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An analysis of Interstate freight mode choice between truck and rail: A case study of Maryland, United States

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Abstract

Freight mode choice is a critical part in modeling freight demand. Due to limited freight data, considerably less research has been conducted on freight mode choice than that in passenger demand analysis. This paper investigates unobserved factors influencing freight mode choices, including truck and rail. Revealed preference data is collected from Freight Analysis Framework database and aggregated to be used in this study. Binary probit and logit models are developed to compare the modal behavior and to verify the differences of mode choice behavior among the three zones in Maryland. Different factors which are significantly influencing the freight mode choice can be found for the shipments originated from these zones. Identifying these factors may help the freight modelers to establish and calibrate better freight demand models for Maryland, and can help the policy makers to take actions to reduce highway congestion and air pollution which is caused by trucks.

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Keywords: Freight mode choice; discrete choice; probit model; logit model

1. Introduction

In recent years, freight transportation is clearly increasing in the United States, which makes critical contributions to the nation's economy, security, and quality of life (NCFRP, 2011). The demand for truck transportation service has been increasing at the fastest growth speed among all modes of transportation-trucking, rail, waterways, air, and pipelines. However, this growth generates many serious negative effects, such as traffic congestion, air pollution, and traffic accidents. Thus, the studies on the freight mode choice, especially the competition between truck and rail are becoming critical to improve the efficiency of freight transportation system (Forkenbrock, 2001).

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Based on the nature of the data source, there are two types of analytical methods in freight modal choice in the literatures: aggregated and disaggregated models (Winston, 1983). The aggregated model applies an aggregated share of a freight mode at a certain geographical level. This type of model focuses on describing the group behaviour of firms, and it is useful to capture general trends and changes due to policies based on general characteristics observed (Shen and Wang, 2012). In the state of mode split of travel demand models, a direct comparison of shipment costs and travel costs was the primary method in the early freight mode choice models (Cunningham, 1982; Jeffs and Hills, 1990). Lewis and Widup (1982) estimated a dynamic mode split model for rail and truck utilizing the transport cost function based on the data gathered between 1955 and 1975 from several sources such as the American Trucking Association, the Association of American Railroads. Some of other studies related to the issue of commodity aggregation for micro-model calibration. Nam (1997) applied an aggregated binary logit model over heterogeneous commodity types to test the significance of different variables. Shen and Wang (2012) used binary logit model and a regression model to study the cereal grains movement between states by truck and rail in the United States using the Freight Analysis Framework database. Disaggregated choice models focus more on individual behavioral aspects of the shipment decision makers. Data are collected from individual shipper, companies. Evers, Harper, and Needham (1996) conducted a survey of Minnesota manufacturing firms to obtain the shippers' perceptions of 17 transportation characteristics provide by rail, truck, and intermodal modes. Six essential factors were found using principal components analysis. Jiang, Johnson, and Calzada (1999) used a large-scale, national, disaggregated revealed preference database for shippers in France in 1988 to test mode choice of private and public transportation. The results showed that travel distance, shipper's accessibility to transportation infrastructure, and shipment packaging were the critical determinants of the demand for rail and combined transportation. Jong and Ben-Akiva (2007) developed a microsimulation model based on a behavioral framework. The model can be addressed as a logistics module and can analyze the consequences of policy changes. Arunotayanun and Polak (2011) used a mixed logit model to investigate the prevalence of observed and unobserved taste heterogeneity influencing shippers' mode choice behaviour based on stated preference (SP) data collected in Java, Indonesia. Samimi, Kawamura, and Mohammadian (2011) used binary logit and probit models to explain how truck and rail are chosen by the shippers, third party logistics, and receivers based on the data collected from a nationwide establishment survey. The sensitivity of freight mode choice changes with fluctuations in fuel cost was also tested. Ravibabu (2013) used a nested logit model with rail container and road truck on one branch, total cost and transit time were found to be influencing the mode choices significantly among the transport attributes.

