 DOI: 10.20858/tp.2023.18.3.03

Keywords: freight transport; freight mode choice; binary logistic regression; firth logistic regression; complete separation; truck; train; Iraq

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A STUDY ON INTERSTATE FREIGHT MODE CHOICE BETWEEN TRUCKS AND TRAINS USED TO TRANSPORT OIL PRODUCTS: A CASE STUDY OF IRAQ

Summary. Freight mode choice is an important stage in shipping demand modeling. Transporting oil products using trucks between cities has several issues, including increased risk of accidents, higher transportation costs, environmental impact, and traffic congestion. Due to the absence of local studies, in addition to the few global studies that deal with freight mode selection used to transport oil derivatives between cities, the aim of the study is to develop transport mode choice models for trucks and trains transporting oil products between the interstate capital of Baghdad and the government of Basra for export. The revealed preference survey was used for 277 goods transport data collected with the help of personal interviews, questionnaires, and government institutions. The collected data were processed using two statistical approaches: binary logistic regression and Firth logistic regression. The study's findings assist decision-makers in selecting sustainable modes of transport.

1. INTRODUCTION

The freight transportation system plays an essential role in the vitality of local and regional economies [1], and freight mode selection is crucial in freight demand modeling [2]. Rail, road, sea, air, and pipeline are the primary modes of freight transportation [3]. Railways are an environmentally friendly mode of transport used to transport low-value commodities. This transportation mode is preferable for shipping large volumes of commodities over long distances. Road transport is widely used due to the availability of transport networks covering large areas that allow the transportation of goods from door to door [4, 5]. The demand for transporting goods by road using trucks is increasing compared to other modes of transportation. However, this increasing demand has led to many adverse effects, such as traffic congestion, accidents, pavement damage, and pollution.

There are relatively few studies that deal with freight mode choices. Some of these studies are as follows. Using logit models, researchers evaluated the freight mode selection between truck and rail for freight started in Maryland and shipped to other states [2]. According to the findings, the transportation distance ratio, time value, product, commerce type, place of origin, and price of fuel play important roles in freight mode choice. Other research investigated the effect of environmental and individual variables on route selection by using the conventional logistic regression approach and Firth logistic regression method to choose pedestrians for a specific road path in an urban area [6]. The study's findings indicate that Firth logistic regression can deal with the complete separation of data. Another study used a binary logit model to explain why shippers, third-party logistics, and receivers choose trucks and trains [7]. It was discovered that shipment-specific variables, haul time, and shipping cost significantly influenced mode choice. This result shows that rail shipments were more cost-sensitive than road shipments, but road freight was more time-sensitive. Fuel price had little influence on mode selection as well.

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Another study investigated the effect of travel distance and delivery time reliability on the value of time [8]. An adaptable experiment was undertaken on potential intermodal transportation consumers in China's Yangtze River Delta region. Binary logit models were computed for eight parameters. The data show that shipper characteristics and product characteristics have a significant impact on mode-select behavior. In addition, the study advocated for a shift in the mode of transportation from truck to road-rail container intermodal transportation. Other researchers examined freight transportation mode choice using a new approach, multi-criteria decision analysis, from the perspectives of many industries and experts in the field [9]. Data were obtained from online surveys from practitioners, industry experts, and academics and were evaluated using the best worst technique. According to the findings, transportation costs are the most critical element, followed by on-time reliability and CO_2 emission reduction.

Other researchers developed freight mode choice models for trucks and rails transporting general goods between two Brazilian states using a multinomial and mixed logit approach [10]. The data included travel time, travel cost, reliability, availability, and cargo theft risk. The findings revealed that shippers' preferences are insensitive to travel cost and travel time. A policy that combines railway operation strategy and road mode tariffs could be an alternative. The most effective strategy is to increase rail service availability, eventually reaching door-to-door service. Infrastructure development, such as terminal availability, routes, and terminal access, is critical for increasing rail transport usage in the state. In other work, researchers used the binary logit model to examine the parameters influencing the selection between truck and train shipments used to transport fish commodities in India [11]. The study revealed that providing freight corridors enhances speed, delivery time reliability, and traffic safety. Shafting from rail roll-on-roll-off truck facilities can reduce transport costs and traffic congestion. Allowing piecemeal service on goods trains reduces costs and shifts road freight to rail, increasing speed and frequency. These policy measures reduce energy usage and encourage a shift from road to rail.

