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Expenditure-based segmentation of freight travel markets: Identifying the determinants of freight transport expenditure for developing marketing strategies

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A R T I C L E I N F O

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A B S T R A C T

There is a substantial body of literature relating to freight transport sector's economic impact at the macro-level, but less is known about how freight demand gets translated to an establishment's expenditures at the micro-level. This paper addresses this research gap by collecting data about expenditure patterns of establishments and applying market segmentation technique based on finite mixture models. Three latent segments - heavy spenders, medium spenders and light spenders – and their associated profiles are identified. The results indicate that significant differences exist between the three expenditure-based segments of establishments in terms of spending patterns, business size indicators, locational characteristics and freight travel patterns. The heavy spenders tend to be strongly influenced by employment, gross-floor area, business age and fleet ownership levels. The length of haul and truck type choice have a strong incremental effect on the volume of expenditures and larger shipment sizes are associated with expenditure reduction due to economies of scale. The diverging characteristics of expenditure segments emphasizes the need of the logistics providers to "identify their markets" and planners to "identify how demand translates to transport expenditures". The overall conclusion is that segmenting establishments based on unobservable heterogeneity with respect to their freight transport expenditure is preferable and more informative than treating them as one homogeneous group. The study findings provide important information that planners and logistics providers can utilize in developing effective logistics plans and marketing strategies.

1. Introduction

Over the last decade, significant media coverage, government attention, and scholarly inquiry have been directed to both passenger transportation expenditure (PTE) and freight transportation expenditures (FTE). While it is widely understood how PTE is influenced by household characteristics (Rivigo, 2018), location (Haas, Morse, Becker, Young, & Esling, 2013), and travel pattern (Li, Dodson, & Sipe, 2015), effects of their freight system counterparts – establishment characteristics, location and freight travel pattern – on FTE have remained elusive. This is a critical research gap in the context of increasing requirements faced by freight transport systems to augment their capacity and, in turn, reduce the costs of mobility (Giuliano, 2014; Rowell, Gagliano, & Goodchild, 2014). An average establishment's logistics cost amounts up to 10 to 12% of their sales, of which 4 to 6% amounts to the expenditure on freight transportation (EDD, 2016). The growing body of literature on freight flow analysis (Guerrero & Proulhac, 2014; Kijewska, Iwan, Konicki, & Kijewski, 2017) which indicate that these figures are set to further increase in the upcoming years. Naturally, this is concerning as high freight transport expenditures diminish the economic competitiveness of businesses (Malik, Sánchez-Díaz, Tiwari, & Woxenius, 2017). Due to the spectrum of cost components and level of services involved in them, substantial differences exist in freight expenditure across the world. In a competitive market where moving freight is a service that can be bid on, these costs are heavily influenced by the freight rates charged by the logistics providers. Apart from the direct out-of-pocket expenses based on these freight rates, freight expenditure also includes time costs and costs related to possible inefficiencies. Since the latter can only be fully assessed after the shipment has reached, the direct components of freight transport expenditure form the base of mode, truck type and route choice by shippers and forwarders (Tavasszy & Jong, 2014).

Examining the determinants of FTE patterns and how they vary with respect to freight activities and establishment characteristics (i.e.,

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shippers) are also key issues in the planning of freight facilities and policy instruments. This is especially useful from the perspective of freight carriers as it would help them to identify those activities and settings that are linked to higher than average establishment expenditures. Since the effectiveness of freight transport services have long been identified as a crucial contributor to the economic vibrancy of a region (Gonzalez-Feliu & Peris-Pla, 2017), better understanding of establishments' expenditure patterns would help the local governments to reduce the overall logistics cost as well. However, modelling the variation of expenditure patterns in relation to establishment characteristics and freight travel demand is a challenge that has not been adequately addressed in the literature. This paper addresses this research challenge by determining whether expenditure-based segmentation of establishments is a valuable technique for providing planners, carriers and transport authorities with important information that could be utilized in development of logistics strategies. More specifically, this research aims to provide an assessment of establishments' business size, relative location and industrial characteristics by segmenting them using FTE patterns. The research questions guiding this study are: (i) Do spending patterns significantly differ by expenditure segment? (ii) Is there a significant relationship between expenditure segments and establishment characteristics? (iii) How do freight travel characteristics differ by expenditure segments and (iv) Are there significant differences between locational characteristics of establishments in expenditure segments? By answering these research questions, this paper contributes to freight literature with knowledge about freight transport expenditure. This study also evaluates a methodology that is expected to be more accurate and precise than the previous research on market segmentation literature, since the unobservable heterogeneity is also taken into consideration.

The rest of the paper is organized as follows. Next section provides a brief background of the relevant research. Thereafter, the methodology and data used in this study are elaborated. The results and discussions are presented next, followed by the implications of this study for policy and practice. The final section concludes this paper with recommendations for further research.

2. Research background

2.1. Freight transport expenditure

The determinants of freight transport expenditures have been the subject of investigation for several authors who focus on different aspects of freight research such as geographical disadvantages of businesses (Limão & Venables, 2001), locational effects on trade (Behrens & Picard, 2011), port efficiency (Wilmsmeier, Hoffmann, & Sanchez, 2006), port management (Micco & Pérez, 2002) and surcharges (Slack & Gouvernal, 2011). A review of these literature suggests that freight transport expenditures are dependent on the following factors: (i) length of haul; (ii) relative location, (iii) type of product, (iv) empty backhaul, (v) economies of scale, (vi) truck type choice, (vii) competition and regulation and (viii) taxes and tolls. Among these factors, length of haul is perhaps the most obvious factor that determines freight transport expenditure; greater the distance between the receivers and shippers, higher the expected transport expenditure for their trade (Micco & Pérez, 2002). The relative location of establishments (with respect to ports, city centers, arterials, large traffic generators, etc.) determines freight transport expenditures since it signifies accessibility differences and friction of distance (Holguin-veras & Thorson, 2000). For instance, establishments in landlocked cities tend to have higher transport costs and in turn, lower freight movements as compared to cities in the same state that have direct access to maritime transportation (Rivigo, 2018). The type of product affects the expenditures owing to the variations in transport intensity and handling requirements across each shipment by an establishment. The insurance component of transport expenditures is another reason for product type to cause variations in freight transport expenditures; products with higher unit value tend to have higher charges per unit weight. The empty backhauls (about 30 to 40% of total trips) affect the expenditure since it is often difficult to find perfect matches between an inbound and a return trip (Holguín-Veras et al., 2012). The economies of scale achieved in shipments due to larger shipment sizes (often by means of spatial centralization of stockholding) is another important factor that affect the expenditure. In addition, truck type decisions play an important role in determining transport expenditure since advancements in containerized transport allow for large cost reductions in cargo handling and trans-shipment. The competitive and regulatory environment constituting a dynamic spot market related to freight travel decisions determine the extent of expenditures incurred by an establishment. For instance, transport services provided in highly competitive market segments tend to offer lower freight rates than segments with limited competition. Finally, taxes and tolls levied on the usage of transportation assets affect the total freight transport expenditure.

