generalized ordered logit model with the *gologit2* command on STATA.

Table 6: The result from Generalized ordered Logit Model

Model		LR chi2 (6)	1162.83	
		Prob > chi2	0.0000	
		Pseudo R2	0.4184	
		Log-likelihood	-808.1385	
Coeff.			**P > | z |**	**Odds Ratio**
Small capacity freigth veh.	*ltdp*	-1.1011	0.000	0.3325
	comv	0.001585	0.296	1.0015
	comc	-0.103976	0.272	0.90125
	lgth	0.0440459	0.000	1.04503
	comw	0.0032695	0.000	1.00328
	_cons	-8.78499	0.000	0.000153
Medium capacity freigth veh.	*ltdp*	1.296909	0.000	0.3325
	comv	-0.002415	0.144	1.0015
	comc	0.4091289	0.002	0.90125
	lgth	0.0250962	0.000	1.04503
	comw	0.0023532	0.002	1.00328
	_cons	-11.85214	0.000	6.65e-08

The next step involves modelling the stereotype logistic regression are shown in Table 7 below.

Table 7: The result from Stereotype Logit Model

Model		Wald chi2 (5)	235.27	
		Prob > chi2	0.0000	
		Pseudo R2	0.474	
		Log-likelihood	-728.73358	
Coeff.			**P > | z |**	**Odds Ratio**
Small capacity freight veh.	*1.ltdp*	-3.64132	0.000	0,026
	comv	0.02344	0.000	1.024
	comc2	-2.18337	0.005	0.113
	comc3	-1.41204	0.036	0.244
	lgth	0.20709	0.000	1.230
	comw	0.00399	0.123	1.004
phi	*phi_1*	1		
	phi_2	0.17537		
	phi_3	0		

Once the results of the stereotype logistic regression model with the *fitstat* command are obtained, the calculations and recapitulation of the log-likelihood parameters, chi-square, R2 and the value of the information criteria (IC) are conducted. The comparison between *gologit2* and *slogit* modelling results is shown in Table 8 below.

Table 8: Comparison of model parameters with *fitstat*

Parameters	**gologit2**	**slogit**
Log-likelihood		
Model	-808.139	-731.498
Intercept-only	-1389.555	-1389.555
Chi-square		
Deviance	1616.277	1462.996
LR	1162.833	235.737
p-value	0.000	0.000
R2		
McFadden	0.418	0.474
McFadden (adjusted)	0.413	0.468
Cox-Snell/M.L	0.438	0.479
Cragg-Uhler/Nagelkerke	0.568	0.641
IC		
AIC	1630.277	1478.996
AIC divided by N	0.808	0.733
BIC	1669.543	1523.871

By choosing a greater value for log-likelihood and R2, and a smaller one for chi-square and IC, *slogit* is a better model for this case. The stereotype logistic regression in Table 6 shows that the overall model is statistically significant. The Pseudo R2 value shows that the model explains 47.4% of the response variability data around its mean. Pseudo R2 value at 0.474 is considered as an excellent model fit. Based on the value P> | z |, *ltdp*, *comv* and *lgth* were statistically significant, while *comc* and *comw* were not significant. Phi (ϕ) is the coefficient related to the scale parameter. The table in the output shows odds ratios for five predictor variables compared to large capacity freight vehicle vs small capacity freight vehicles (3 vs 1). By substituting the coefficient value (Table 7) into Equation (8) the following is obtained;

$$logit[\pi(j,J)] = \alpha j - \phi j((-3.64132(ltdp) + 0.02344(comv) - 2.18337(comc2) - 1.41204(com3) + 0.20709(lgth) + 0.00399(comw)) \quad (9)$$

The next process is carried out by comparing categories based on the OR value of predictor variables.