From previous studies, freight mode choice depends on transportation demand, infrastructure, as well as service supply characteristics. On the supply side, the major explanatory variables are transportation cost, time, and frequency. However, on the demand side, less research has been conducted to examine freight demand characteristics due to the absence of suitable data (Jiang, Johnson, and Calzada, 1998). Existing studies suggest that, freight demand characteristics, such as the commodity type to be transported, the origin of shipment, and highway or railway network, strongly influence modal choice.

The purpose of this paper is to analyze how and to what extent freight characteristics influence freight mode choice (truck and rail) in the state of Maryland. Binary probit and logit models are developed to compare the modal behavior and to test the differences of mode choice among the three zones in Maryland. The results are helpful for the policy maker to identify major contributing factors of freight movement in Maryland. The contents of the paper are organized as follows: the next section describes the data sources and variables, and then model development is discussed. The empirical results and discussion are presented in section three. The final section presents conclusions.

2. Data and Model

2.1. Data sources

Freight analysis framework (FAF) is the main data source for this study, as it contains all major resources with fright data like commodity flow survey (CFS). FAF (version three) provides the existing commodity movement for the year 2007 as well as forecasting through 2040 based on four factors of origin, destination, commodity, and mode types. In this database, the value and weight of shipments from 123 domestic zones and 8 foreign zones have been tabulated based on 43 individual types of commodity regarding the commodity specifications. The information is tabulated in a way to address the total value and weight of shipment transported annually in terms of 43 commodity types, 123 origin and destination zones, and 7 modes. Another important data source is the National Transportation Atlas Database (NTAD) which provides the highway and rail network information in a GIS format. This study uses the 2006 NTAD truck and rail networks processed within *TransCAD*4.8.

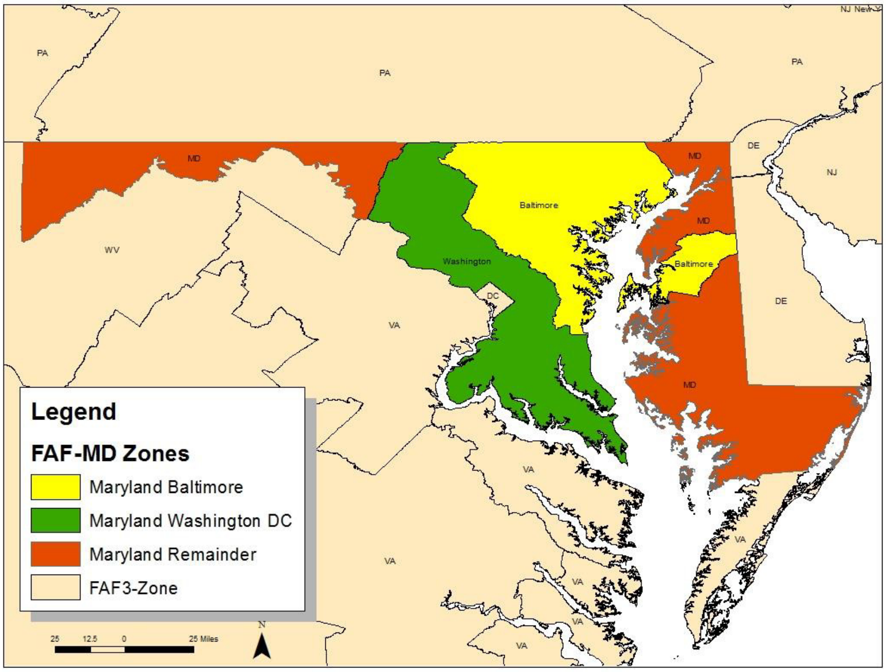

Fig. 1. FAF zones in Maryland

We selected all the freight trips originated from Maryland as the scope of work. The rest of the data beyond the region scope were eliminated from the dataset. As illustrated in Figure 1, there are three FAF zones in the study area: Baltimore, Washington D.C. (Maryland part), and remainder of Maryland. The transportation mode for both domestic and foreign shipments in the original database is categorized into seven modes: truck, rail, water, air, multiple modes and mail, pipeline, and other. We only focus on the truck and rail as they represent the dominant share of freight movement.