2.2. Expenditure-based segmentation

Market segmentation has long been a mainstay in travel research and is based on the premise that “heterogeneity in demand functions occur in a market and demand can be disaggregated into segments with distinct demand functions” (Shani, Wang, Hutchinson, & Lai, 2010). This is a widely recognized tool for market and policy interventions because it assists in identifying distinct groups (establishments in this context), that have similar needs, demand functions and motivations for travel. Profiling these segments allows logistics providers to develop the right services and assets for each segment and to tailor the marketing efforts to the segments with maximum profitability. One important issue with market segmentation is how to best divide the markets. The segmentation criteria used in freight research have largely been limited to ‘a priori’ classification systems such as industrial classification systems (Pani, Bhat, & Sahu, 2020; Pani & Sahu, 2019b), land-use classification systems (Holguín-Veras et al., 2012) and geographical delineations (Pani, Sahu, Patil, & Sarkar, 2018). Few of the ‘a posteriori’ segmentation approaches in literature are limited to creating homogeneous ensembles of aggregation levels based on ‘a priori’ classification systems (Pani & Sahu, 2019c; Pani, Sahu, Chandra, & Sarkar, 2019). This is in contrast with the market segmentation literature, mostly in disciplines such as tourism and hospitality research, which starts from the premise that there is little point in addressing an average consumer, or in this context, an average establishment distinguished using existing classification systems. Several other segmentation criteria and approaches are prevalent in these disciplines, including socio-demographics, psychographics, trip activities, motivations or benefits sought during travel and expenditure patterns (Oh & Schuett, 2010). While there is no consensus on a single criterion that researchers agree on, expenditure-based segmentation has received substantial research attention lately due to the practical need for documenting the economic impacts of travel and increasing the revenue of freight transport sector. Being able to segment the establishments based on spending (say, high and low spenders), may find several applications related to logistics planning and operations. For example, these segments would provide a structure to the demand for the services rendered by logistics providers. An improved understanding of these market segments could also be useful for the logistic providers in matching the service requirements of the establishments. Identification of these segments will assist the logistics providers to develop better marketing strategies, fleet allocation plans and operational strategies. Although freight transprtation and logistics operations are an important economic activity globally, scholarly inquiry into expenditure-based segmentation of establishments is missing from the literature.

3. Methodology and data

The methodological approaches to carry out expenditure-based segmentation include two broad categories: (i) segmentation based on threshold values; (ii) segmentation based on clustering analysis. The first approach uses thresholds such as quantiles (e.g., quartile) of the distribution of expenditure variable as the segmentation method. The second approach uses clustering analysis (typically, K-means) to segment the objects based on their volume of expenditures. While the threshold-based approach is somewhat arbitrary, the clustering approach does not provide necessary statistics for inference and fails to account for unobserved heterogeneity. The applications of finite mixture models (FMM) to model the probability of belonging to each unobserved group (i.e., an expenditure segment) and to estimate distinct parameters of regression models are, however, scarce in the literature on market segmentation (Mortazavi & Lundberg, 2019). FMMs can assign the probability of belonging to each expenditure segments based on the level of spending and allows statistical inferences to be made regarding segmentation effectiveness. This paper uses FMM approach and identifies unobserved groups of freight transport expenditure patterns among establishments through a probabilistic framework.

3.1. Analysis methods

3.1.1. Finite mixture models

FMMs are closely linked to the more common latent class analysis (LCA); however, unlike LCA, FMM uses continuous latent variables to account for heterogeneity in observed data. Using maximum likelihood estimation, FMMs treat the properties of the latent classes (e.g., means along observed variables for each class) as unknown and maximizes their likelihood in relation to the observed data (Kemperman & Timmermans, 2009). The resulting latent classes are groups of establishments who exhibit more homogeneity as a cluster than the total sample from which they are drawn. With an interest towards model parsimony and interpretability of the solution, models with different number of classes are compared along both statistical and substantive grounds to choose the most appropriate latent class structure. This process entails developing a series of FMMs starting from two classes and comparing the model fit statistics.

3.1.2. CHAID

Chi-squared automatic interaction detector (CHAID) is used to analyze the relationship between the dependent variable (i.e., latent clusters of expenditure patterns) and freight travel pattern (i.e., freight production, freight trip production, and length of haul). The final models are presented in the form of a tree, in which each final node represents a mutually exclusive subgroup of homogeneous categories concerning the dependent variable.

3.2. Data

Data for this research are taken from a larger study on the urban freight demand modelling of establishments in India, which was conducted during August to October 2013. The survey coverage included shippers which consist of manufacturing units, assembling companies, and raw material production sites. Simple random sampling was used to conduct the survey on a sampling frame of 54,170 establishments developed using economic census. Face-to-face interviews were used for collecting the responses from the logistic managers/owners of establishments and the final response rate was 30.3%. The survey questionnaire covered a broad range of sections including the establishment characteristics (employment, business age, and gross floor area), shipment characteristics (total quantity of goods produced and received), expenditures, and truck ownership. When collecting the expenditure information, logistic managers/owners were asked to recall or estimate the expenditure for shipments forwarded during a week (6 working days) depending on the day they were interviewed. The establishments employing other modes of transportation, such as rail, air or sea represented a miniscule part of the sample. In the absence of sufficient data on multimodal and intermodal freight activity, we have restricted our sample and analysis to road freight transportation. The expenditure information subsumes different components of the total cost: toll charges, fuel cost, and transporter commission. In order to avoid recall bias and telescopic effect, respondents were asked to verify their responses with shipment logs and the collected data were cross verified and cleaned using publicly available freight rate websites such as TCI (Transport Corporation of India, 2013) or NFI (Rivigo, 2018). International Standard Industrial Classification (ISIC) system was adopted to achieve homogeneous classes of establishments and investigate the influence of industry categories on freight transport expenditure. It may be noted that ISIC codes are comparable in their taxonomy to industry classification systems followed in North America (NAICS codes) and Europe (NACE codes). The industry sectors as per ISIC classification is given below along with the relevant classification codes (Pani & Sahu, 2019c).

- Sector 1 : Food products (ISIC 10)
- Sector 2 : Beverages, tobacco and related products (ISIC 11)
- Sector 3 : Textile mills (ISIC 13)
- Sector 4 : Textile products (ISIC 14)
- Sector 5 : Wood, wood products, furniture and fixtures (ISIC 16)
- Sector 6 : Paper, paper products and printing (ISIC 17–18)
- Sector 7 : Basic chemicals, chemical products and pharmaceuticals (ISIC 20–21)
- Sector 8 : Plastic and rubber products (ISIC 22)
- Sector 9 : Non-metallic mineral products (ISIC 23)
- Sector 10 : Basic metal, alloy, metal products (ISIC 24–25)
- Sector 11 : Machinery and equipment (ISIC 26–28)
- Sector 12 : Transportation equipment (ISIC 29–30)
- Sector 13 : Other manufacturing industries (ISIC 32)

The fleet ownership data were classified according to their gross vehicle weight (GVW) into three types: (i) light-duty vehicles (LDVs) – GVW < 3.5 tons; (ii) medium-duty vehicles (MDVs) – 3.5 < GVW < 12 tons; (iii) heavy-duty vehicles (HDVs) – GVW > 12 tons. The truck type used for transporting the shipment was divided into 10 categories based on their payload capacity. The truck categories included in LDV are 1-ton vans or pickups and 2-ton tempos (2 ton). MDVs, on the other hand, include 6-ton trucks with 4 tyre, 7.5-ton trucks with 6 tyre and 9-ton trucks with 6 tyre. The truck categories included in HDVs are 16-ton trucks with 10 tyre, 22-ton trucks with 12 tyre, 25-ton trucks with 14 tyre, 28-ton trucks with 18 tyre and 34-ton trucks with 22 tyre. More information on the survey, research context, sampling characteristics, response rates, and representativeness of sample can be found in Pani and Sahu (2019b) and Pani and Sahu (2019a). The final sample includes 1613 shipment records from 432 establishments.

4. Results and discussion

4.1. Formulation of expenditure segments

As a first step, an OLS regression analysis was performed with independent variables which are found to be in significant in previous research on freight travel patterns (Holguín-Veras et al., 2012, 2016; Pani et al., 2018; Sahu & Pani, 2019). The dependent variable for analysis is the total freight transport expenditure incurred by establishments in a week (measured in INR). The variables found to be significant in determining expenditure at a confidence level of 90% were

Table 1
Model fit of the finite mixture models.