The authors of another study utilized a binary logit model to investigate freight transportation by truck and train in Gresik, Indonesia [12]. The costs of shipping and delivery times were obtained using the stated preference method. The data revealed that respondents were concerned about delivery time and shipping costs. When the costs of shipping and delivery time were similar, the probability of using a truck was 77%. However, industrial freight transporters changed their choices when the cost of shipping and delivery times were greater when using a truck than a train. When the cost was IDR 500,000 less for a train compared to a truck and when the delivery time was two days faster for a train than a truck, the train was chosen with a probability of 65%. The authors of a different study analyzed freight transport mode choice for processed agricultural products from northeastern Thailand using a binary logit model [13]. The study utilized a survey of stated preferences. Delivery time, cost, reliability, scheduling employee availability, and the distance between the factory and the railway station were revealed to be variables influencing container transport mode selection. According to the research, reliability most significantly affected companies' choices of shifting to rail transportation, followed by transportation costs. The findings also demonstrated the necessity of station employees' availability. Although delivery time was essential, it did not appear to be as critical as reliability or cost. Finally, the station's distance had an insignificant impact.

According to previous research, freight mode selection is influenced by several primary factors, including shipping cost, haul time, delivery time reliability, frequency, flexibility, and security, as well as secondary factors, such as the value of the goods, the possibility of damage, and carbon emissions.

This research aims to define the most critical factors influencing the choice between two modes of transport (trucks and trains) used to transport oil derivatives between two cities. Also, models were established for choosing the mode of transport through the conventional binary logistic regression and Firth logistic regression methods. This study's outputs help decision-makers choose the most efficient and sustainable mode of transportation. The paper's contents are divided into introducing the subject, separating issues with data, defining the study area and methodology, and finally, presenting the results and conclusions.

2. SEPARATION ISSUE WITH FREIGHT TRIP DATA

A complete separation in logistic regression, also known as perfect prediction, occurs when the outcome variable separates an explanatory variable [14]. A common issue in modeling conventional logistic regression is the inability of the likelihood maximization algorithm to converge. This problem usually occurs through data patterns known as complete separation or quasi-complete separation. As a result, maximum likelihood predictions do not exist for these data [15].

Several traditional options can be employed to solve the problem of separation in data. First, increasing the sample size may contribute to solving the problem of data separation by involving additional cases that were not taken into account due to the small sample size. However, this option is financially impractical and requires extra time and effort to collect additional data. Second, combining an explanatory variable that suffers from a separation problem with another variable may help solve this problem, but combining variables causes the variable to lose its unique meaning. Third, the explanatory variables with the separation problem are omitted in the model. However, this option is not recommended if the explanatory variable strongly influences the prediction of the outcome variable since this leads to a biased prediction of other explanatory variables in the model [6].

There are also three statistical approaches to solving the problem of data separation. The first method is exact logistic regression, which is a useful approach when the data set is limited and the model does not have more than one explanatory variable. The second method is the Bayesian method, which can be used when there is more information on the parameter estimate of explanatory variables. Lastly, Firth logistic regression method uses the penalized likelihood estimation method. It works with more than one explanatory variable and large sample sizes to produce coefficient estimates that are probably unbiased [6, 15].

All of the above methods can be suitable for solving quasi-complete separation, and Firth logistic regression is preferred for complete separation.

3. STUDY AREA

Iraq ranked fifth in the world in the list of oil-producing countries in 2022, with a production rate of 4.4 million barrels per day. It is also the fifth-largest oil reserve in the world, with 145 billion barrels of oil, representing about 8.4% of the total global oil reserves [16]. There are many oil fields and refineries throughout the country. According to the information mentioned earlier, the Iraqi national economy depends mainly on revenues from oil exports.