2.2. Model specifications

The model used in this study is the binary discrete choice model which has been by far most widely used in the field of passenger transport choice studies. With different assumptions regarding error structure in the utility function (1), two widely used forms of the discrete choice models are created: probit model and logit model. The core difference lies in the distribution of the error terms. Probit model assumes normal distribution for the error terms, while the logit model assumes logistic distribution for the error terms (Train, 2009)

$$U_i(j) = V_i(j) + \varepsilon_i(j) = \sum_{j \in C_i} \alpha(j) x_i(j) + \varepsilon_i(j) \tag{1}$$

where $U_i(j)$ is the utility of the decision maker i for alternative j; $V_i(j)$ is the observable portion of the utility, it means decision maker i selects the alternative j; $\varepsilon_i(j)$ is the unobservable component of the utility; $x_i(j)$ is the independent variable related to the alternative choice; $\alpha(j)$ is the parameter to be estimated; C_i are the available alternatives in a mode choice set.

The form for the probit choice probability can be expressed as follows:

$$p_{ij} = \int_{-\infty}^{V_i(j)} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}t^2} dt \tag{2}$$

And the form for the logit choice probability can be expressed as follows:

$$p_{ij} = e^{V_i(j)} \Big/ \sum_{h \in C_i} e^{V_i(h)} \tag{3}$$

2.3. Explanatory variables and description

The dependent variable is the mode choice between truck and rail. The explanatory variables are listed in Table 1, which includes the characteristics of commodity, shipment, network, and fuel cost.

There are 43 types of commodities recorded in the FAF data using the two-digit standard classification of transported goods (SCTG). Some of the commodities share similar characteristics were regrouped together into 13 groups based on the approach applied in Viswanathan, Beagan, and Mysore's studies (2008). To classify the importance of commodity in terms of time value, we give each of the SCTG classification with the value of time at three levels based on the proportion of air transport for each type commodity. For example, the value of time for live animals and fish is high, thus more percentage of air transport for these. According to the mean air transportation proportion, commodities with high value of time is defined with over 16% air transport, and low value of time is defined with under 6% of air transport. To capture the mode choice differences between the three FAF zones in Maryland, we use the location variables of origin in Maryland.

The characteristics of the commodity shipment take the form of shipment weight and value. These measurements for the commodity are given in units of kiloton and millions of US dollars. Highway distance between shipment origin and destination for truck, multiple modes and mail travel is computed in *TransCAD*. The FAF zones are added as a layer to the nationwide highway network. The shortest path algorithm is used to compute the distances between zones. Similar approach is adapted to compute the rail O-D distance. However, there is no distance information from Hawaii, and therefore we don't consider the shipments from Maryland to Hawaii. Due to different zone areas, differences in highway and railway mileage among zones are significant. Thus, transportation mileage ratio (highway mileage/railway mileage) is used in the model to reflect the transportation network's level of service. Eastman (1981) compared the use of fuel in freight transportation among modes, and he proposed a method for estimating the fuel cost of freight transportation, as follows:

$$FC_i = \omega \times BTU_i / m \tag{4}$$

where FC_i is fuel cost per ton-mile by mode i ; ω is fuel cost per gallon; BTU_i means British thermal units (BTU) per ton-mile measured as the total BTU consumed for that year for the mode divided by the total ton-mile for the mode; m means the number of BTU's equal to one gallon of fuel.

Shen and Wang (2012) collected the data of the truck and rail ton-miles, BTU, and fuel consumption in America in 2002, so we can estimate the fuel cost in gallons per ton-mile for each mode using equation (4). Based on the total ton-mile for each shipment by mode from FAF, we can obtain the total fuel cost for each shipment by truck and rail. Another important variable commodity trade type (domestic, import, and export) is used in the model. Nominal variables are represented using dummy variables in our study.

