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Temporal stability of shipment size decisions related to choice of truck type

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ABSTRACT

The choice of shipment size is a vital decision in logistics and has a strong indirect influence on freight transport demand, via the choice of mode and truck type choice. Through time, shipment sizes can change as a result of new decisions in the logistics process or due to conditions external to the supply chain. This study investigates the temporal stability of shipment size choices, relating these to the choice of truck types. It uses repeated cross-sectional data for the years 2015, 2017, and 2019 collected from cordon and business establishment surveys in Addis Ababa city, Ethiopia. The integrated choice and latent variables (ICLV) and latent growth (LG) models were used to assess the time-dependent patterns of choosing shipment sizes, both at the level of the entire freight system as well as the specific truck types. The model results reveal that shipment size decisions are temporally unstable where, in our case, shipment sizes exhibited a declining trend.

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Shipment size; freight mode choice; time dependent; temporal stability; discrete–continuous models

1. Introduction

Many factors drive demand for freight transport, but particularly the rise in consumer demand, increasing trade, advances in production and supply chain technologies, and changes in the logistics system. The logistics system is undergoing structural shifts with the concept of agile and lean logistics, omnichannel logistics, electronic platforms and the advent of physical internet (Tavasszy 2020). Similarly, freight transport demand involves many different decisions of firms and consumers, referred to as agents, in organising and executing the logistics processes (Tavasszy, Ruijgrok, and Davydenko 2012). With the overall objective of minimising the logistics costs, receivers or shippers make decisions on shipment size, frequency, and mode of transport (Holguín-Veras et al. 2021a). Choice of mode and shipment size are interrelated and are part of the same logistics decisions made by firms, with the literature strongly suggesting that the two choices should be modelled jointly (McFadden, Winston, and Boersch-Supan 1985; Abdelwahab 1998; Pourabdollahi,

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Karimi, and Mohammadian 2013; Cantillo, Visbal, and Arellana 2018). In econometric modelling, discrete-continuous model forms are often considered suitable for joint modelling of choice of mode and shipment size. Here, truck types or modes are the discrete variable and shipment size is the continuous variable. Previous studies on freight mode choices have considered different modes (truck, rail, waterways, air, intermodal, parcel), scopes (theoretical or empirical), and geographical ranges (national or regional) (Holguín-Veras et al. 2021a). Recently, the choice of truck type has become particularly relevant in the urban or metropolitan geographic context (De Jong 2014). Here, the choice between various truck types, ranging from pick-ups to semi-trailers, is essential due to significant differences in their loading capacities, operational characteristics, and negative externalities (Holguin-Veras 2002). Until now, researchers have only reported on cross-sectional models, not accounting for changes through time. The current paper addresses this gap.

The freight movement follows the logic of economic rationality and involves a range of complex decisions, including the choice of transport mode (Ortúzar and Willumsen 2011). Changes in economic conditions directly affect those decision layers and the demand for freight. In other words, the freight activity level constantly changes with the economic conditions or set-ups between different economic sectors (Holguín-Veras et al. 2011a). With the economic order quantity (EOQ) model, the optimal shipment size depends on (firm level) demand, transport costs, ordering and inventory costs. The shipment size is an inventory management decision regarding the size and frequency of the supplies at the company's level (Baumol and Vinod 1970). Demand at the company level depends on the economy, including domestic and international trade. Therefore, the question asked in this research is whether shipment size choices are stable over multiple time-periods.

The stability of freight demand over time is vital to accurately forecast the future conditions of freight transport, for planning or decision-making purposes. To the best of the authors' knowledge, studies on the temporal or geographic stability of transport demand have primarily focused on passenger trip generation and choice of travel mode. In spite of its importance, only a few studies have empirically investigated the stability of freight demand models in terms of FG (Freight generation) and FTG (Freight trip generation). FG is the amount of cargo in tonnage, and FTG is the number of truck trips required to transport FG, where FG directly reflects the establishment size, but FTG is related to the logistics decisions (shipment size) made by firms (Holguín-Veras et al. 2014). Holguín-Veras et al. (2011a) examined the temporal stability of freight generation (FG), trip distribution, and empty trips. Oliveira-Neto, Chin, and Hwang (2012) studied the geographic and temporal stability of FG at an aggregate level. The spatial (Holguín-Veras et al. 2013) and temporal (Holguín-Veras, Ramirez-Rios, and Pérez-Guzmán 2021b) stability of freight trip generation (FTG) were explored. Several studies have investigated the geographic and temporal stability of FG at aggregate level for cities in India (Pani et al. 2018; Pani et al. 2019; Sahu and Pani 2020; Pani, Sahu, and Bhat 2021). No research addressed the temporal stability of shipment size, despite being an essential decision in freight transportation demand and a key influencer of freight mode or vehicle type choice.

The main goal of this study was to examine the joint choice of truck type and shipment size, and its changes over time, with a connection to the changes in socio-political and economic phenomena. The authors use three repeated cross-sectional freight surveys collected from the same study area over five years period. The study evaluates the changes over time at an aggregate level, i.e. at the system level and at the level of each truck type. Moreover, the study provides discussions on the changes in relation to the dynamics of economic growth. The findings substantiate the need to consider trends in economic performance when forecasting freight demand, including their impact on the choice of shipment size and freight mode or vehicle type.

The rest of this paper is built up as follows. Section 2 summarises the relevant literature on shipment size and freight mode/vehicle type choice models, as well as time-dependent patterns of freight demand models. Section 3 describes the data used and discusses the methods used in the analysis. Section 4 presents the analysis results and discusses their implications. Finally, Section 5 concludes the paper with a summary of key findings and recommendations for research.

2. Background to the study

2.1. Shipment size and freight mode choice models

Freight transport demand is generally represented as a set of flows, and its modelling follows the approach used in traffic modelling. Often, these models represent firms' logistics behaviour only to a limited extent. The shipment size embodies an important decision in freight transport demand, and its characteristics can represent the logistics activity of a firm. However, it is difficult to integrate shipment size decisions into models, due to the absence of data with sufficient details on the underlying processes and limited information concerning the drivers of logistical decisions made by firms (Combes 2009). In addition, the interaction between the agents (shippers, carriers, receivers) determines the operational conditions of freight transportation, including the choice of mode or truck type. The behavioural aspect of those interactions is often regarded as complex, due to their unobservable and dynamic nature combined with the influences of fluctuations within the market economy (Holguín-Veras et al. 2021a).