No of classes	*Npar*	*LL*	BIC(LL)	*p*-value	AIC	CAIC(LL)
1	2	−3123.81	6259.7542	0.000	6251.6173	6261.754
2	36	−2846.42	5911.3031	0.000	5764.8398	5947.303
3	70	−2710.23	5845.2484	0.000	5560.4586	5915.248
4	104	−2653.11	5937.3362	0.000	5514.22	6041.336
5	138	−2602.65	6042.7375	0.000	5481.2948	6180.738
6	172	−2556.58	6156.92	0.000	5457.1508	6328.92
7	206	−2519.19	6288.4831	0.000	5450.3874	6494.483
8	240	−2468.66	6393.7335	0.000	5417.3114	6633.734
9	274	−2438.18	6539.1185	0.000	5424.3699	6813.119
10	308	−2399.58	6668.2271	0.000	5415.152	6976.227

Npar – Number of Parameters in LCCA model; *LL* – Final log-likelihood of the model; *df* – degrees of freedom; *BIC* - Bayesian Information Criterion.

selected for application in FMM approach. To determine the appropriate number of expenditure segments, FMM models were estimated and the fit of consecutive models starting from one latent class to ten latent classes are presented in Table 1. The dedicated mixture model package Latent Gold (Vermunt & Magidson, 2005) was used to estimate the models. For evaluating the number of latent classes that fits the data best, comparison of Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) and conventional log-likelihood values were used. Furthermore, different versions of AIC such as consistent AIC (CAIC) were calculated for weighing both model-fit and parsimony. These criteria are presented in Table 1. The BIC values reach their minimum when the number of classes is three, indicating that the classifying the original dataset into three clusters is the optimal solution. The average spending pattern and probability of one random establishment to belong to each latent class is presented in Table 2. The average spending is about 14,261 INR per week (about $210) for the first segment which is labelled as "light spenders", 35,633 INR (about $520) for the second segment, "medium spenders" and 90,664 INR (about $1320) for "heavy spenders". The purchasing power of heavy spenders among the establishments are indeed of significant interest to logistics providers, especially since there are a lot of smaller establishments in a developing country like India with much lower purchasing power. The magnitudes of expenditure in each of these segments, however, are expected to vary significantly in developed countries with notably different establishment sizes. The interquartile ranges of the spending pattern observed in each segment are relatively narrow indicating a rather good precision of the estimates.

4.2. Profiling expenditure segments

The establishment and trip characteristics of each latent segment is presented in Table 3. As can be seen, the first segment – light spenders – is composed mostly of establishments with employment levels lower than 22 (about 80%). These establishments are characterized with low gross floor area and business age as well – 82.3% have area less than 2060 m^2 and 77% have less than 20 years of business age. The fleet ownership levels of establishments in this segment are low since more than 60% of establishments do not own either of LDV, MDV or HDV. The average haulage of establishments in this segment (112 km) is lower than the sample average (150 km) with major share belonging to the trips covering less than 75 km (36%). The preferred truck type for establishments in this segment include LDV tempo with 2-ton capacity (28%), followed by MDV trucks with 6-ton capacity (22%) and 9-ton capacity (15%). The selection of HDVs is rather uncommon in this segment, except for a minor share of establishments choosing 16-ton and 22-ton HDVs.

The second segment – medium spenders – differ from the first with regards to employment, gross floor area and business age. For instance, a significantly larger share of establishments with employment between 23 and 38, area between 207 and 282 m^2 and business age between 29 and 53 years belong to medium spenders. The fleet ownership pattern of medium spenders, however, is not different from that of the light spenders. This suggest that establishments in both segments are largely outsourcing freight operations since it possibly transfers their financial burden of staffing and daily operations to carriers. Regarding length of haul, significant difference can be identified between the segments since shipments forwarded by medium spenders are covering a larger geographical extent as compared with light spenders. For example, approximately 37% establishments in medium spenders indicated that they cover at least 222 km/trip, compared with the 16% in light spenders. The preferred truck types for shipments among medium spenders are MDV 6-tons (24%) and LDV 1-ton (21%). The share of HDV-based shipments among medium spenders (31%) are significantly higher than that of light spenders (18%).

The segment characteristics of third segment – heavy spenders – reveal that these establishments have significantly large business size indicators, whether it is employment, area or business age. Approximately 50% of establishments in this segment have employees greater than 39, compared with the 16% in medium spenders and 7% in light spenders. The average gross floor area of these establishments is about 1258 m^2, whereas the sample average is merely 774 m^2. Regarding the business age, majority of these establishments are far older than the ones in medium and light spenders. The fleet ownership patterns among establishments in heavy spenders differ from other segments with ownership about 54% - 56% of LDVs and MDVs, compared to 27% - 28% for medium spenders and 35%–39% for light spenders. The preferred truck types for shipments among establishments in heavy spenders are MDV 6-ton and HDV 16-ton. The establishments in heavy spenders make the least number of trips with LDVs (10%), as compared with medium spenders (40%) and light spenders (40%). The large share of LDV ownership among establishments in heavy spenders may thus be driven by the need for making service trips or waste disposal trips, which are often overlooked as a component of commercial vehicle activity (Holguín-Veras et al., 2016).

4.2.1. Industrial profile

The conditional probabilities of establishments from an industry sector (e.g., ISIC 10) belonging to each of the three expenditure segments were computed based on the FMM model and the results are presented in Fig. 1. It may be noted that choice probabilities are rescaled to sum to one over latent classes of expenditure segments. For instance, given that an establishment belongs to ISIC 10 (food products), there is 61% probability that it is a medium spender, as opposed to a heavy spender (28%) or light spender (11%). As it can be seen,

Table 2
Latent class mean expenditure (in 100 INR).

Latent class	Mean	Std. Err.	z	p > |z|	Label	Spending pattern			
						Q1	Q2	Q3	IQR
1	142.61	4.92	28.99	0.000	"Light Spenders"	123.8	140.3	163.3	39.5
2	356.33	9.17	38.86	0.000	"Medium Spenders"	280.9	348.9	431.7	150.8
3	906.64	38.65	23.46	0.000	"Heavy Spenders"	631.2	821.3	1138.3	507.1

Q1, Q2 and Q3 represent the first, second and third quartiles, respectively; IQR denote the interquartile range.

Table 3
Cluster percentages and cluster variable means for 3-cluster latent class solution.