Table 1. Explanatory variables used in models

Variable Name	Variable Description	Mean	St. Dev.
Commodity type	Agricultural products (1=yes), 0 otherwise	0.05	0.210
	Minerals (1=yes), 0 otherwise	0.09	0.286
	Coal (1=yes), 0 otherwise	0.01	0.097
	Food (1=yes), 0 otherwise	0.12	0.325
	Nondurable manufacturing (1=yes), 0 otherwise	0.07	0.259
	Lumber (1=yes), 0 otherwise	0.05	0.218
	Chemicals (1=yes), 0 otherwise	0.10	0.299
	Papers (1=yes), 0 otherwise	0.04	0.204
	Petroleum products (1=yes)	0.05	0.212
	Durable manufacturing (1=yes)	0.34	0.475
	Clay, concrete, glass, and stone (1=yes), 0 otherwise	0.03	0.179
	Waste (1=yes), 0 otherwise	0.02	0.145
	Miscellaneous (1=yes), 0 otherwise (Reference variable)	0.02	0.150
Value of time	Low (1=yes), 0 otherwise	0.36	0.481
	Medium (1=yes), 0 otherwise (Reference variable)	0.42	0.493
	High (1=yes), 0 otherwise	0.22	0.414
Trade type	Domestic (1=yes), 0 otherwise	0.54	0.499
	Import (1=yes), 0 otherwise	0.22	0.415
	Export (1=yes), 0 otherwise	0.24	0.427
Origin	Baltimore (1=yes), 0 otherwise (Reference variable)	0.50	0.500
	Washington D.C. (MD part) (1=yes), 0 otherwise	0.25	0.431
	Remainder of Maryland (1=yes), 0 otherwise	0.25	0.435
Transportation mileage ratio in origin zone	Transportation mileage ratio is defined as 'Highway mileage/Railway mileage' in origin zone	1.47	0.493
Transportation mileage ratio in destination zone	Transportation mileage ratio is defined as 'Highway mileage/Railway mileage' in destination zone	1.25	0.598
Weight	Weight of shipment (kiloton)	3.58	44.701
Value	Value of shipment (million $)	4.24	35.772

Highway distance	Highway distance between each origin- destination pair (thousand miles)	0.85	0.729
Railway distance	Railway distance between each origin- destination pair (thousand miles)	0.962	0.794
Truck fuel cost	Fuel cost for total ton-mile of a shipment by truck (thousand gallons)	29.13	323.446
Rail fuel cost	Fuel cost for total ton-mile of a shipment by rail (thousand gallons)	3.20	35.579

3. Empirical Results and Analysis

The analysis is divided into two parts: part I is to identify what and to what extent factors that influence fright mode choice in general. In order to capture mode choice differences among three geographic zones in Maryland, we develop the part II analysis, which provides detailed independent models for three origin zones in Maryland. The software *Biogeme* (Bierlaire, 2003) was used to estimate both binary probit and logit models. For all the estimation results on the freight mode choice, the referenced alternative is rail.

3.1. Part I---Identifying overall contributing factors

Estimation results are presented in Table 2, where the shipment origin was set as an independent variable. The probit model (final log-likelihood equal to -3709.014) is significantly superior than the logit model (final log-likelihood equal to -3822.773), and the estimation results pass the likelihood ratio test clearly. The adjusted rho-squared statistics imply that there is a good explanatory power of the probit and logit model. The model results suggest that there is no major difference between the probit and logit models, except that Washington D.C. (Zone 49) is a significant variable only in the probit model. With respect to shipments from Baltimore (Zone 48), shipments from Washington D.C are found to show a negative propensity to use truck, and shipments from remainder of Maryland (Zone 50) are found to show a positive propensity to use truck.

Table 2 Binary choice model estimations for the shipments from Maryland

Variable	Probit model (*N*=21366)		Logit model (*N*=21366)	
	parameter	*t*-test	parameter	*t*-test
Agricultural products	0.00488	0.04	-0.0328	-0.14
Minerals	-0.105	-0.70	-0.108	-0.40
Coal	0.0531	0.19	0.0655	0.13
Food	0.248	1.69	0.23	0.88
Nondurable manufacturing	0.639	4.49***	0.68	2.79***
Lumber	0.128	0.93	0.146	0.60
Chemicals	0.113	0.87	0.229	0.99
Papers	-0.0615	-0.45	-0.15	-0.62
Petroleum products	-0.0127	-0.08	0.0228	0.08
Durable manufacturing	0.128	1.06	0.366	1.71
Clay, concrete, glass, and stone	0.116	0.81	0.136	0.53
Waste	-0.227	-1.30	-0.132	-0.39
Low value of time	-0.0165	-0.22	0.14	1.04
High value of time	0.254	5.45***	0.58	6.10***