The choice of mode is among the logistics decisions firms have to make and is closely linked to shipment size, so changes in shipment size may result in changes in the mode of transportation. Previous studies strongly indicate that the choice of mode and choice of shipment size form part of the same logistical decision made by firms and encourage the use of a joint framework to model those two decisions (Abdelwahab 1998; Holguin-Veras 2002; De Jong and Ben-Akiva 2007; Cavalcante and Roorda 2010; Windisch et al. 2010; Holguín-Veras et al. 2011b; Pourabdollahi, Karimi, and Mohammadian 2013; Irannezhad et al. 2017; Stinson et al. 2017; Keya, Anowar, and Eluru 2019; Sakai et al. 2020; Ahmed and Roorda 2022). However, the nature of the relationship within the joint modelling framework is not clearly defined, as the choices can be sequential or simultaneous (Ahmed and Roorda 2022). For instance, shippers select the shipment size for freight transport between the origin and destination (OD) locations, including the handling requirements. Freight operators (carriers) then assess the shipment size and select appropriate vehicle types among those available (Holguin-Veras 2002). On the other hand, if the receivers want to lower the inventory costs by receiving more frequent deliveries of smaller shipment sizes, this could induce the shift to smaller vehicle types to lower the transportation costs.

A joint model of discrete and continuous choice for mode-shipment size choice was first introduced by (McFadden, Winston, and Boersch-Supan 1985) for truck versus rail based on the logic of the inventory model. Abdelwahab and Sargious (1992) used the simultaneous switching equations model with a binary probit choice approach. The results confirmed that the two choices are highly linked, and modelling these two separately would result in biased outcomes. The correlation between discrete and continuous choices leads to an endogeneity problem, which results in estimation bias. Methods to correct the endogeneity problem differ based on the assumptions considered and usually take two forms: (i) indirect methods, such as control functions or instrumental variables, and (ii) direct methods, such as bias correction term, expected values, and full information (Mannering and Hensher 1987). The indirect method using instrumental variables was used (Holguin-Veras 2002; De Jong 2007; Abate and De Jong 2014). The direct methods consider explicit econometric interaction between the two choice models. The use of a latent variable construct for shipment size has the advantage of explicitly treating the interaction between the factors affecting the choice process. The method was first introduced by (Ben-Akiva and Boccara 1995) and was applied to freight vehicle choice (Cantillo, Visbal, and Arellana 2018) and in several other contexts (Walker et al. 2010; Márquez, Cantillo, and Arellana 2014; Cantillo, Arellana, and Rolong 2015). This paper uses a discrete-continuous model formulation that treats the shipment size as a latent variable integrated into the vehicle type choice model, also referred to as the integrated choice and latent variable model (ICLV).

The ICLV method models the specific econometric interactions between the two choices simultaneously and uses the full information maximisation likelihood approach in the latent variable models to address endogeneity. This method has been successfully applied earlier to the simultaneous choice of freight trucks and shipment size (Cantillo, Visbal, and Arellana 2018). Several other econometric model structures have been used to estimate the choice models simultaneously. The copula function was used to jointly estimate both the mode choice and shipment size as a discrete choice through the use of multinomial logit (MNL) formulation (Bhat and Eluru 2009; Irannezhad et al. 2017). Other studies categorised shipment sizes into discrete groups and modelled joint mode-shipment size choice as a discrete-discrete model (Chiang, Roberts, and Ben-Akiva 1981; De Jong 2007; Pourabdollahi, Karimi, and Mohammadian 2013; Ahmed and Roorda 2022).

The freight mode choice literature examined different modes, including truck, rail, waterway, air, intermodal, and parcel. Road transport dominates when the geographical range becomes urban/metropolitan/regional, and vehicle type choice then becomes more relevant (De Jong 2014). Modelling intra-modal competition between commercial vehicle types is essential due to differences in their impacts on infrastructure, congestion, and the environment (Holguin-Veras 2002). Thus a vital research endeavour in freight transportation is to determine how freight operators choose commercial vehicle types for a haul (Abate and De Jong 2014). Among previous freight mode choice studies, only a few have focused on the choice of truck type. The choice of commercial vehicle type involves a range of alternatives with different carrying capacities, such as passenger cars, pick-up/vans, single-unit or rigid trucks, and truck trailers. Holguin-Veras (2002) investigated the choice of commercial vehicle type jointly with shipment size, using pick-up trucks, two and three-axle trucks, and semi-trailers in Guatemala City. Studies since then have modelled the choice between passenger cars, pick-up/cube vans, single-unit trucks, and truck trailers in the Toronto area (Cavalcante and Roorda 2010; Ahmed and Roorda 2021; Ahmed and Roorda 2022) and between classes of trucks, including rigid and articulated trucks (Abate and De Jong 2014). Others have tested MNL and nested logit (NL) models for modelling the choice between automobile, pick-up/van/minivan, sport utility vehicle, single-unit truck, and combination truck (Wang and Hu 2012), and have used an MNL model for choosing between a small car, light goods vehicle, and medium goods vehicle (Nuzzolo and Comi 2014). Irannezhad et al. (2017) used a coupla function in MNL formulation to model the choice between van, truck, heavy truck and trailer by shippers and carriers.

2.2. Time-dependent patterns of freight demand and shipment size

Economic growth is the main driver of freight demand. The change in the economic condition directly affects the demand for freight which can be explained with freight models in two ways. First, the trade-off between transport and large inventories where larger shipment size and more flows between firms are only due to the economic order quantity (EOQ) at work (De Jong and Ben-Akiva 2007; Abate and De Jong 2014). Second, the changes in the supply chains and technology which is also the focus of our study to investigate how the dynamics within the economy affect the freight demand. The link between economic sectors that determines the level of freight activity is constantly changing with shifts in economic conditions or inter-sector set-ups (Holguín-Veras et al. 2011a). Thus changes in economic conditions over time can result in changes in the freight demand models, so knowledge of temporal stability is vital for accurately forecasting the demand level.

The stability of models also referred to as transferability, assesses the ability of the models developed in one context to explain the behaviour in another context. The capability of the models to produce an accurate estimate at different points in time indicates temporal stability, whereas geographic stability refers to their transferability to another spatial area from initially estimated. The temporal stability of shipment size choices related to freight vehicle choice models is the main focus of this study.