Variables		Cluster 1 *Light Spenders*	Cluster 2 *Medium Spenders*	Cluster 3 *Heavy Spenders*	Sample Total
Cluster Size		28.31%	49.52%	22.17%	100%
Mean Expenditure (in 100 INR/week)		142.61	356.33	906.64	417.82
Employment	1–8	**38.25%**	20.61%	4.3%	**21.99%**
	9–13	21.25%	20.69%	12.26%	18.98%
	14–22	20.21%	20.71%	10.4%	18.28%
	23–38	13.31%	**22.11%**	23.41%	19.91%
	39–76	6.98%	15.88%	**49.63%**	20.84%
	Mean	15.88	23.84	50.55	27.5
Gross Floor Area (in 10 m^2)	1–71	**30.74%**	18.35%	9.55%	19.91%
	72–141	27.4%	20.17%	10.79%	**20.14%**
	142–206	24.16%	20.13%	13.97%	19.91%
	207–282	9.79%	**27.05%**	17.9%	20.13%
	283–360	7.91%	14.3%	**47.8%**	19.92%
	Mean	49.75	71.49	125.822	77.3792
Business Age	1–9	27.13%	18.6%	9.42%	18.98%
	10–15	**30.18%**	**23.02%**	11.32%	**22.45%**
	16–20	19.78%	21.36%	18.91%	20.37%
	21–28	15.39%	20.68%	15.6%	18.05%
	29–53	7.52%	16.36%	**44.74%**	20.15%
	Mean	16.08	19.61	27.8667	20.4439
Number of Owned LDVs	0	**61.36%**	**72.47%**	44.37%	**63.42%**
	1	16.23%	13.9%	9.82%	13.66%
	2+	22.41%	13.62%	**45.81%**	22.92%
Number of Owned MDVs	0	**65.6%**	**72.65%**	**46.27%**	**64.81%**
	1	18.97%	14.32%	17.94%	16.44%
	2+	15.43%	13.04%	35.79%	18.76%
Number of Owned HDVs	0	**65.96%**	**64.67%**	**69.95%**	**66.21%**
	1	18.92%	18.58%	6.38%	15.97%
	2+	15.12%	16.75%	23.68%	17.82%
Length of Haul (km/trip)	1–74	**35.5%**	18.42%	4.36%	**20.14%**
	75–145	27.92%	22.04%	4.89%	19.9%
	146–221	20.16%	22.7%	13.33%	19.9%
	222–295	12.31%	**22.64%**	24.53%	**20.14%**
	296–377	4.1%	14.2%	**52.89%**	19.92%
	Mean	112.16	139.27	221.22	149.76
Truck Type Choice	HDV 10 tyre (16 ton)	13.16%	14.95%	14.54%	14.35%
	HDV 12 tyre (22 ton)	5.26%	7.73%	2.10%	5.79%
	HDV 14 tyre (25 ton)	0.00%	6.53%	2.11%	3.7%
	HDV 18 tyre (28 ton)	0.00%	1.40%	2.10%	1.16%
	HDV 22 tyre (34 ton)	0.79%	2.11%	7.86%	3.01%
	LDV Tempo (2 ton)	**27.72%**	18.55%	9.82%	19.21%
	LDV Vans (1 ton)	12.47%	21.37%	0.01%	14.11%
	MDV 4 tyre (6 ton)	21.84%	**24.06%**	**46.82%**	**28.48%**
	MDV 6 tyre (7.5 ton)	4.09%	0.47%	7.32%	3.01%
	MDV 6 tyre (9 ton)	14.67%	2.83%	7.32%	7.18%

Numbers in boldface indicate highest share of establishments in a segment with respect to each cluster variable.

establishments from industry sectors such as ISIC 11, 13, 17–18 are found to be more likely to be heavy spenders. The industry sectors with more propensity to be light spenders, on the other hand, include ISIC 14, 22, 23, 26–28 and 29–30. The remaining industry sectors are more likely to be medium spenders.

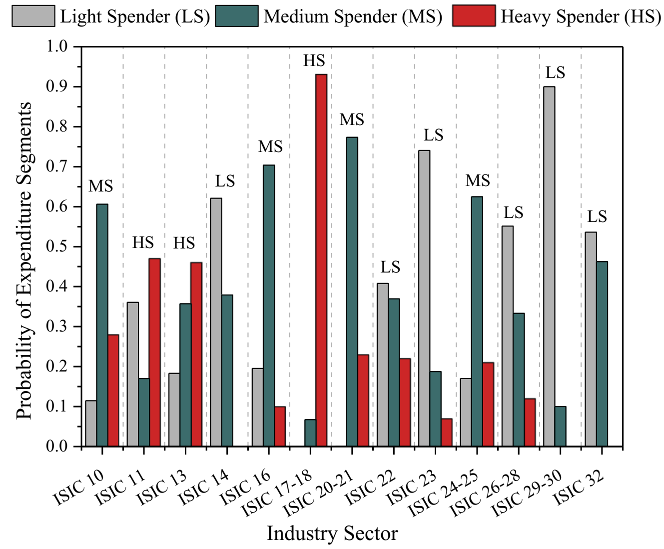

Fig. 1. Industry profile of expenditure segments.

4.2.2. Freight travel profile

The freight travel characteristics of each segment are presented in Fig. 2(A) using freight production or FP (tons/week), freight trip production or FTP (trips/week) and length of haul or LH (km/trip). Several differences can be identified among the expenditure segments in terms of FP, FTP and LH. For instance, heavy spenders are associated with a median FP of 35 tons/week and FTP of 6 trips/week and cover a geographical extent of 210 km/trip. Light spenders, on the other hand, are having much lesser FP of 6 tons/week, FTP of 1 trip/week and LH of 106 km/trip. Medium spenders are, expectedly, associated with values higher than light spenders and lower than the heavy spenders. It may be noted that heavy spenders, on an average, produce six times the tonnage, six times the trips and two times the haulage, as compared with light spenders.

4.2.3. Locational profile

The proximity of an establishment to large traffic generators or major arterials, city center and ports (Pani et al., 2018) are reported to have a bearing on the freight activity, although it is not investigated in the context of freight transport expenditures. This association is based on the logical notion that a premium space near to the city center would generate more freight activity than an isolated space in suburban area. In order to examine the effect of relative location of establishments, three variables are used in this study – proximity to city center, proximity to port, and proximity to major arterial. The posterior intervals of these three variables for each expenditure segment is presented in Fig. 2(B). The box plots indicate that the establishments in the heavy spender segment is located relatively closer to the port, farther from the city center. The association of expenditure segments with arterial proximity appears to be rather weak, since the median values are not distinct.

4.3. Modelling freight transport expenditure patterns

The freight transport expenditure was modelled using OLS regression models (total analysis sample) and the three latent class FMMs for light spenders, medium spenders and heavy spenders. The model estimation results are presented in Table 4. In the results, some of the variables have different effects on the dependent variable in the different segments. The significance in determining freight transport expenditure differs too in some cases. The OLS parameters are mostly close to the parameters estimated for the medium spenders, which is logical since almost half of the sample (49%) belongs to this segment.