The Dora refinery is located southeast of the capital city of Baghdad. It is the third-largest refinery in Iraq, with a refining capacity of about 140,000 barrels per day, and is located on 250 hectares. The refinery provides oil products to meet Baghdad’s and nearby cities’ local needs for substance gasoline, liquid gas, aircraft fuel, gas oil, diesel, fuel oil, crude oil, grease, asphalt, and other commodities. In contrast, oil products (fuel oil) surplus to local needs is transported by trucks and trains to the port of Umm Qasr in Basra Governorate, located in the far south of the country, to be exported, as shown in Fig. 1. According to the State Oil Marketing Organization, the average quantity exported from the Dora refinery and other refineries between 2020 and 2021 amounted to 7 million tons per year, with a financial return of around 3 billion dollars [17]. This indicates the importance of exporting fuel oil and its contribution to increasing the country’s revenues.

4. METHODOLOGY

4.1. Sample size

Several methods and references are used to estimate the sample size required for the study, but the estimate mainly depends on confidence intervals and levels [19]. The sample size in this study is 277, calculated using Equation 1, proposed by Roess et al. [20], with a tolerance of ±0.6 and a standard deviation of 5:

$$N \geq \frac{Z^2 . Sd^2}{e^2} \ , \qquad (1)$$

where N - sample size, Z - confidence level (1.96 for 95%), Sd - standard deviation, and e - tolerance.

Fig. 1. Transport path for trucks and trains between the two cities [18]

4.2. Data collection

A revealed preference survey is mainly utilized to collect data on present behavior, such as trip characteristics [21]. In this research, trip characteristics were collected for trucks and trains that transport fuel oil from the Dora refinery to the port of Umm Qasr by using various techniques. Truck trip data were collected by conducting personal interviews with drivers at the Dora refinery's entrance utilizing a survey questionnaire. In contrast, train trip data were obtained from the General Company for Iraqi Railways. Fortunately, the train is equipped with a tracker device (GPS) that provides all trip information to the central control room at the station. Data include the delivery time, transportation cost, average trip speed, and shipping quantity per trip.

The sample size in this study is 277, comprising 88 train trips collected from June 7 through November 4, 2022, and 189 truck trips collected from October 15 through 20, 2022, precisely during daytime from 9:00 a.m-12:00 p.m. We also note that the traffic and weather conditions were generally favorable throughout the data collection period.

4.3. Analysis procedure

This study uses two statistical approaches that are usually applied in transportation planning studies: binary logistic regression and Firth logistic regression. The revealed preference survey data were analyzed using logistic regression by STATA v15 software to study the most important variables affecting the choice between two modes of transport used in Iraq to transport oil products.

Binary logistic regression. Binary logistic regression is used when two outcome variables exist in travel mode choice analysis. It is commonly used because its simple mathematical form allows easy prediction and interpretation [22]. It utilizes the maximum likelihood to predict the probability of the outcome variables. Models are built according to the utility function, which is considered an index value influencing mode selection [23]. Generally, the utility function is expressed by a linear regression model. The outcome variable is the utility of the specific mode and various explanatory variables that influence mode selection [24].

The general utility function is represented by the following equation:

$$U_k = b_0 + b_1 \,.\, X_1 + b_2 \,.\, X_2 + b_3 \,.\, X_3 \;..... +b_{\,i} \,.\, X_{\,i}\,, \qquad (2)$$

where U_k - utility function of mode' k', b_0 – constant, b_i - the slope coefficients for each explanatory variable, and X_i - explanatory variables related to mode selection.

Firth logistic regression. Firth [25] proposed penalized maximum likelihood estimation for reducing bias in logistic regression in small samples. Heinze and Schemper [26] demonstrated that this approach always produces unbiased parameter estimates under complete or quasi-complete separation. Therefore, Firth logistic regression is a promising new approach to dealing with separation.

5. RESULTS AND DISCUSSION

5.1. Identification of explanatory variables

After gathering the necessary data for this study, the first step is to calculate the descriptive statistics of the variables that affect the choice of the mode of transportation, as shown in Tab. 1.