Stability over time of a mode choice has been extensively tested in the literature related to passenger transport (Watson and Westin 1975; Ben-Akiva and Atherton 1977; McCarthy 1982; Karasmaa and Pursula 1997; Sanko and Morikawa 2010). The findings from those studies suggest the stability of models over short periods, even with changes in transportation infrastructure, but not necessarily over longer periods. In contrast, the temporal stability of freight demand models is understudied in the freight literature. To give an overview, Holguín-Veras et al. (2011a) examined the temporal stability of FG for freight origin-destination samples collected in Colombia from 1999- 2005 and found statistically significant time-dependent effects. Oliveira-Neto, Chin, and Hwang (2012) analysed the temporal stability and predictive accuracy of aggregated FG models for two-time points (2002, 2007), using the USA census data. The FG models did not result in sufficient predictive power and suggested the inclusion of other factors, such as changes in productivity or economic growth. Holguín-Veras, Ramirez-Rios, and Pérez-Guzmán (2021b) investigated the time-dependent patterns in Freight Trip Generation (FTG) models using multi-year establishment data collected between 2005 and 2014, and the analysis result indicates most FTG models exhibited time-dependent effects. In addition, considering time-dependent effects in the FTG models improved the model accuracy when compared to the static models. On the other hand, an assessment of the geographical stability of FTG models found that the models were spatially stable or were not significantly affected by locational effects (Holguín-Veras et al. 2013), while an assessment of the geographical transferability of establishment-level FG models found that models for several industry sectors were transferable across the sampled cities (Sahu and Pani 2020). However, a study testing FG models for seven cities in India found that the locational variable in the models and its interaction with establishment characteristics significantly affected model patterns. A study examining the spatial transferability of FG and FTG models within and between two states of India found that FG models were more transferable than FTG models and had higher transferability between cities within the same state than across states (Pani, Sahu, and Bhat 2021). Sahu et al. (2019) found space-time dependence in freight flows through India's major seaports. All these studies only assessed the stability of freight demand using FG and FTG models and did not study the temporal stability of shipment size choice which affects freight transport patterns.

The quality of the transportation system and economic growth have a strong mutual relationship. The link between the increase in freight transport intensity and economic growth has been receiving much interest from many scholars over recent decades. The EU White Paper on Transport Policy 2001 suggested the possibility of decoupling economic and freight transport growth and proposed a reduction in freight transport without affecting economic progress (Stead 2006). After decoupling became a vital issue, several studies analysed the structural relationship between freight transport and economic development using different metrics, such as industrial sector production rather than GDP (McKinnon 2007), GDP along with logistics industry added value, total employment, freight volume, and traffic turnover volume (Reza 2013), and industrial structure, transport intensity, and haulage distance (Zhu, Wu, and Gao 2020). The studies on the internal relationship between freight transport and economic growth have also encompassed different economic decisions and/or major events. They have shown, e.g. that the 2009 economic crisis in Greece had a considerable impact on the country's transport sector (Moschovou 2017) and that a decline in freight transport services in the USA due to the great recession between 2007 and 2009, and its recovery afterwards, showed a similar pattern to the GDP rate (US-DoT 2017). Thus, all the decomposition efforts of freight demand into its drivers should consider the changes in these metrics over time.

3. Methodology

3.1. Data description

The data used in this research originate from cross-sectional revealed preference surveys conducted in Addis Ababa city, the capital of Ethiopia, during 2015, 2017, and 2019. The 2015 data were collected with interviews of truck drivers at cordon points, particularly at the city entrance/exit points and major market locations inside the city. The 2015 sample size has 601 observations. The 2017 data were similarly collected through direct interviews with truck drivers at 27 internal and seven external cordon points of the city and has a sample size of 2349 observations. The 2019 data comprised a survey of 446 business establishments in freight-intensive sectors and considered the characteristics of loaded freight trips attracted to the establishments. The locations of all three revealed preference surveys are shown in Figure A1 (in the Appendix).

The resulting combined dataset captures attributes that account for the characteristics of the trip, the truck type, and the characteristics of the freighted commodity, including shipment size. It encompasses 3396 commercial vehicle hauls over a five-year period (2015–2019), with two-year intervals between surveys. The unit of observation for all the

Table 1. Summary statistics on the combined dataset from the three surveys.

		Combined dataset	
Definition	Variable	Mean	Std. dev.
Payload or shipment weight (metric tons)	PL	13.84	13.2
Maximum legal carrying capacity (metric tons), weighted average	M	22.45	15.46
Distance/trip length (km)	L	195.2	280.62
Total operating cost per ton (US dollars), weighted average	CW	24.25	68.13
Dummy variables			
Port dummy variable, 1 if origin & destination (either of the OD ends at a seaport or inland dry port)	*P_D*	569	
Special body type, 1 if specialist body truck (dump truck, cement mixer, garbage truck, log carrier truck, refrigerated truck)	BT_D	1037	

Table 2. Truck types and number of trips based on origin and destination (OD) location (inter-city trips).

	Inter-city			
Vehicle type	Trip number	Mean payload	Std. dev.	**Gross weight Limits (metric tons)[a]**
LT-1	77	1.37	0.81	na
LT-2	258	3.50	1.55	na
T-2	238	5.63	2.19	16
T-3	243	12.80	4.58	24
T-4	443	20.18	5.46	32
ST – 23	308	29.98	7.10	44
ST – 33	395	37.42	6.33	52
Total	1962			

[a]Based on legal limits for axle loads in Ethiopia (NEGARIT-GAZETA 1990). na = not applicable.

datasets is the truck, grouped into different types. The variables of interest included vehicle attributes (vehicle type, truck body type, operating cost per metric ton), shipment characteristics (commodity class, shipment weight/payload), and haulage characteristics (trip distance, origin-destination locations with their industrial sector category and special consideration of trips either starting or ending at sea/hinterland ports) (Table 1).

The combined dataset comprising seven different truck types, ranging from light trucks to semi-trailers, is presented in Table 2. These truck types are identified by their loading capacity, explained by the number and configuration of the axles. The type of truck follows the Ethiopian vehicle classification standards and legal axle load limits (NEGARIT-GAZETA 1990). The categories LT-1 and LT-2 indicate 2-axle light-duty vehicles with loads below 12 metric tons, while T-2 to T-4 are rigid trucks of up to 32 metric tons capacity, and ST-23 and ST-33 concern multi-axle tractor-trailer combinations of up to 52 metric tons. The combined dataset was split based on trip OD into trips with both ends within the city (intra-city trips) and trips connecting the city with other cities or regions (inter-city trips). Intra-city trips have been dominated by haulage using light truck types LT-1 and LT-2 over shorter distances. In contrast, inter-city trips have a balanced utilisation of all truck types. Mixing the inter-and intra-city trips could bias the freight analysis and undermine model estimates. Therefore, the authors focused on the intercity trip part of the combined dataset.