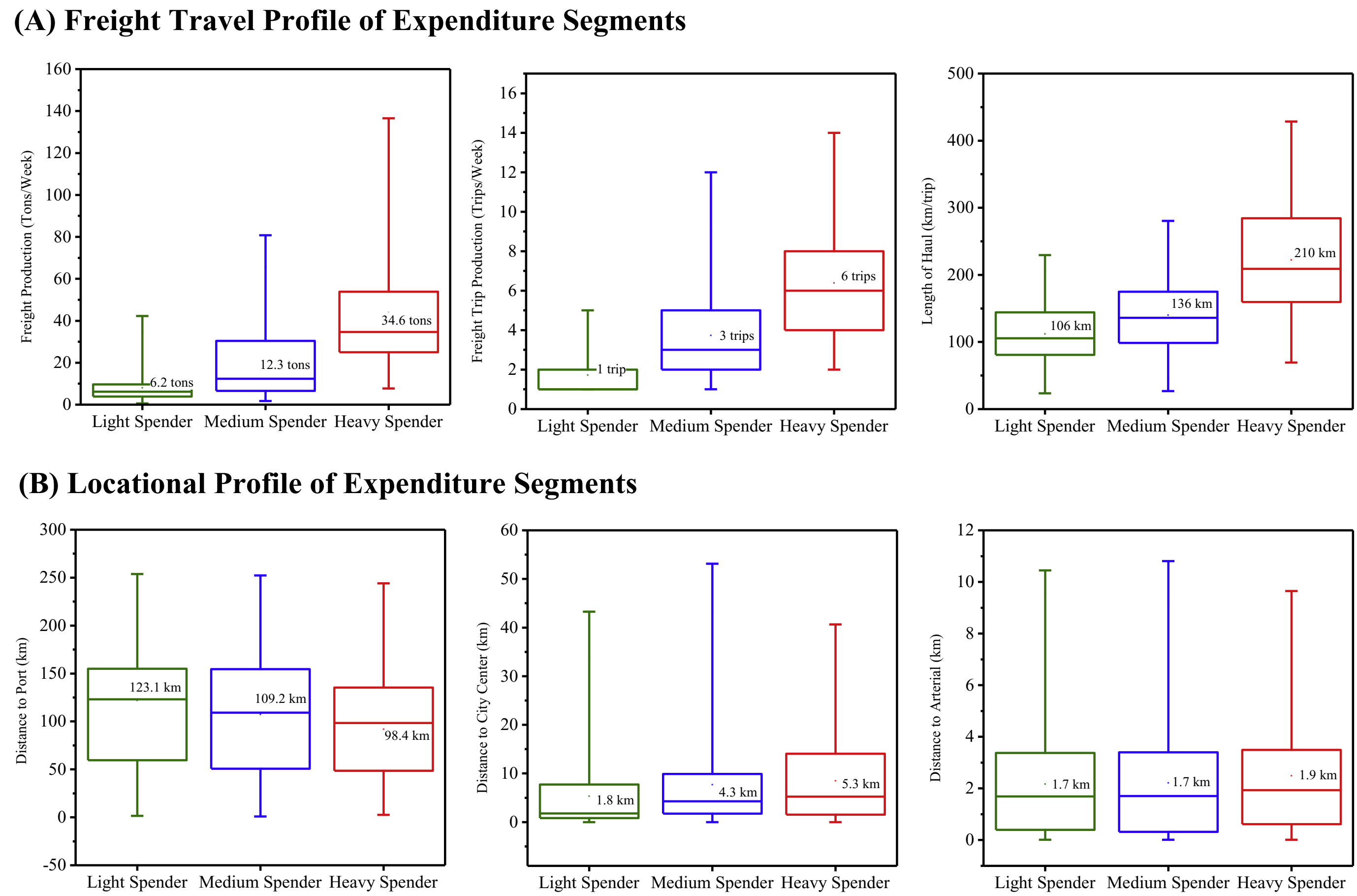

Fig. 2. Profile of expenditure segments using (A) freight travel characteristics and (B) locational characteristics.

The explanatory power of FMM results are clearly superior to the OLS results. In terms of error variances also, FMM perform better than OLS models. Among the latent segments, heavy spenders show the highest variability, while the light spenders show the least variability.

A closer look at the results reveal that the estimated coefficients are quite different for the three segments. For instance, incremental effect of employment on weekly freight transport expenditure is 153 INR/employee among light spenders, 108 INR/employee among medium spenders and 339 INR/employee among heavy spenders. Similar variation in incremental effect of gross floor area can be found between the segments, although the effect is not statistically significant in the case of medium spenders. The OLS model shows that an establishment's business age increases weekly expenditure by 276 INR for every additional year in business, possibly due to the expansion of business networks. The effect of business age, however, becomes inverted in the case of heavy spenders such that the expenditure reduces by 431 INR for every additional year. This may be due to the steady lane volume achieved with carriers which leads to effective utilization of empty backhauls. Regarding fleet ownership, OLS model suggests that owning an additional MDV and HDV is associated with increased expenditures of 2632 INR/week and 3159 INR/week. This suggests that outsourcing is a better strategy for light and medium spenders as it leads to cost reduction in the expenses on hiring, training and maintaining a transportation staff and driver force.

The heavy spenders, as shown by the FMM model, can reduce their expenditure by 9064 INR/week and 4526 INR/week due to LDV and MDV ownership. HDV ownership, however, increases total expenditures significantly (9402 INR/week) in the case of heavy spenders. The positive association with owning HDV and expenditure could be related to increased length of haul in the case of heavier loads. Considering the possibility of several interpretations in this regard, future investigations are needed to derive robust conclusions regarding fleet ownership and expenditure patterns. The industry sectors significantly vary in their expenditure patterns as well.

The incremental effect of haulage on expenditure by heavy spenders (322 INR/km/trip) is substantially higher than that of medium spenders (231 INR/km/trip) and light spenders (107 INR/km/trip). This may be explained in terms of the larger tonnage associated with heavy spenders (35 tons/week), compared with light and medium spenders (see Fig. 2). Most of the coefficients denoting truck type in the OLS model are not statistically significant, barring the exception of 34-ton HDV, 2-ton LDV and 1-ton LDV. The coefficients in FMMs suggest that the selection of LDVs decrease the expenditure regardless the segment membership. The reduction in cost due to LDVs is substantially higher in the case of heavy spenders, possibly due to their increased share of LDV ownership. The incremental effect of HDV selection among heavy spenders decreases as the capacity of truck type increases from 16 ton to 25 ton. This can be explained in terms of the economies of scale achieved due to larger shipment sizes. The reduction in expenditure in the case of larger HDVs are reflected in the case of both medium and light spenders, barring the exception of 28-ton HDVs. The coefficients in FMMs for locational characteristics suggest that establishments located close to the arterials (< 2 km) and city centers (< 3.6 km) are associated with higher transport expenditure, especially among the heavy and medium spenders. The proximity to port, conversely, is found to reduce the weekly expenditures of establishments in heavy spenders by 5935 INR/week. However, these empirical findings are not generalizable without a comprehensive micro-level investigation into spatial effects on freight transport expenditure with due consideration given to other underlying confounding factors (e.g., land value, delivery restrictions).