Table 1

Descriptive statistics of explanatory variables

Outcome		Explanatory variables			
		Delivery time (hours)	Average speed (kilometers/hour)	Quantity (tons/trip)	Transportation cost ($/ton)
Trucks	Mean	12.40	48.79	30.47	33
	Median	12	48	30	
	Mode	12	48	30	
	St.Dev.	3.080	11.029	1.034	
	Range	12	42	8	
	Mini.	8	29	27	
	Maxi.	20	71	35	
Trains	Mean	25.92	24.13	993.16	25
	Median	24.50	24.50	1000	
	Mode	23	21	1000	
	St.Dev.	6.813	4.548	30.491	
	Range	44	21	200	
	Mini.	19	10	800	
	Maxi.	63	31	1000	

Regarding freight trips using trucks, it is noted that the average delivery time is 12.4 hours, with a 12-hour range between the lowest and highest delivery time. This is due to various factors, including the truck driver's behavior in terms of vehicle speed and delays caused by rest stops and roadside checkpoints. While, for freight trips that use trains, the average delivery time is 25.92 hours, with a range of 44 hours, which is relatively significantly different compared to transport using trucks. This is due to several reasons, the most important of which is the occurrence of stopping delays at stations since the railway line consists of one track that is used back and forth, and this requires conversion between freight trains and passenger trains at stations. Another reason is the delay caused by the train's slow speed due to problems in some railway sectors. The statistics of the train stopping delays are presented in Tab. 2. It is noted that the average train delay is six hours. So establishing an effective schedule and maintenance of some railway sectors may contribute to reducing the delivery time from 25.92 hours to about 20 hours.

The speed of trucks and trains is not constant across road or rail segments. Therefore, the average speed was adopted by dividing the overall distance traveled by the delivery time. Of note, the length of the road that connects the Dora refinery to the port of Umm Qasr is 567 km, and the length of the railway track connecting these points is 588 km.

Petroleum products (fuel oil) are transported (door to door) by a train pulling 22 tanks, each with a capacity of 45.5 tons; therefore, the quantity transported from the refinery to the port is about 1,000 tons per trip, and one trip is made every two days. In contrast, trucks transport approximately 30 tons per trip. Therefore, it is concluded that the amount of petroleum products transported for each trip by train is approximately 33 times that transported by truck.

Finally, the cost of transporting fuel oil by train is lower than that of transporting freight by truck, which is considered an advantage of freight transport by rail.

Table 2

Descriptive statistics of train delays

Descriptive statistics	Stopping delay (hours)
Mean	**6**
Median	5
Mode	2
St. Dev.	5.655
Range	44
Mini.	1
Maxi.	45

5.2. Modeling of freight mode choice

This study has four explanatory variables, two of which are free from complete separation (delivery time and average speed). This allows us to build models for these variables using the conventional binary logistic regression approach. In contrast, the other variables (transportation cost and transported quantities) suffer from complete separation, resulting in the inability to find coefficients using binary logistic regression based on maximum likelihood estimators. As a result, we used Firth logistic regression, which estimates coefficients using the penalized maximum likelihood and produces approximately unbiased coefficient estimates.

Ten models were created with statistical significance (p-values less than 0.05) in selecting the mode of transport, three of which use the conventional binary logistic regression and seven of which use Firth logistic regression by combining explanatory variables, as shown in Tab. 3.

It is shown in Tab. 3 that the first model is considered better than other models in terms of the application's simplicity and from a statistical point of view, as the value of pseudo-R^2 is 0.924. In addition, the delivery time variable is an essential factor in choosing the mode of transporting goods. The second model, although considered reasonable from a statistical point of view, shows that the average speed is considered an undefined variable when choosing between freight modes because the transport distance is not equal between the path of trucks and trains. The third model consists of two variables with a pseudo-R^2 value of 0.932; it needs to test linearity and multilinearity, which will be discussed later. The fourth and fifth models have a pseudo-R^2 of 1; that is, their predictions are entirely based on the separation of the two variables transportation cost and the quantity of transportation for each trip. The sixth, seventh, and ninth models were built by merging two variables because it is impossible to obtain statistically significant models by entering the variables separately, owing to the complete separation of data. The eighth model has a pseudo-R^2 value of 0.6 and is considered lower than the rest of the models in terms of prediction. As mentioned previously, the tenth model is statistically good, but the average speed variable is not considered when selecting the freight mode.