The three datasets can be combined as repeated cross-sectional datasets that enable reliable comparisons over time. These surveys captured the freight flows between relatively

Table 3. Inter-sector (IS) flows of inter-city trips in the combined datasets.

Sector	Retail	Wholesale	Manufacturing	Other
Retail	89	40	45	1
Wholesale	164	82	84	12
Manufacturing	254	243	202	164
Other	143	178	220	41

similar establishments. These can be emphasised with two-level assessments. First, using the checklist in Rafferty, Walthery, and King-Hele (2015) to determine whether there are changes between datasets (before intra/inter-city trips split) with their variable names and definitions, wording and application of questions, and sampling strategy. The observation unit in all the datasets is truck trips, confirming the uniformity of attributes across the three surveys. The variables are similarly defined and categorised across these surveys to capture three main attribute groups: vehicle characteristics, shipment characteristics and haul characteristics. The survey questions were constructed to correspond to the observable variables and applied the same way with the face-to-face interview of the respondents.

In addition, the sampling strategy for the 2019 survey stratified business establishments based on their industry sectors using Standard Industrial Classification (SIC) and business size (with the number of employees and gross floor area). These two-step stratifications enabled more diverse sampling and captured a range of freight flows. Similarly, the cordon surveys captured freight flows between various business firms using different truck types. The other important aspect is the survey locations. As explained above, the surveys were located mainly at the city entrance/exit points, market and other prime business locations distributed within the city. From the intercity freight trip standpoint, all the surveys captured flows of various freight activities linking the city with other cities or regions.

The second level focuses on the part of the data used for the subsequent analysis (the inter-city trips). The cumulative density graph in Figure A2 shows the distributions of trip distances of the three datasets. The freight flows in these surveys exhibited relatively similar distance distributions. Moreover, the inter-sector flows across the three datasets had a closely similar distribution of establishment categories, as depicted in Table A1. The maximum difference is only around 3% for flow between the three main sectors and 5% for the category others. Therefore, the three cross-sectional surveys were consistent with each other and can be combined to create repeated cross-sectional datasets that allow the analysis of patterns over the years.

Commodity characteristics influence the choice of truck types. Figure 1 depicts the share of trips by commodity and truck types. Light trucks (LT-1 and LT-2) are used mostly for manufacturing industry outputs with less voluminous cargo, including textile, wood, pulp, and chemical and plastic products. The largest truck type, ST-33, is used for bulk cargo, such as metallic products, non-metallic mineral products, and coal, and has a lower cost per freight unit. The rigid truck types (T-2 to T-4) show higher versatility in carrying different commodity types.

The freight flows link different industry sectors. The different types of industrial sectors in the data were consolidated into four sectors: manufacturing and primary production, wholesale, retail, and other. Table 3 shows the distribution of flows between these sectors (inter-sector flows) by the inter-city trips.

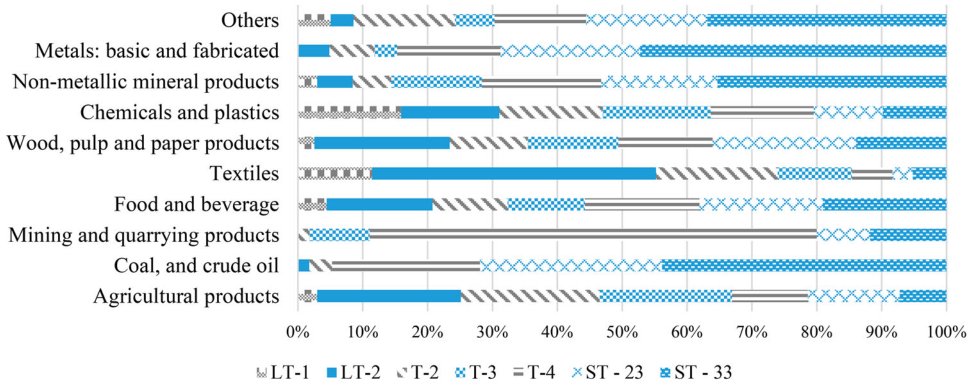

Figure 1. Distribution of commodity groups with truck type for inter-city trips from Addis Ababa.

3.2. Econometric models

The choice of freight vehicle is part of a joint decision with the choice of shipment size. A critical aspect of the choice of freight vehicle type and shipment size is the interaction between the agents (shippers, carriers, and receivers) in making decisions and the nature of the choice process (sequential or simultaneous). The sequential approach assumes independence between the two choice decisions, whereas the simultaneous approach makes specific assumptions about the nature of the dependence. This study used a two-step approach to analyse the temporal stability in freight mode choice models, focusing on the time-dependent pattern of shipment size decisions using the repeated cross-sectional dataset. The first step was to model the simultaneous choice of truck type and shipment size at the overall system level using the ICLV model framework. The second step was to analyse shipment size decisions for each truck type over the study period using the latent growth (LG) model.

3.2.1. Integrated choice and latent variable (ICLV) model

The ICLV model treats shipment size as a latent variable that becomes an explanatory variable in choice models. These formulations integrate the latent variable models into the choice settings with structural and measurement equations and estimate these parameters simultaneously. The ICLV approach developed in this study (Figure 2) can solve the joint choice model of truck type and shipment size.

In the ICLV model, the utility of each truck type is assumed to be a latent variable, and observable truck choices are manifestations of the underlying utility, also constructed as a latent variable. The observable variables that are manifestations of the latent constructs are called *indicators*. In Figure 2, a dashed arrow, representing a *measurement equation*, links the unobservable utility of the trucks to the observable indicator of truck choice. The solid arrows represent the *structural equations* (i.e. cause-and-effect relationships governing the decision-making process) that link the observable payload and the latent shipment size variable to truck utility.