Import	-1.03	-17.78***	-1.07	-10.00***
Export	-1.60	-31.68***	-2.45	-27.37***
Washington D.C.	-0.424	-5.10***	-0.077	-0.51
Remainder of Maryland	0.861	11.83***	1.71	12.36***
Transportation mileage ratio in origin zone	1.10	12.38***	1.31	8.08***
Transportation mileage ratio in destination zone	0.568	15.07***	1.28	14.79***
Weight	-1.94E-05	-0.05	-3.63E-04	-0.49
Value	4.70E-04	0.54	0.00379	1.16
Distance	-0.202	-1.02	-0.243	-0.63
Fuel cost	-1.11E-04	-2.58***	-1.56E-04	-2.51**
Final log-likelihood	-3709.014		-3822.773	
Likelihood ratio test	22201.536		21974.020	
Rho-square	0.750		0.742	
Adjusted Rho-square	0.748		0.740	

Note: ***indicates significance at the 1 per cent level; **at the 5 per cent level.

For the shipment from Maryland, the *t* statistics indicate that nondurable manufacturing, high value of time, import, export, remainder of Maryland, transportation mileage ratio in origin zone and destination zone, and fuel cost are statistically significant at above the 5 per cent level for the choice between truck and rail. However, variables such as some commodity types, low value of time, shipment weight, value, and distance are insignificant. According to the relative terms based on probit model, we can rank the commodity types in propensity to use truck: Nondurable manufacturing> Food> Lumber> Durable manufacturing> Clay, concrete, glass, and stone> Chemicals> Coal> Agricultural products> Miscellaneous> Petroleum products> Papers> Minerals. Commodities with high value of time show a propensity to be undertaken by truck mode. Trade type variable (import and export) are found to have negative coefficients, indicating that higher import and export commodities lead to a greater propensity to engage rail transportation. The coefficients on transportation mileage ratio variable (origin zone and destination zone) are positive, indicating that higher transportation mileage ratio contribute to a lower propensity to rail use for shipment trips. As expected, high fuel cost are found to contribute positively to the use of the rail mode. However, weight, value, and distance are insignificant, which is unexpected.

3.2. Part II --- Differences among zones

The results are shown in Table 3 and Table 4, indicating that there are significant estimation differences among the three zones in Maryland. The estimates of probit and logit model for Baltimore and Washington D.C. are similar to each other. The final log-likelihood values of the logit model for Baltimore and remainder of Maryland are respectively 1.72 and 50.828 points than the probit model, small but significant. The final log-likelihood of the probit model is -619.046 for Washington D.C., which is 8.488 points higher than the final log-likelihood of the logit model. Thus, logit model is superior to probit model for the shipments from Baltimore and remainder of Maryland, and probit model is superior to logit model for the shipments from Washington D.C. Agricultural products, minerals, food, lumber, papers, petroleum products, clay, concrete, glass, and stone are significant for the shipments from Baltimore and Washington D.C. However, these variables are insignificant for the shipments from remainder of Maryland.

Table 3 Binary probit choice model estimations for the shipments from three zones in Maryland