Table 3

Logistic regression analysis results

Statistical approach	Model No.	Explanatory variables	Coefficient	Odds ratio	p	Pseudo-R^2 (Nagelkerke)
(Conventional) binary logit models	1	Constant	-25.730	-	0.000	0.924
		Delivery time	1.331	3.784	0.000	
	2	Constant	22.289	-	0.000	0.905
		Average speed	-0.734	0.480	0.000	
	3	Constant	-66.030	-	0.001	0.932
		Delivery time	2.494	12.104	0.000	
		Average speed	0.588	1.800	0.007	
Firth logit models	4	Constant	39.906	-	0.000	1.001
		Transportation cost	-1.389	0.249	0.000	
	5	Constant	-6.286	-	0.000	1.016
		Quantity	0.011	1.011	0.000	
	6	Constant	26.266	-	0.001	0.992
		$\frac{\text{Transportation cost}}{\text{Delivery time}}$	-17.588	0.000	0.001	
	7	Constant	-7.163	-	0.000	1.002
		$\frac{\text{Quantity}}{\text{Delivery time}}$	0.501	1.650	0.003	
	8	Constant	8.046	-	0.000	0.600
		$\frac{\text{Average speed}}{\text{Transportation cost}}$	-7.497	0.000	0.000	
	9	Constant	-6.198	-	0.000	1.006
		$\frac{\text{Quantity}}{\text{Transportation cost}}$	0.288	1.333	0.000	
	10	Constant	-6.116	-	0.000	1.005
		$\frac{\text{Quantity}}{\text{Average speed}}$	0.314	1.368	0.000	

Note: Reference category = Truck

5.3. Assumptions of logistic regression

Linearity is one of the critical assumptions in logistic regression that impose the presence of a linear relationship between the explanatory variables and the logit (log odds = probability of choosing a train divided by the probability of choosing a truck) of the outcome. This assumption was checked by using the Box-Tidwell test to check the linearity of the models established through the conventional binary logistic regression by taking an interaction term to be added as a new variable, which will be explanatory variables * ln(explanatory variables), as shown in Tab. 4. In the first and second models, the p-value for interaction terms larger than 0.05 indicate that the assumption is satisfied. In the third model, although a p-value for interaction terms larger than 0.05, but the high value of standard error indicates that the relationship is not explicitly linear, especially when a more extensive study sample is taken or applied to the population.

The models created by Firth logistic regression method will be tested visually by a scatter plot because of the complete separation of the explanatory variables. As shown in Fig. 2, all models have a linear relationship between the explanatory variables and the log odds of the outcome.

Table 4

Linearity test for binary logit models

Model No.	Explanatory variables	Coefficient	Standard error	*p*
1	Constant	-46.500	88.160	0.598
	Delivery time	5.584	17.858	0.755
	Delivery time*ln(Delivery time)	-1.073	4.490	**0.811**
2	Constant	37.341	56.241	0.507
	Average speed	-2.945	8.167	0.718
	Average speed*ln(Average speed)	0.502	1.850	**0.786**
3	Constant	-8810.833	582,657.897	0.988
	Delivery time	512.732	43,985.745	0.991
	Average speed	404.343	25,205.527	0.987
	Delivery time*ln(Delivery time)	-98.856	8870.843	**0.991**
	Average speed*ln(Average speed)	-74.382	4900.853	**0.988**

The second assumption important in logistic regression is multicollinearity, which means no strong correlation exists between two or more explanatory variables. The multicollinearity test was conducted for the third model, which consists of two explanatory variables, which are the delivery time and the average speed (Tab. 5). It is noted that the value of the Variance Inflation Coefficient is between 1 and 10, which indicates that the regression may be biased. This, in addition to the tolerance value of 0.2, indicates a possible correlation since the average speed is the result of dividing the distance by the delivery time. As a result, this can be considered a critical model.