Table 9: Odds Ratio for Predictor Variables Across Two Comparisons

Category comparison	**Y=3 vs. Y=1**	**Y=3 vs. Y=2**
Variable	**Odds Ratio**	**Odds Ratio**
ltdp	0.0262	0.5280
comv	1.0237	1.0041
comc2	0.1127*	0.6819*
comc2	4.1043	1.2810
lgth	1.2301	1.0370
comw	1.0040*	1.0007*

p-value > 0.01

For the *ltdp* predictor (the exporter company scale), the value OR = 0.0262, indicates that the odds of being in the base category 3 versus category 1 for *ltdp* are 0,.0262 times the odds for non-*ltdp* in case all the other predictors are held constant. In other words, larger-scale companies often prefer a smaller capacity freight vehicle with contradicts the prevailing logic. The subject that explained in the previous section can be elaborated by displaying the tabulations of the two variables, as shown in Table 10.

Table 10: Tabulation of company scale (*ltdp*) by the type of freight vehicle (*tpfv*)

Scale of the company	Type of freight vehicle			Total
	Small capacity	Mediu m capacity	Large capacity	
0 (=small)	6	1,240	48	1,294
1 (=larger)	71	240	412	723
Total	77	1,480	460	2,017

The values in the table show that smaller companies have fewer shipments with small freight vehicles compared to larger companies with a ratio of 6 : 71. Smaller companies carry out shipments using a more medium freight vehicle with a comparison of 1,240 : 240. The *tpfv* regression results as dependent and *ltdp* as independent variables are shown in Table 11 below.

Table 11: Regression result of the type of freight and scale of the exporter company

F(1,2015	Prob > F	R-squared	P > | t |
480.99	0.0000	0.1927	0.000

Table 11 shows that at F (1, 2015) 480.99, Prob> F is 0.000, which means that the independent variable is a reliable predictor of the dependent variable. The p value > | t | = 0.000 also shows that this coefficient is statistically significant. However, the R-squared value of 0.1927, which is the company scale, only affects the selection of freight vehicles by 19.27 percent (there are 80.73% of other variables that influence the choice of vehicle types).

Based on Table 9, the *comv* predictor OR = 1.0237 is greater than 1. It means the odds increased by the 1.0237 factor for a single unit increment words in the value when the effects of other variables are held constant. The higher the value of the commodity being transported, the greater the capacity of the vehicle used.

In the *lgth* predictor (distance length), OR = 1.2301, which is greater than 1. It shows that the odds increase (by the 1.2301 factor for an increase of one length unit) in case the effect of the other variable is held constant. Therefore, the farther distance between the starting and the endpoints of the trip, greater the capacity of the vehicle used.

The *comc* and *comw* have insignificant results, showing that there is no relationship between the predictor and the odds. Therefore, the commodity weight was not significant in the vehicle capacity selection model and required further elaboration. Table 12 shows the regression results from the type of freight vehicles and weight.

Table 12: Regression result of the type of freight (*tpfv*) and scale of the exporter company (*ltdp*)

F(1,2015	Prob > F	R-squared	P > | t |
20.78.99	0.0000	0.0102	0.000

Table 12 shows that the p-value associated with F-value is very small (0.000), which means that the independent variable can be relied upon in predicting the dependent variable. The value P > | t | from 0.000 also shows that this coefficient is statistically significant. However, the value of R-squared 0.0102 or the company's scale only affects the selection of vehicles by 0.0102, or 1.02% percent. It means there are 98.98% other variables affecting the decision making.

From Figure 3 below, there is no specific patterns that indicate a strong correlation between *comw* and *tpfv*. The circles with the letters A, B and C indicate that low-weight loads are transported by both small vehicles, truck boxes and large trucks. The data are plotted with letters D and E indicating that cargo weighing over 7.0 tons was transported well with medium and large capacity freight vehicles. This inefficiency indicates that there is no proper transportation management in the study area.