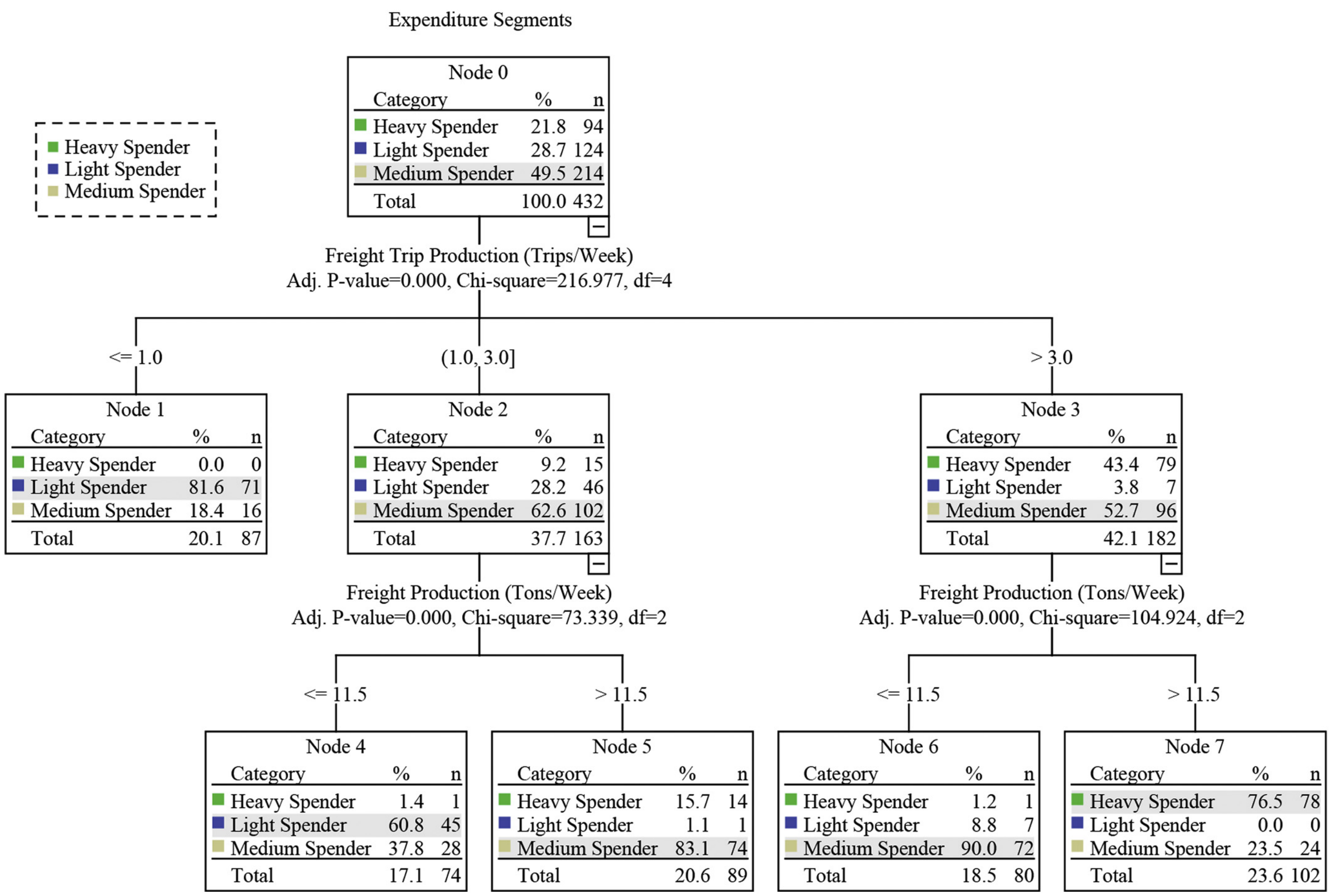

Fig. 3. Results of CHAID Analysis to find the association between freight travel patterns and expenditure segments.

4.4. *Effect of freight travel pattern on expenditure segments*

CHAID was used to examine the relationships between the expenditure segments and the freight travel patterns of establishments, specifically FP (tons/week), FTP (tons/week) and LH (km/trip). The results of CHAID decision tree are presented in Fig. 3. The tree diagram is partitioned based on the analysis of the selected variables, with each segment highlighting the differing composition of expenditure segments. While the best predictors of expenditure segments are FP and FTP, LH did not result in any statistically significant splits. FTP, the most important predictor, splits the total analysis sample (node 0) into three groups: node 1, node 2, and node 3. The first node includes establishments which produce about 1 trip/week. A substantial number of establishments in this group (81.6%) belong to light spenders.

The second node comprises of establishments which produce at most 3 trips/week and the third node consists of establishments producing more than 3 trips/week (up to 14 trips/week as shown in Fig. 2). The composition of second node reveals a large share of medium spenders (62.6%), followed by light spenders (28.2%) and heavy spenders (9.2%). While the third node also contains a large share of medium spenders (52.7%), the share of heavy spenders is much higher (43.4%) than that of the node 2. The second step of the partition in tree diagram represents the influence of FP on the expenditure segments. Two nodes each are formed from node 2 and node 3. The splits from node 2 suggests that establishments that produce 1 to 3 trips/week can either belong to node 4 with lower FP values ($\leq$ 11.5 tons/week) or node 5 with higher FP values ($\geq$ 11.5 tons/week). The former node has with a significant share (60.8%) of establishments which are light spenders and medium spenders are predominant (83.1%) in the latter node. In a similar manner, node 3 is split into a lower FP node ($\leq$ 11.5 tons/week) comprising a major share of medium spenders (90%) and a higher FP node ($\geq$ 11.5 tons/week) consisting mostly of heavy spenders (76.5%).

5. Managerial implications and policy insights

The findings of this study have several important theoretical and managerial implications. The first theoretical implication is that it is the maiden study to divide establishments into different segments based on their freight transport expenditures. Previous segmentation approaches in freight research have largely been limited to application of ‘a priori’ industrial classification systems (e.g., NAICS in North America, NACE in Europe and NIC in India), land use classification systems (NYCZR in USA), geographical delineations (census tracts, zoning systems) or ‘a posteriori’ segments based on ensembles of ‘a priori’ classes. This study provides a distinctive contribution to freight literature by demonstrating that consideration of expenditure patterns may be warranted for better understanding of the freight travel market. Specifically, the study findings show that freight travel market cannot be regarded as homogeneous, and that logistics strategies must therefore be differentiated. The diverging characteristics of the identified expenditure segments – light, medium and heavy spenders – emphasize the need of the logistics providers to “identify their markets” and planners to “identify how demand translates to transport expenditures”. On a managerial front, results presented in Table 3 show the occurrence of sizable segments for specific types of services, implying the opportunity to employ marketing communications to influence how establishments make use of their fleets. For example, a logistic provider setting up base in a new city should primarily target the heavy spenders with greater than 23 employees, 2830 sq. meter area and 29 years of business age.

Table 4
Regression results from FMM with three classes.

Variables	OLS model		Finite mixture model					
	Total analysis sample		Cluster 1		Cluster 2		Cluster 3	
			Light spenders		*Medium spenders*		*Heavy spenders*	
	Coeff.	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*
Establishment characteristics								
Employment	1.19**	(0.54)	1.53***	(0.34)	1.08*	(0.64)	3.39***	(0.72)
Gross Floor Area (10 m^2)	0.50**	(0.20)	–	–	0.58***	(0.19)	1.01***	(0.22)
Business Age	2.76***	(1.04)	1.73***	(0.53)	2.52*	(1.44)	−4.31**	(1.79)
Truck ownership								
Number of LDVs	–	–	–	–	–	–	−90.64***	(21.85)
Number of MDVs	26.32*	(13.96)	–	–	19.28*	(10.01)	−45.26**	(21.48)
Number of HDVs	31.59*	(16.88)	–	–	–	–	94.02***	(23.07)
Industry sector								
ISIC 10	222.3***	(39.02)	−61.84***	(23.02)	194.76***	(75.65)	533.02***	(77.06)
ISIC 11	260.91***	(51.16)	−131.35***	(33.08)	151.55**	(71.76)	633.29***	(78.8)
ISIC 13	–	–	155.62***	(39.76)	−68.2*	(41.13)	–	–
ISIC 14	–	–	−56.68*	(36.63)	–	–	–	–
ISIC 16	−144.31**	(57.48)	86.44**	(37.97)	−86.13*	(47.85)	−451.75***	(118.27)
ISIC 17–18	276.13***	(57.45)	335.09***	(39.44)	–	–	315.18***	(99.04)
ISIC 20–21	263.24***	(36.91)	55.4**	(22.72)	208.76***	(31.09)	505.15***	(60.82)
ISIC 22	70.26*	(40.45)	−89.33***	(25.27)	126.43*	(69.64)	−189.56**	(81.08)
ISIC 23	−323.61***	(55.67)	−193.4***	(34.65)	−195.41***	(56.79)	−353.61***	(139.05)
ISIC 24–25	−124.55**	(51.95)	–	–	–	–	−358.06***	(102.89)
ISIC 26–28	–	–	–	–	–	–	–	–
ISIC 29–30	−292.39**	(61.81)	–	–	−141.02**	(56.43)	−555.66***	(107.18)
ISIC 32	–	–	–	–	–	–	−144.78*	(82.98)
Trip characteristics								
Length of Haul (km/trip)	2.57***	(0.18)	1.07***	(0.12)	2.31***	(0.12)	3.22***	(0.27)
Truck type choice								
HDV 10 tyre (16 ton)	–	–	51.48***	(21.13)	119.12***	(29.14)	118.14***	(44.03)
HDV 12 tyre (22 ton)	–	–	−40.46*	(23.28)	54.35*	(33.28)	108.82***	(98.96)
HDV 14 tyre (25 ton)	–	–	−53.78*	(29.76)	−85.24*	(47.5)	102.58*	(61.68)
HDV 18 tyre (28 ton)	–	–	−142.43**	(59.93)	255.1***	(84.09)	–	–
HDV 22 tyre (34 ton)	193.56***	(−57.35)	228.65***	(55.58)	–	–	–	–
LDV Tempo (2 ton)	−120.66***	(−44.4)	–	–	−121.26***	(45.47)	−298.12***	(66.76)
LDV Vans (1 ton)	−91.47**	(−51.08)	−79.63***	(30.67)	–	–	−359.69***	(76.1)
MDV 4 tyre (6 ton)	–	–	52.32**	(22.5)	–	–	126.26**	(52.38)
MDV 6 tyre (7.5 ton)	–	–	−163.09***	(29.58)	72.69**	(36.43)	225.96***	(86.45)
MDV 6 tyre (9 ton)	–	–	−54.84*	(32.92)	−48.94**	(23.5)	−183.85***	(61.13)
Locational characteristics								
Proximity to arterial								
Close < 2 km	–	–	−23.41***	(6.22)	36.62***	(8.16)	56.19***	(13.31)
Proximity to city center								
Close < 3.6 km	–	–	−12.53**	(5.65)	34.51***	(12.99)	37.49***	(15.38)
Proximity to port								
Close < 108 km	–	–	–	–	–	–	−59.35***	(16.58)
Intercept	−135.51**	(55.41)	86.04***	(31.93)	−81.93*	(49.24)	78.29	(89.10)
R^2	0.709		0.869		0.973		0.964	
Var (error)	32,657.3		2268.7		3108.6		8681.6	