Table 5

Collinearity statistics

Explanatory variables	Tolerance	Variance Inflation Coefficient
Delivery time	0.2	5.012
Average speed	0.2	5.012

5.4. Final models

Based on the previous discussion, it is concluded that freight mode choice statistically correlates with delivery time, transportation cost, and shipping quantity per trip. Tab. 6 presents the final models for choosing the freight mode. The probability of using a train (P_{train}) is represented by Equation 3. In contrast, the probability of using a truck (P_{truck}) can be obtained from Equation 4.

Table 6

Freight mode choice models

Model No.	Explanatory variables	Coefficient	Odds ratio	*p*	Pseudo-R^2 (Nagelkerke)
1	Constant	-25.730	-	0.000	0.924
	Delivery time	1.331	3.784	0.000	
4	Constant	39.906	-	0.000	1.001
	Transportation cost	-1.389	0.249	0.000	
5	Constant	-6.286	-	0.000	1.016
	Quantity	0.011	1.011	0.000	
6	Constant	26.266	-	0.001	0.992
	Transportation cost/Delivery time	-17.588	0.000	0.001	
7	Constant	-7.163	-	0.000	1.002
	Quantity/Delivery time	0.501	1.650	0.003	
9	Constant	-6.198	-	0.000	1.006
	Quantity/Transportation cost	0.288	1.333	0.000	