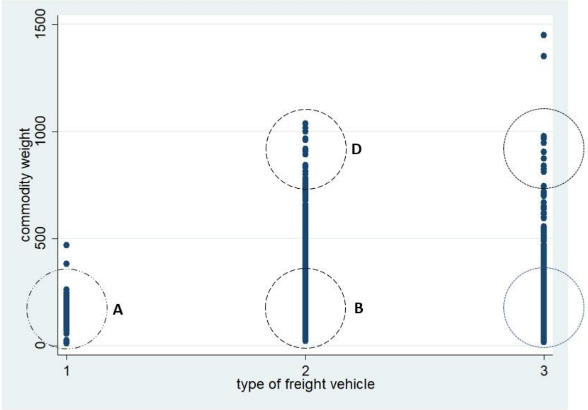

Figure 3: The relationship between weight of commodity (*comw*) and type of freight vehicle (*tpfv*)

If the exporter company does not have several vehicles with different capacities, freight services are used. They carry out the management, including the consolidation of goods, and therefore efficiency can be improved.

6. CONCLUSION

This paper contributes to the analysis of the characteristics of the choice of cross-border transport modes by adopting the logistic regression model method. The novelty of this paper emphasizes the application of non-multinomial multi-response models in the analysis of freight transport modes choice. Generally, in multi-response modelling, the model used is multinomial logit. It is used to predict the probability of the dependent variable being categorically distributed but not under ordered categories.

The study on cross border freight transport provides a unique case where the type of freight vehicle is limited. In general, most of the cross-border freight transportation use land vehicle mode. In the research area, all commodity shipments use in the same type of vehicle, with the difference between them being capacity.

From the secondary data on 2,017 shipments from 2016 to 2018, the variables have ordinal characteristics, and therefore, the initial assumptions can be resolved with the ordered logistic regression method. However, tests using the *omodel* on STATA confirm that ordered logistic regression based on the assumption of proportional odds cannot be used. In that case, there are two choices, including the use of generalized ordered logit or stereotype logistic regression. After comparing statistical parameters, it was established that stereotype logistic regression was a more appropriate model. In the calculation and recapitulation by *fitstat* (Table 8), the entire model is statistically significant. It explains 47.4% of the variability of response data around the average (McFadden's R2).

In the final stage, analysis of odds stereotype logistic regression is used to determine the relationship between the independent and dependent variables. From the five independent variables analyzed, commodity classification (*comc*) and weight (*comw*) were statistically insignificant.

The interpretation result of the comparison of odd ratio (OR) category shows the following.

1. Essentially, *lgth* or length influence the choice of the transportation mode based on its capacity. The farther the delivery distance, the greater the probability of selection of vehicles with large capacity.
2. The commodity value (*comv*) has a relatively significant influence where a higher commodity value leads to a greater possibility of using a vehicle with a large capacity.
3. In the variable scale predictor of exporters (*ltdp*), the change from the limited partnership company to individual ownership reduces the possibility of using vehicles with greater capacity.

From the two variables with insignificant statistical results, there is a need for further analysis of the weight of the commodity. In general, the weight of the shipped commodity is a function in the choice of vehicle type/capacity. In the case of cross-border export shipments, the weight of the commodity has no significant effect. Based on the distribution of weight values, there is no specific pattern that relates to vehicle capacity. The random distribution of commodity weight is influenced by fluctuations and limited supply from the fishing port. Still, the minimum value of commodity weights is affected by transport vehicle operating or shipping costs incurred by exporters. This condition is detrimental to exporters, where a small amount of cargo transported using a large freight vehicle requiring quite an enormous transportation cost. The recommended solutions include using freight forwarding services that consolidate cargo. Shipments from several exporters in less than truckload (LTL) can be consolidated into one truck. It leads to lower transportation costs for exporters because, in the LTL delivery system, the costs can be shared. Costs incurred are based on the weight of the goods sent and the distance or duration of the trip.

There is a need for further research in the cross-border freight transportation systems. The transportation system with long-distance truck trips and high capacity freights transportation can be more optimized. This optimization is expected to have an impact that increases the exports and become more beneficial to all stakeholders involved, including exporters, fisheries sector entrepreneurs, and the government obtaining Local Own-Source Revenue and export duties.

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