*$p < .1$; **$p < .05$; ***$p < .01$;

The profile of each segment depicted in terms of location and industry sector would be of help to further narrow down the operational strategies of logistics providers. These findings also have implications towards minimizing the negative externalities of increased freight travel needs in a market-based economy (Botha, Slabbert, Rossouw, & Viviers, 2011). For instance, Spencer (2010) suggests that the agencies adopting expenditure-based segmentation approach may be able to achieve their economic objectives using fewer customers with bigger purchasing power. Some managerial implications can be provided for local trade and regional development authorities as well. The regional policies on developmental lines, land use plans, industrial cluster formation can be directed to those establishment types that generate higher levels of local development by focusing on the high-spending niches (Díaz-Pérez, Bethencourt-Cejas, & Álvarez-González, 2005). Overall, study findings and approach have several unrealized possibilities to help in maximizing the revenue of logistics providers by focusing on the freight travel needs of relatively smaller number of heavy spending establishments.

6. Conclusions and future research

The main objective of this study was to segment industrial establishments by total weekly freight transport expenditures using a finite mixture modelling (FMM) methodology. The advantage of FMM, which identifies latent segments, is that both observed and unobserved heterogeneity are be taken into consideration. To the best knowledge of authors, this is the first research to systematically investigate freight transport expenditure patterns using this methodology. The results indicate the existence of three expenditure segments which are defined as light, medium and heavy spenders. The independent variables found to be significant in determining freight demand in previous research are also found to be significant in determining freight transport expenditures in this study, overall, or in latent segments. In particular, it is found that business size indicators, such as employment, area or business age significantly influence the weekly freight transport expenditure. These indicators have different effects in different latent segments and the significance of the variables are different as well. The findings imply that considering latent classes and unobserved heterogeneity when segmenting freight travel market is relevant. One example that shows the relevance of FMM approach is the effect of fleet ownership levels on freight transport expenditures. For the light spender segment, none of the fleet ownership categories (LDV, MDV, HDV) variables have statistically significant effects on freight transport expenditures. The expenditures of establishments in heavy spender segment, in contrast, are strongly influenced by each of the fleet ownership categories. It can also be seen that the incremental effect of haulage on expenditure in heavy spenders is substantially higher than that of medium spenders and light spenders. While the OLS model suggests that locational characteristics have no effect of expenditures, FMM results show that the establishments located close to the arterials (< 2 km) and city centers (< 3.6 km) are associated with higher freight transport expenditure, especially among the heavy and medium spenders. Without taking the unobserved heterogeneity into consideration and forming latent classes based on segmentation approach, the variables denoting business size, relative location, industry sector and shipment characteristics may be under- or over-estimated in explaining freight transport expenditure. Overall, the results show that segmenting the freight travel market based on expenditure, using unobserved heterogeneity, is relevant and adds crucial knowledge about the determinants of freight transport expenditure.

The findings derived from this study are relevant to logistics providers, freight transport planners and policymakers. Logistics providers can increase the effectiveness of their fleet allocation plans and marketing strategies by being more selective in targeting and positioning of services. Freight transport planners can use the findings to identify the gross spenders among the establishment populations and incorporate them in larger research efforts aimed at improving transportation system infrastructures and operations. Policymakers can use the findings about the segment characteristics to better evaluate the impact of policy measures on establishments' freight transport expenditures. The expenditure-based segments identified in this study have several applications towards the deep decarbonization strategies, especially since transport emissions are unequally distributed with gross polluters responsible for a disproportionate share of total emissions (Brand & Preston, 2010). Heavy spenders in freight system are of particular interest since they are the key contributors to climate change in terms of energy consumption and greenhouse gas (GHG) emissions. Empirical analyses of sustainability strategies have so far, however, focused on total emissions and have insufficiently studied the heavy spenders in freight system, where such insights could help to stimulate the decarbonization transitions. By positioning the heavy spenders within the sustainable transition literature and providing a target segment for schemes like carbon taxes, this paper enables future work for facilitating and steering the transition among heavy spenders towards deep decarbonization.

A possible limitation of this research, however, is that it utilized a cross-sectional design in which data were collected in the rather peak season (August to October). An interesting research question that could not be answered in this study and that could be of interest for further investigation is: what is an establishment's propensity to decrease expenditure during an off-peak season or in a scenario where the financial situation worsens? An opportunity for future research is, therefore, to conduct freight surveys over a peak season and an off-peak season and evaluate the differences in expenditure patterns. Identification of those segments having a low propensity to reduce freight transport expenditure despite the financial slow down would be helpful to understand the stability of these expenditure-segments. Another possible research avenue is to conduct analysis on the impacts of mode of transportation (e.g., rail, sea or air) on freight transport expenditure. Finally, generalizability of the findings to other markets or countries would have to be empirically tested in further studies. The large traffic generators in developed countries are, nonetheless, expected to generate higher trip frequency, length of haul and in turn, higher freight transport expenditure. It would be interesting to replicate this study to other establishment populations, especially in developed countries and compare the findings. The research efforts in this direction are essential steps to enhance the ability of freight transportation industry to meet the needs of their markets.

Declaration of Competing Interest

None.

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None.

References

Behrens, K., & Picard, P. M. (2011). Transportation, freight rates, and economic geography. *Journal of International Economics, 85*(2), 280–291. https://doi.org/10.1016/j.jinteco.2011.06.003.

Botha, K., Slabbert, E., Rossouw, R., & Viviers, P.-A. (2011). Expenditure-based segmentation of visitors to Aardklop National Arts Festival. *South African Theatre J. 25*(2), 142–166. https://doi.org/10.1080/10137548.2011.639168.

Brand, C., & Preston, J. M. (2010). “60-20 emission”-The unequal distribution of greenhouse gas emissions from personal, non-business travel in the UK. *Transport Policy, 17*(1), 9–19. https://doi.org/10.1016/j.tranpol.2009.09.001.

Díaz-Pérez, F. M., Bethencourt-Cejas, M., & Álvarez-González, J. A. (2005). The segmentation of canary island tourism markets by expenditure: Implications for tourism policy. *Tourism Management, 26*(6), 961–964. https://doi.org/10.1016/j.tourman.2004.06.009.