Note: Reference category = Truck

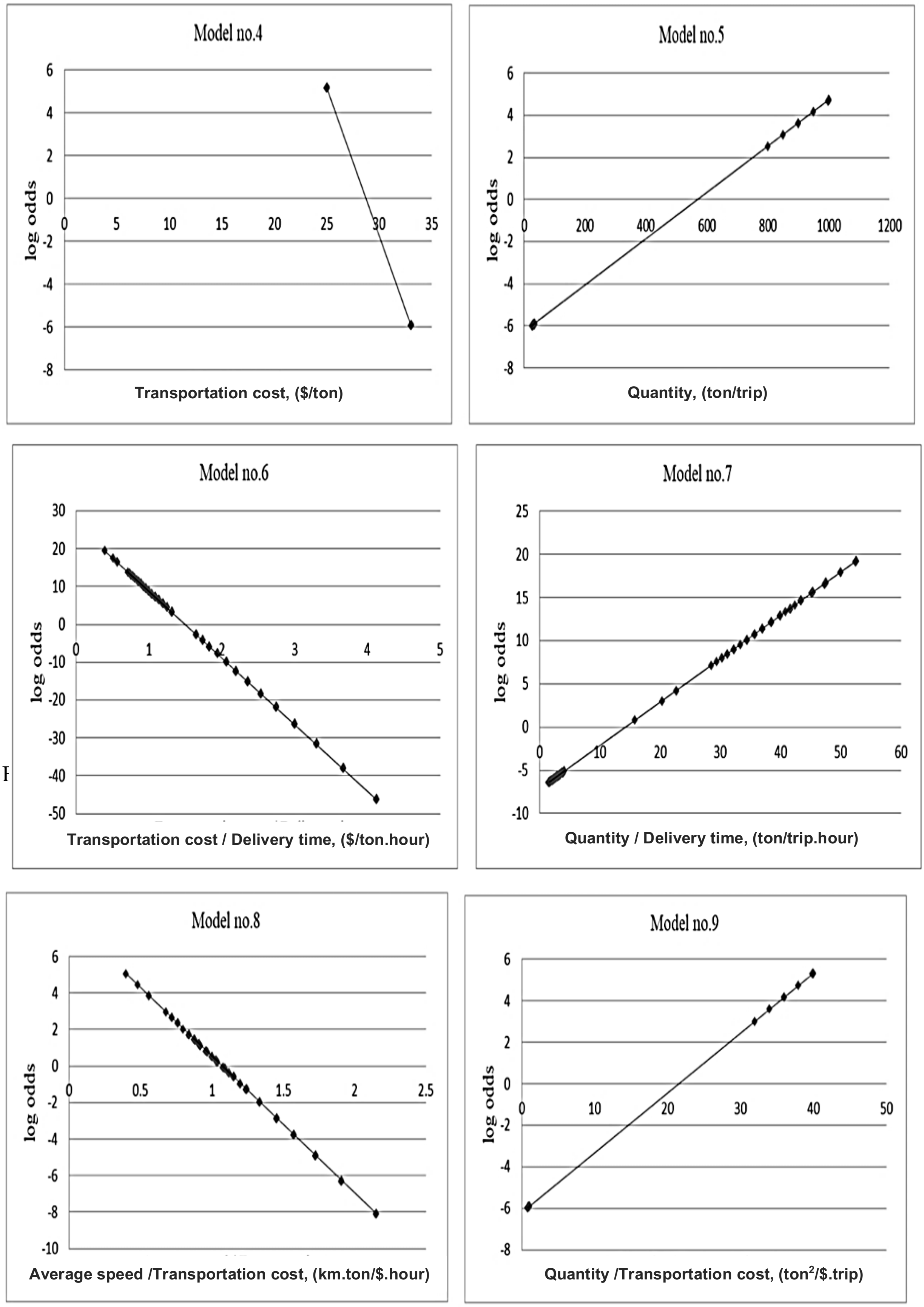

Fig. 2. Linearity test for Firth logit models

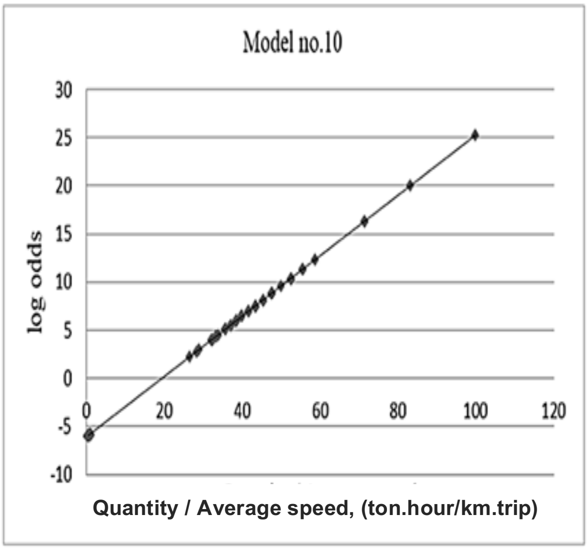

Fig. 3. Linearity test for Firth logit models (*continued*)

$$P_{train} = \frac{e^{U_{train}}}{1+e^{U_{train}}} \tag{3}$$

$$P_{truck} = 1 - P_{train} \tag{4}$$

In the above equations:
U_{train} – the utility function of the train mode of transport,
P_{train} – the probability of choosing a train,
P_{truck} – the probability of choosing a truck, and
e – the base of natural logarithms (approximately 2.718).

6. CONCLUSIONS

The study's main findings can be summarized as follows:

1. The choice of freight mode for transporting oil products between trains and trucks is statistically correlated with delivery time, transportation cost, and quantity of shipping per trip.
2. Trains transport oil products from the refinery to the port (door to door) at a lower transportation cost than trucks, making them a strong competitor to trucks.
3. Trains transport large amounts per trip (approximately 1,000 tons, which is equivalent to 33 trucks). As a result, shifting from trucks to trains helps to reduce traffic congestion, traffic accidents, pavement deterioration, and air pollution.
4. It is recommended to establish an effective schedule to reduce stopping delays due to the intersection of freight trains with passenger trains at stations, as well as to maintain some railway sectors, as doing so may contribute to reducing the delivery time to about 20 hours.
5. This study's outputs can help decision-makers choose the most sustainable mode to freight oil products.
6. This study highlighted the possibility of Firth logistic regression approach to solving the complete separation issue in data.

Acknowledgments

The authors would like to express their appreciation to Mustansiriyah University (www.uomustansiriyah.edu.iq) and the General Company for Iraqi Railways in Baghdad, Iraq, for providing the support necessary to carry out the present work.

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Received 19.12.2021; accepted in revised form 31.08.2023