The latent variable in the choice model corrects the endogeneity problem with the full information maximum likelihood (ML) approach whereby the latent variable integrates out to calculate the likelihood function. The conditional distribution of the latent variable can

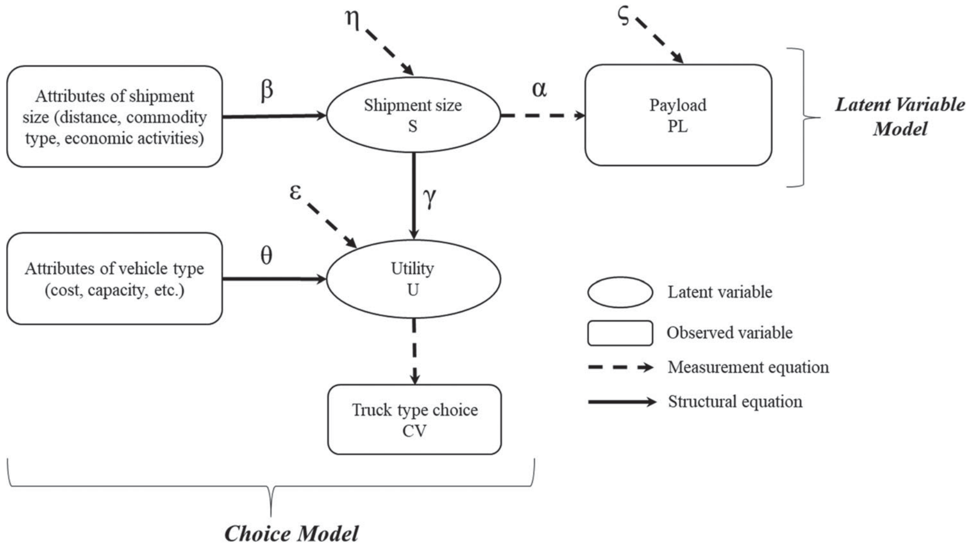

Figure 2. Discrete-continuous model framework with integrated choice and latent variable model (adapted from Ben-Akiva and Boccara (1995)).

be written using structural and measurement equations (Walker and Ben-Akiva 2002). The ICLV model results reveal the latent variable that best fits both the choice model and the indicator variables.

The payload and shipment size represent the amount of freight to be transported in tonnage but have slightly different meanings in our vehicle choice modelling. The interaction between choice of truck type and shipment size are modelled with a discrete (vehicle type)-continuous (shipment size) choice model structure in the ICLV model approach. The payload is the observed indicator of the shipment size in the latent choice model (Figure 2). The shipment size is an estimator that breaks the correlation (endogeneity) between the payload and vehicle type choice. The shipment size is used as a latent variable and estimator of payload in the vehicle type model. These enable the specific econometric interaction between the discrete and continuous choice models.

The specification of the shipment size *S* model (Holguin-Veras 2002):

$$S = \ln(d)\left\{\beta_0 + \sum_{i=1}^{n} \beta_i \delta_i\right\} + \eta \tag{1}$$

where d is the trip distance (km); $\delta = (\delta_1, \delta_2, \ldots \delta_n)$ is a vector of binary variables representing commodity classes, type of activities at the trip ends, trip characteristics (whether it starts/ends at a port location), the specialist body trucks required to transport the shipments and data collection year. The binary variable representing the data collection year has an essential implication of whether time-dependent patterns in shipment size decisions will be detected. The η is an error term, assumed to be normally distributed with $\eta \sim N(0, \sigma_\eta)$. The functional specification provides consistent representation of the problem. The marginal contribution of the binary variables to the shipment size is represented with the interaction terms (i.e. between the trip distance and the binary variables).

The observed payload of trucks is considered the indicator variable of actual shipment size in the measurement equation:

$$\mathrm{PL_n} = \alpha \mathrm{S_n} + \varsigma \tag{2}$$

Where PL is the observed payload for vehicle class n, and α is the parameter of the latent variable to be estimated with the measurement model (expected to be close to 1). The error term ς is assumed to be normally distributed, with $\varsigma \sim N(0, \sigma_\varsigma)$.

The choice of truck type considers random utility maximisation theory and the corresponding utility of the truck type U_n, given as:

$$\mathrm{U}_n = \theta_n \mathrm{Cw}_n + \gamma \mathrm{V}_n + \varepsilon_n \tag{3}$$

where Cw_n is the average operating cost per ton, representing the vector of attributes of the trucking company and the vehicle. V_n is a function of shipment size, specified as an index for the unused loading capacity of trucks given as $\mathrm{V}_n = |\mathrm{M}_n - \mathrm{S}_n|$, where M_n is the maximum capacity of truck class n. ε_n is a vector of independent and identically distributed (i.i.d) Type 1 extreme value error terms. The index V_n, provides an indication of how appropriate a particular truck type n is for handling a given shipment. In essence, the larger the value of V_n for truck class n, the lower its chance of being selected.

The choice probability in the case where the latent variable is not present would correspond exactly to the standard choice probability of choosing truck type *CV* given a set of estimated parameters θ and γ along with the explanatory variable $\mathrm{Cw_n}$ that can be denoted as $P(CV_n|\theta, \gamma, Cw_n)$. In the setting with observed latent variable S, the choice probability would be represented by $P(CV_n|\theta, \gamma, S, Cw_n)$, where θ and γ are unknown parameters in the choice model. The latent variable is not actually observed, and the choice probability is obtained by integrating the conditional probability over the whole space of *S* (Train 2009):

$$P(CV_n|\theta, \gamma, \beta, \delta, Cw_n) = \int_S P(CV_n|S, \theta, \gamma, Cw_n).g(S|\beta, \delta)dS \tag{4}$$

which is an integral of dimension equal to the latent variable *S* and g(.) is the density function of the latent variable.

The measured payload PL_n is introduced as an indicator variable to characterise the unobserved latent variable S_n and permit the identification of the choice model with the latent variables. The joint probability of observing CV_n and PL_n is given as:

$$\mathrm{P}(CV_n, PL_n|\theta, \gamma, \beta, \delta, \mathrm{d}, \alpha, \sigma\eta, \sigma\varsigma, Cw_n) = \int_S P(CV_n|S, \theta, \gamma, Cw_n)\, h(PL_n)\, g(S|\beta, \delta)dS \tag{5}$$

where CV_n and PL_n are assumed to be correlated only due to the presence of the latent variable S_n. The unknown parameters (θ, β, γ, α) can be estimated using simulated maximum likelihood from the observed type of truck choices. For identification of the model, the variance of the structural model is fixed at 1.

The next step is the validation of the ICLV model estimates. Here, the reproducibility of the probability results of the model is evaluated against the real choice in the data using cross-validation. The cross-validation procedure repeats the holdout sampling process multiple times to produce a set of randomly split estimation-validation data pairs. The notation of the cross-validation estimator (CV) is given as (Parady, Ory, and Walker 2021):

$$CV = \frac{1}{B}\sum_{b=1}^{B} H_b \tag{6}$$

where B is the number of data pairs generated (estimation-validation), and H_b is the holdout estimator for set b. The type of cross-validation used here was repeated k-fold cross-validation, where the data are partitioned into K subsets that are mutually exclusive, $B = K$, and the process is repeated R times.