EDD (2016). *Logistics Cost and Service.* 2015 Issue May.

Giuliano, G. (2014). Introduction to the volume: Managing freight in urban areas. *Research in Transportation Business and Management, 11*, 2–4. https://doi.org/10.1016/j.rtbm.2014.06.011.

Gonzalez-Feliu, J., & Peris-Pla, C. (2017). Impacts of retailing attractiveness on freight and shopping trip attraction rates. *Research in Transportation Business and Management, 24*(June), 49–58. https://doi.org/10.1016/j.rtbm.2017.07.004.

Guerrero, D., & Proulhac, L. (2014). Freight flows and urban hierarchy. *Research in Transportation Business and Management, 11*, 105–115. https://doi.org/10.1016/j.rtbm.2013.12.001.

Haas, P., Morse, S., Becker, S., Young, L., & Esling, P. (2013). The influence of spatial and household characteristics on household transportation costs. *Research in Transportation Business and Management, 7*, 14–26. https://doi.org/10.1016/j.rtbm.2013.03.004.

Holguín-Veras, J., Jaller, M., Sanchez-Diaz, I., Wojtowicz, J., Campbell, S., Levinson, H., ... Tavasszy, L. (2012). NCFRP 19: Freight Trip Generation and Land Use: Final Report. http://onlinepubs.trb.org/onlinepubs/ncfrp/ncfrp_rpt_019.pdf.

Holguín-Veras, J., Lawson, C., Wang, C., Jaller, M., González-Calderón, C., Campbell, S., ... Ramirez, D. (2016). *NCFRP 37: Using Commodity Flow Survey Microdata and Other Establishment Data to Estimate the Generation of Freight.* Freight Trips, and Service Tripshttps://doi.org/10.17226/24602.

Holguin-veras, J., & Thorson, E. (2000). Trip length distributions in commodity-based and trip-based freight demand modeling. *Transportation Research Record, 1707*(0–910), 37–44. https://doi.org/10.3141/1707-05.

Kemperman, A., & Timmermans, H. (2009). Influences of built environment on walking and cycling by latent segments of aging population. *Transportation Research Record, 2134*(1), 1–9. https://doi.org/10.3141/2134-01.

Kijewska, K., Iwan, S., Konicki, W., & Kijewski, D. (2017). Assessment of freight transport flows in the city Centre based on the Szczecin example - methodological approach and results. *Research in Transportation Business and Management, 24*(November 2016), 59–72. https://doi.org/10.1016/j.rtbm.2017.07.003.

Li, T., Dodson, J., & Sipe, N. (2015). Differentiating metropolitan transport disadvantage by mode: Household expenditure on private vehicle fuel and public transport fares in Brisbane, Australia. *Journal of Transport Geography, 49*, 16–25. https://doi.org/10.1016/j.jtrangeo.2015.10.001.

Limão, N., & Venables, A. J. (2001). Infrastructure, geographical disadvantage, transport costs, and Trade. *The World Bank Economic Review, 15*(3), 451–479.

Malik, L., Sánchez-Díaz, I., Tiwari, G., & Woxenius, J. (2017). Urban freight-parking practices: The cases of Gothenburg (Sweden) and Delhi (India). *Research in Transportation Business and Management, 24*(March), 37–48. https://doi.org/10.1016/j.rtbm.2017.05.002.

Micco, A., & Pérez, N. (2002). *Determinants of maritime transport costs.* In Working Paper No 441https://doi.org/10.2139/ssrn.1817241.

Mortazavi, R., & Lundberg, M. (2019). Expenditure-based segmentation of tourists taking into account unobserved heterogeneity: The case of Venice. *Tourism Economics*. https://doi.org/10.1177/1354816619841713.

Oh, J. Y. J., & Schuett, M. A. (2010). Exploring expenditure-based segmentation for rural tourism : Overnight stay visitors versus excursionists to fee-fishing sites. *Journal of Travel & Tourism Marketing, 27*(1), 37–41. https://doi.org/10.1080/10548400903534824.

Pani, A., Bhat, F., & Sahu, P. (2020). Effects of business age and size on freight demand : Decomposition analysis of Indian establishments. *Transportation Research Record*. https://doi.org/10.1177/0361198120902432 (In Press).

Pani, A., & Sahu, P. K. (2019a). Modelling non-response in establishment-based freight surveys : A sampling tool for statewide freight data collection in middle-income countries. *Transport Policy*. https://doi.org/10.1016/j.tranpol.2019.10.011 (In Press).

Pani, A., & Sahu, P. K. (2019b). Planning, designing and conducting establishment-based freight surveys: A synthesis of the literature, case-study examples and recommendations for best practices in future surveys. *Transport Policy, 78*, 58–75. https://doi.org/10.1016/j.tranpol.2019.04.006.

Pani, A., & Sahu, P. K. (2019c). Comparative assessment of industrial classification Systems for Modeling Freight Production and Freight Trip Production. *Transportation Research Record, 2673*(3), 210–224. https://doi.org/10.1177/0361198119834300.

Pani, A., Sahu, P. K., Chandra, A., & Sarkar, A. K. (2019). Assessing the extent of modifiable areal unit problem in modelling freight (trip) generation : Relationship between zone design and model estimation results. *Journal of Transport Geography, 80*(September), 102524. https://doi.org/10.1016/j.jtrangeo.2019.102524.

Pani, A., Sahu, P. K., Patil, G. R., & Sarkar, A. K. (2018). Modelling urban freight generation: A case study of seven cities in Kerala, India. *Transport Policy, 69*, 49–64. https://doi.org/10.1016/j.tranpol.2018.05.013.

Rivigo (2018). National Freight Index. https://nationalfreightindex.co.in/.

Rowell, M., Gagliano, A., & Goodchild, A. (2014). Examining carrier categorization in freight models. *Research in Transportation Business and Management, 11*, 116–122. https://doi.org/10.1016/j.rtbm.2014.06.006.

Sahu, P. K., & Pani, A. (2019). Freight generation and geographical effects: Modelling freight needs of establishments in developing economies and analyzing their geographical disparities. *Transportation.*. https://doi.org/10.1007/s11116-019-09995-5.

Shani, A., Wang, Y., Hutchinson, J., & Lai, F. (2010). Applying expenditure-based segmentation on special-interest tourists: The case of golf travelers. *Journal of Travel Research, 49*(3), 337–350. https://doi.org/10.1177/0047287509346852.

Slack, B., & Gouvernal, E. (2011). Container freight rates and the role of surcharges. *Journal of Transport Geography, 19*(6), 1482–1489. https://doi.org/10.1016/j.jtrangeo.2011.09.003.

Spencer, D. M. (2010). Segmenting special interest visitors to a destination region based on the volume of their expenditures: An application to rail-trail users. *Journal of Vacation Marketing, 16*(2), 83–95. https://doi.org/10.1177/1356766709357486.

Tavasszy, L., & De Jong, G. (2014). *Modelling Freight Transport. Elsevier* (First). Elsevierhttps://doi.org/10.1016/B978-0-12-410400-6.00008-2.

Transport Corporation of India (2013). Indian Road Freight Index. http://tcil.com/tcil/indian-road-freight-index.html.

Vermunt, J. K., & Magidson, J. (2005). Technical guide for latent GOLD choice 5.1: Basic, *Advanced and Syntax* (Issue 617). http://www.statisticalinnovations.comhttp//www.statisticalinnovations.comorcontactusat.

Wilmsmeier, G., Hoffmann, J., & Sanchez, R. J. (2006). The impact of port characteristics on international maritime transport costs. *Research in Transportation Economics, 16*(6), 117–140. https://doi.org/10.1016/S0739-8859(06)16006-0.