Variable	Zone 48 (*N*=10699)		Zone 49 (*N*=5261)		Zone 50 (*N*=5406)	
	parameter	*t*-test	parameter	*t*-test	parameter	*t*-test
Agricultural products	1.10	10.50***	0.96	4.26***	0.194	1.05
Minerals	0.673	5.06***	0.902	3.27***	0.165	0.71
Coal	0.433	1.79	23.3	0.01	0.0904	0.18
Food	1.12	8.42***	1.16	4.52***	0.328	1.49
Nondurable manufacturing	2.07	14.94***	1.40	6.45***	0.597	3.29***
Lumber	1.28	12.09***	1.08	4.90***	0.28	1.41
Chemicals	1.22	13.12***	1.16	5.98***	0.334	2.02**
Papers	1.04	9.74***	0.91	4.14***	0.108	0.58
Petroleum products	0.778	5.26***	0.889	2.92***	0.14	0.54
Durable manufacturing	1.43	19.90***	1.13	6.88***	0.432	3.13***
Clay, concrete, glass, and stone	1.36	11.57***	1.19	4.76***	0.36	1.67
Waste	0.721	4.09***	0.0807	0.27	-0.322	-1.17
Low value of time	0.299	2.93***	0.0364	0.20	0.407	2.70***
High value of time	0.263	4.43***	0.326	2.73***	0.411	3.94***
Import	-0.66	-11.80***	0.01	0.01	0.01	0.01
Export	-1.02	-17.20***	-2.01	-15.56***	-1.35	-16.63***
Transportation mileage ratio in destination zone	0.551	14.03***	1.44	11.53***	1.67	14.75***
Weight	1.27E-04	0.09	0.0492	3.81***	0.0117	3.89***
Value	0.00207	1.39	0.116	2.86***	0.00513	0.67
Distance	-0.438	-1.74	-3.85	-5.78***	-0.673	-1.83
Fuel cost	-7.73E-05	-1.32	-0.0109	-4.79***	-0.00178	-4.52***
Final log-likelihood	-2437.731		-619.046		-759.828	
Likelihood ratio test	9956.502		6055.203		5974.651	
Rho-square	0.671		0.830		0.797	
Adjusted Rho-square	0.668		0.824		0.791	

Note: Variable transportation mileage ratio in destination zone is not in the models because the values are same for one zone. ***indicates significance at the 1 per cent level; **at the 5 per cent level.

The variables nondurable manufacturing, chemicals, durable manufacturing, high value of time, export, and transportation mileage ratio in destination zone are statistically significant for the shipments form all the three zones in Maryland, which is certain consistent with the part I analysis results. With respect to miscellaneous, it is found that the coefficients on nondurable manufacturing, chemicals, and durable manufacturing are positive, indicating that these commodities are more likely to be transported by truck than by rail. Commodities with high value of time show a propensity to be undertaken by truck mode. As we expected, there is a positive effect for transportation mileage ratio in destination zone, indicating that high transportation mileage ratio is more likely to be transported by truck with respect to rail. This is intuitive since high highway infrastructure provides high opportunity for the companies to use truck-related freight shipping choice.

For the shipments from Baltimore, most commodities are found to contribute positively to use truck as shipment mode, except coal. Commodities with low or high value of time both show a negative propensity to use rail. The coefficients on import and export commodities are negative, indicating that import and export commodities tend to be transported by rail with respect to domestic commodities. The coefficient on distance is negative, indicating that longer distance is found to contribute positively to use rail, which is consistent with previous studies. The commodity types are ranked as follows according to the propensity to use truck: Nondurable manufacturing> Clay, concrete, glass, and stone> Durable manufacturing> Lumber> Chemicals> Agricultural products> Papers> Food> Petroleum products> Minerals> Waste> Coal> Miscellaneous.

Table 4 Binary logit choice model estimations for the shipments from three zones in Maryland

Variable	Zone 48 (*N*=10699)		Zone 49 (*N*=5261)		Zone 50 (*N*=5406)	
	parameter	*t*-test	parameter	*t*-test	parameter	*t*-test
Agricultural products	1.82	8.78***	1.75	4.20***	1.39	3.44***
Minerals	0.75	2.75***	1.64	3.22***	1.32	2.60***
Coal	0.474	1.00	15.9	3.90***	0.467	0.45
Food	1.68	6.07***	2.18	4.63***	1.91	4.10***
Nondurable manufacturing	3.49	12.31***	2.60	6.21***	2.38	5.63***
Lumber	2.25	10.42***	1.93	4.70***	1.49	3.39***
Chemicals	2.13	11.20***	2.10	5.71***	1.69	4.78***
Papers	1.70	8.17***	1.64	4.08***	1.30	3.26***
Petroleum products	1.00	3.32***	1.64	2.92***	0.977	1.83
Durable manufacturing	2.47	16.64***	2.02	6.58***	1.66	5.38***
Clay, concrete, glass, and stone	2.49	9.97***	2.06	4.47***	2.31	4.29***
Waste	0.682	1.99***	0.273	0.46	0.0188	0.03
Low value of time	0.74	3.43***	0.00519	0.02	0.122	0.40
High value of time	0.516	4.24***	0.639	2.79***	0.61	2.89***
Import	-1.43	-12.12***	0.01	0.01	0.01	0.01
Export	-2.17	-17.62***	-3.92	-15.51***	-3.87	-16.23***
Transportation mileage ratio in destination zone	1.22	14.29***	2.86	11.65***	2.77	11.36***
Weight	0.00138	0.36	0.0798	3.21***	0.0222	3.15***
Value	0.00334	1.11	0.195	2.41**	0.00714	0.43
Distance	-1.60	-3.07***	-6.74	-5.36***	-6.67	-7.54***
Fuel cost	-1.42E-04	-1.19	-0.018	-4.25***	-0.00344	-3.51***
Final log-likelihood	-2436.011		-627.534		-709.000	
Likelihood ratio test	9959.941		6038.226		6076.308	
Rho-square	0.672		0.828		0.811	