3.2.2. Latent growth model

The ICLV method was used in the structural equation modelling (SEM) framework with both the observed variables (payloads and vehicle choice) and the latent variables (shipment size and utility of trucks), along with several exogenous predictors. The ICLV model results was used as an input to the latent growth (LG) model which means the LG model was integrated into the ICLV to analyse shipment size trajectories over time at the level of each truck type. The complete path diagram for the shipment size growth curve model for individual truck types is shown in Figure A3 (in Appendix).

The matrix notation of the LG model has a data model, a covariance structure, and a mean structure. The LG model with shipment size observations at three-time points is given below using the matrix notations (Preacher et al. 2008). The data model represents the relationship between the factors and the repeated measures of shipment size (SS) as:

$$\mathrm{SS} = \tau + \Lambda\varphi + \mu \tag{7}$$

where τ is the intercept (3×1) (typically fixed to zero for identification reasons), Λ is the factor loadings of the intercept and slope (3×2), μ is the residual term (3×1), and φ is the latent intercept and slope, with latent means λ_1 and λ_2 (2×1). The latent intercept and slope φ can be expressed as:

$$\varphi = \lambda + \rho \tag{8}$$

where the residual ρ is the individual deviation from the mean (also referred to as random effects).

The covariance structure comprises the variances and covariances of the repeated measures of shipment size as functions of the model parameters:

$$\Sigma = \Lambda\psi\Lambda' + \omega_\mu \tag{9}$$

where Σ is the variance and covariance of the shipment size variables (3×3), ψ is factor variance and covariance (2×2), Λ is the fixed loadings of the intercept and slope (3×2), and ω_μ is the matrix of disturbance variances and covariances (3×3).

The mean structure is obtained by taking the expectations of the data model represents the population mean of those repeated shipment size measures as another function of the model parameters, given as:

$$\overline{\mathrm{ss}} = \tau + \Lambda\lambda \tag{10}$$

where $\overline{\mathrm{ss}}$ is the mean of the shipment size variable (3×1) with intercept τ (3×1), factor loadings Λ (3×2), and latent variable mean λ (2×1).

The necessary constraints in our shipment size linear growth analysis model with homoscedastic and uncorrelated residual variance are:

$$\Lambda = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{bmatrix} \psi = \begin{bmatrix} \psi_{11} & \\ \psi_{21} & \psi_{22} \end{bmatrix} \lambda = \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} \omega\mu = \begin{bmatrix} \omega_\mu & & \\ 0 & \omega_\mu & \\ 0 & 0 & \omega_\mu \end{bmatrix} \tag{12}$$

The values of the fixed loading intercepts (first column of Λ) are constrained to 1 to reflect that each intercept remains constant over repeated time measures, and the second column of Λ postulates the growth trajectories over equal time intervals. The variance and covariance of these change aspects are represented by the elements of ψ. The regression coefficient λ is given by intercept ($\lambda 1$) and slope ($\lambda 2$) elements. The slope (λ_2) is the expected change in the shipment size variable associated with a change from one-time point to the next. The ω_μ represents the disturbance variance or the portion of the variance in the data not explained by the LG model of shipment size. This study assumes homoscedastic disturbance variance, which is given as an equal value across the diagonal elements and fixing the off-diagonal values to zero. Therefore, LG model estimation involved a total of six parameters, comprising three parameters of intercept and slope variance and covariance (ψ_{11}, ψ_{21}, ψ_{22}), two mean intercepts and slope (λ_1, λ_2), and a disturbance variance (ω_μ).

4. Results and discussion

The time-dependent patterns of shipment size decisions revealed by the ICLV and LG models with the key implications of these results are presented next.

4.1. Integrated choice and shipment size (ICLV) model

The estimates produced by the joint choice model of truck type-shipment size using the ICLV model framework are given in Table 4. The ICLV model was coded and executed using the *lavaan* package in R software (Rosseel 2012). The explanatory variables of shipment size were: (1) trip distance (km) as an intercept and the other binary variables as an interaction (2) binary variables representing commodity classes; (3) type of economic sector at both ends of the trip or inter-sector flow; (4) binary variable denoting whether or not origin/destination of the trip is a port location and the use of trucks with specialist body types; (5) binary variable indicating the data collection year of the three cross-sectional surveys. These time-specific variables characterised the temporal stability of the overall shipment size construct. The utility of each truck type captured the essence of the truck type selection process with two variables, the index for unused loading capacity of trucks V_n and the average unit operating cost per ton Cw_n. The index V_n is crucial in the vehicle type choice, as it indicates the appropriateness of a particular truck type to handle a given shipment.

The discrete (vehicle type) or continuous (shipment size) forms of the variables and assumptions of the error terms in the measurement and structural equations determine the functional forms in the maximum likelihood (ML) estimation. The functional forms of the parameter are assumed linear, and the error terms have a normal distribution (or extreme value for the choice model). These parameters (including the shipment size) are estimated

Table 4. Integrated choice and latent variable (ICLV) model estimates for truck type-shipment size choices.

Shipment size choice model	Estimate	z-stat
Intercept (β_0)	2.72	5.89
Agriculture products	0.45	2.69
Coal, crude oil and natural gas	1.22	4.41
Quarrying products: sand and stone	0.47	2.78
Food and beverage products	0.65	3.94
Textile and leather products	−0.16	−0.67
Wood, pulp and paper products	−0.04	−0.22
Chemicals and chemical products	0.27	1.89
Non-metallic mineral products	1.70	6.97
Metals: basic and fabricated	0.84	4.90
Retailer – Retailer	−0.38	−1.06
Retailer – Manufacturer	0.17	0.58
Wholesale – Retail	−0.21	−1.07
Wholesaler – Wholesaler	−0.15	−0.65
Wholesaler – Manufacturer	0.23	1.01
Manufacturer – Retailer	−0.32	−1.53
Manufacturer – Wholesaler	0.63	3.41
Manufacturer – Manufacturer	0.23	1.43
Port dummy (trip start/end at port location)	0.82	4.92
Specialist body type truck dummy	−0.27	−2.47
YD_2: year 2017 (compared with 2015)	−0.76	−5.75
YD_3: year 2019 (compared with 2015)	−1.88	−6.30
Vehicle type choice model (reference group ST-33)	**Coefficient**	**z-stat**
ASC for LT-1	−3.05	−6.69
ASC for LT-2	−2.14	−6.19
ASC for T-2	−1.28	−4.02
ASC for T-3	−0.84	−3.69
ASC for T-4	0.49	3.02
ASC for ST-23	0.26	2.33
Average cost per ton, Cw_n	−0.023	−4.10
Unused capacity index, V_n	−0.34	−32.17
Parameter α in the measurement equation	0.97	9.31
Rho-square (adj.)	0.52	
Log-likelihood choice model	−1727.6	
Log-likelihood integrated model	−8409.82	
Chi-square test stat. $\chi 2$ (df = 24) – Robust (p-val $<$ 0.00)	1696.12	
Stand. Root Mean Square Residual (RMSR) – Robust	0.015	
Tucker-Lewis Index (TLI) – Robust	0.89	

with the ML technique (Ben-Akiva et al. 1997). The ML technique yields consistent and normal parameter estimates. The only applicable assumption is the normality of the observed endogenous variables (payload for our case), and no distribution is assumed for the exogenous variables. Our data had non-normal distribution, and the ML estimation was corrected to deal with the non-normal data. As recommended by Rosseel (2012), we used the most popular strategy known as Satorra-Bentler scaled test statistic and robust standard errors in ML estimation. Therefore, the results reported with our study were scaled test statistics (and corresponding model fit indices) and z-values based on robust standard errors.

In the shipment size sub-models (Table 4), the coefficient of trip distance, ln(d), had a positive sign, indicating that larger shipment sizes were transported over longer distances. Except for textile and wood products, all commodity types have a positive effect of distance on shipment size but with varying magnitude. Coal, metals and non-metallic mineral products have a larger positive coefficient; these items have a relatively higher unit weight and are usually transported in bulk. Commodity groups such as agriculture and chemical products had lower coefficient values. In developing countries, these are mostly transported in small units, especially agricultural products.

The inter-sector flows represented by binary variables significantly affected shipment size. The slope of the shipment size function was low when retailers were involved, except for freight flow from retailers to manufacturers. In this case, the retailers might have specialised in providing supplies to the manufacturing process. Trips from manufacturer to wholesaler (and vice versa), usually involving heavier shipments of processed products or inputs for processing (the other direction), had a large coefficient value. The shipment flow between wholesalers was insignificant, indicating competition within the sector.

The characteristics of the haul also have an impact on the selection of shipment size. The hauls involving port locations have a positive coefficient value where ports usually are the import/export hubs and attract heavier consignments. The trucks with special body configurations have a negative slope in the shipment size function where those trucks transport relatively smaller shipments.

The analysis used different cross-sectional surveys conducted in three different years, and thus the binary variable captures the time-dependent nature of shipment size. The observations in the first survey (2015) were used as a reference, and the slope reflected the shipment size function for the other two survey years (2017 and 2019). The results showed a negative slope over both time points, indicating a decreasing trend in shipment size over time.

The overall shipment size and commodity-based trends with travel distance for the three data collection years are shown in Figure 3 and Figure A4, respectively. The shipment size increases with the travel distance, which indicates larger shipments are transported over longer distances. The trend line with the average values exhibits the trajectory of shipment size trend over the travel distance. The trajectories for the three data collection years differ, and the shipment size generally declined from 2015 to 2019. These declines marginally increase with the increase in travel distance. In addition, the shipment size trajectories vary over the commodity types and consistently show a decline over the years. For instance, if we take the mid-distance (500-600 kilometres), closer differences between the shipment size trajectories were found for metallic and non-metallic products. Moreover, agricultural products had relatively transported in smaller shipments for all cases.

The truck type choice submodel in Table 4, is conceptually valid, and the explanatory variables were significant. With the largest truck type (ST-33) used as a reference, the specific coefficient of the next largest truck types, ST-23 and T-4, had a positive sign, indicating that ST-23 and T-4 trucks are natural competitors of ST-33 trucks. Moreover, the choice model implied that these three truck types are preferable over the rest while holding other factors constant. From the standpoint of considering inter-city freight trips for the analysis, the result explained the reality well because these trucks carry – a relatively larger load over longer distances. As expected, the operating cost per ton and unused loading capacity variables have negative signs. The negative sign of unused loading capacity indicates that trucks not fit to carry the payload are less attractive. The coefficient α links shipment size with the observed payload in the measurement model. The value of α is just below one, indicating that the shipment size constructs are slightly larger than the observed payloads.

The ICLV model results were validated using repeated K-fold cross-validation. The dataset was split into 70/30 training/testing data pairs to perform the cross-validation

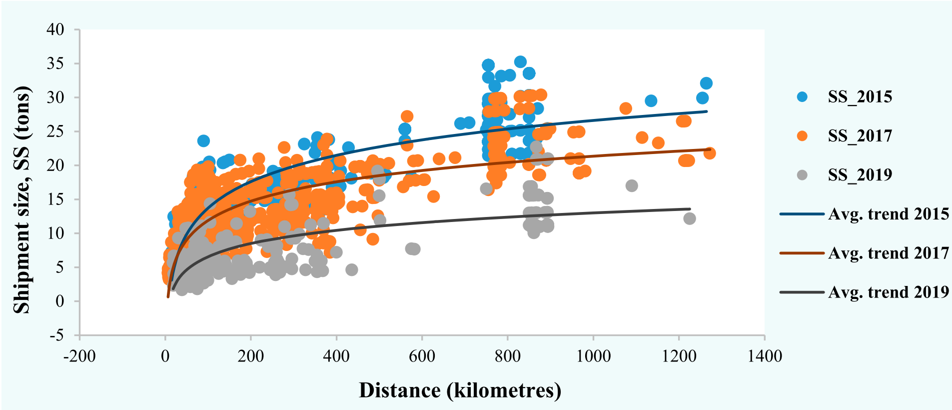

Figure 3. Overall shipment size-trends.

Table 5. Cross-tabulation of the repeated K-fold cross-validation (5-fold, repeated 10×) results.