Adjusted Rho-square	0.669	0.822	0.805

Note: Variable transportation mileage ratio in destination zone is not in the models because the values are same for one zone. ***indicates significance at the 1 per cent level; **at the 5 per cent level.

For the shipments from Washington D.C., most commodities, except coal and waste, are found to contribute positively to use truck, which is similar to the results of the shipments from Baltimore. Commodities with high value of time are found to contribute a higher propensity to use truck, and export commodities are found to show a higher propensity to use rail. The coefficients on weight and value are positive, which is unexpected. This result is contrary to intuition since heavy and high value shipments are primarily shipped by rail. This counterintuitive result may be due to the weight and value data used in this study are aggregated that cannot reflect the weight and value for each shipment. Fuel cost is another significant variable with a negative coefficient, indicating that high fuel cost is favorable for rail. This result presents an expected sign and it is consistent with previous studies. According to the propensity to use truck, the commodity types from Washington D.C. are ranked as follows: Coal> Nondurable manufacturing> Clay, concrete, glass, and stone> Food> Chemicals> Durable manufacturing> Lumber> Agricultural products> Papers> Minerals> Petroleum products> Waste> Miscellaneous.

For the shipments from remainder of Maryland, most commodities, except coal, petroleum products, and waste, are found to contribute positively to use truck. Commodities with high value, export commodities, weight, and fuel cost are significant variables, which are same as the shipments from Washington D.C. According to the propensity to use truck, the commodity types from remainder of Maryland are ranked as follows: Agricultural products> Nondurable manufacturing> Clay, concrete, glass, and stone> Food> Chemicals> Durable manufacturing> Lumber> Minerals> Papers> Petroleum products> Coal> Waste> Miscellaneous.

From the perspective of factors influencing the freight mode choice, on the one hand, it may help the freight modelers to establish and calibrate the freight demand model for Maryland (Mitra, Tolliver, 2009). On the other hand, it can help the policy makers to take actions to reduce truck freight related highway congestion and air pollution. One point worth mentioning is that transportation mileage ratio whatever in origin zone and destination zone is significant influencing the freight mode choice. Policy focusing on improving railway network infrastructure will be more effective to have an efficient freight shipment system. In addition, policies or regulations related to fuel pricing might be helpful to reduce truck-freight shipment (Macharis, Hoeck, and Pekin, et al., 2010).

4. Conclusions

In this paper, we investigated the freight mode choice between truck and rail for the shipments originated from Maryland to other states by using binary probit and logit models. We conducted two-part of analysis by examining the general and detailed model estimates. A variety of variables are tested in the models, including commodity (type, value of time, origin, and trade type), shipment (weight, value), transportation network (mileage ration, and distance), and fuel cost. Results suggest that transportation mileage ratio, the value of time for commodity, trade type, origin, and fuel cost play key roles in model split choice for all the shipments in the part I analysis and part II analysis. The implication of these results can help the freight modelers to establish and calibrate the freight demand model for Maryland, and can help the policy makers to make actions to reduce truck freight related highway congestion and air pollution.

Further study can be improved in depth by using combination of discrete and continuous variables and by adding more factors related to shipment size, warehouse, and land use and zone properties.

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