Cross-validation (training/test sample split 70/30), test sample = 586								
	Modelled choice							
Actual Choice	LT-1	LT-2	T-2	T-3	T-4	ST-23	ST-33	**Total**
LT-1	24	0	0	0	0	0	0	24
LT-2	2	59	22	3	0	0	0	86
T-2	0	18	38	3	0	0	0	59
T-3	0	0	8	71	0	0	0	79
T-4	0	0	0	0	128	0	0	128
ST-23	0	0	0	0	0	43	17	60
ST-33	0	0	0	0	0	26	124	150
Total	26	77	68	77	128	69	141	586
Training accuracy = 0.79 **Kappa = 0.75**					Testing accuracy = 0.79 Kappa = 0.75			

analysis, with K = 5 and R = 10, using the *caret* package in R (Kuhn 2008). The accuracy and kappa are the metrics to measure the precision of the random splitting of the data into training-testing datasets with the given instances or repetitions. The accuracy value indicates the percentage of total repetitions in which the data is correctly classified. The kappa value measures how closely the instances or repetitions classified by the classifier (machine learning) match the observed data labels relative to the expected value by chance. Both metrics showed relatively good precision (around 80%) when randomly splitting the datasets (Table 5). The analysis yielded a more or less similar (only 1% error) change in the choice probability between the training and testing data pairs for all truck types. The model produces a good estimate of the actual choices, with the largest difference of 115% for LT-2 and ST-23. The model overpredicted the shares of truck types LT-1, T-22 and ST-23, whereas LT-2, T-3 and ST-33 were underpredicted. The share of T-4 was correctly predicted. The cross-validation produced good results.

Another essential finding was the insights from choice elasticities, where elasticity reflected the change in the probability of a truck type choice with changes in the value of Cw_n and V_n. The simple average elasticities values, normalised using the initial choice

Table 6. The elasticity of the truck choice model with changes in operating cost (Cw_n) and unused capacity (V_n).

	Truck type						
Variable in the utility function	LT-1	LT-2	T-2	T-3	T-4	ST-23	ST-33
Elasticity of Cw_n in the choice							
LT-1	**−2.21**	0.33	0.21	0.075	0.027	0.003	0.23×10^{-3}
LT-2	0.93	**−1.30**	0.68	0.253	0.088	0.010	0.79×10^{-3}
T-2	0.51	0.59	**−1.45**	0.36	0.13	0.016	0.001
T-3	0.14	0.17	0.28	**−1.10**	0.29	0.042	0.004
T-4	0.075	0.090	0.15	0.44	−0.62	0.29	0.039
ST-23	0.004	0.005	0.009	0.030	0.15	−0.50	0.20
ST-33	0.45×10^{-3}	0.55×10^{-3}	0.97×10^{-3}	0.004	0.026	0.26	−0.24
Elasticity of V_n in the choice							
LT-1	−0.38	0.051	0.040	0.015	0.006	0.001	0.53×10^{-4}
LT-2	0.34	−0.37	0.17	0.072	0.025	0.003	0.25×10^{-3}
T-2	0.57	0.51	**−1.09**	0.20	0.076	0.010	0.92×10^{-3}
T-3	0.37	0.38	0.41	**−1.26**	0.15	0.033	0.48×10^{-2}
T-4	0.35	0.37	0.47	0.67	**−1.18**	0.30	0.084
ST-23	0.035	0.042	0.059	0.13	0.26	**−1.12**	0.44
ST-33	0.47×10^{-2}	0.52×10^{-2}	0.008	0.019	0.068	0.34	−0.36

[a]Values in bold indicate truck-type choices that are elastic.

probabilities of the truck types, are shown in Table 6. Similar results were obtained when normalised with the weighted average value (not shown here).

The direct elasticities (main diagonal values) of choice showed a decrease in the number of truck trips due to a unit increase in both Cw_n and V_n, with values up to – 2.21, indicating strong elasticity. An important finding was that a unit increment in Cw_n caused a change in the choice of truck type with a smaller capacity, i.e. LT-1 to T-3. However, the choice of trucks with higher loading capacity (T-2 up to ST-23) was elastic to the change in V_n. These results imply that small trucks are sensitive to increments in cost, whereas larger trucks are more sensitive to the utilisation of trucks' loading capacity. In essence, any regulation altering weight or axle load limitations will thus influence the choice of truck types with medium to larger loading capacities, while any policy or regulation affecting the operating costs will impact the choice of trucks with lower loading capacities.

In general, cross-elasticities will have higher values for vehicles considered to be competitive. Here, cross-elasticities are low with respect to the changes in both Cw_n and V_n. The only exception is the unit increase in the operating cost of the truck type LT-2, which increased the choice probability of truck type LT-1. This is a logical finding since these two truck types are competitors, where the cost increase for LT-2 induces a shift towards the use of LT-1 for smaller shipment sizes.

The ICLV model results reveal the dynamic nature of the shipment size in the truck type choice model. In the model, shipment size is a latent construct made from the observed payloads, and consideration of these can relate directly to the freight demand derived from the economic outputs. As explained by EOQ model (Baumol and Vinod 1970), the optimum shipment size is the variant of the economic order quantity and grows with the square root of the total freight demand. Consequently, economic growth potentially induces more freight demand, increasing business establishments' desire to receive larger shipments. In our case, the shipment size exhibits a decreasing trend at the system level after the first time

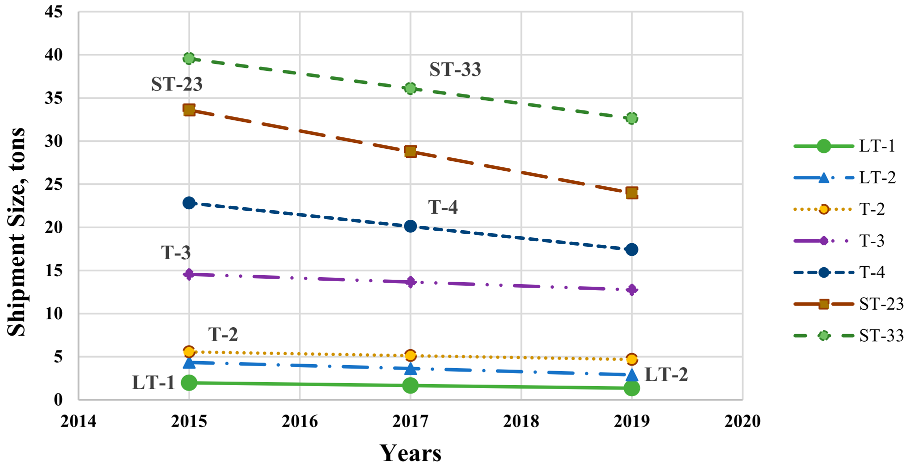

Figure 4. Latent growth curve for different truck types.

point of the analysis (the year 2015). To further investigate the time-dependent characteristics of the shipment size, the next section presents a latent growth model of shipment size for each truck type and establishes its link to the economic performance of the case study location.

4.2. Time-dependent patterns of shipment size with latent growth (LG) models

The time-dependent patterns of shipment characteristics are better analysed along with the modal choices, and this study used the LG method to model their interrelations over time. Table 7 displays the outcomes of the LG model using a linear functional form within the SEM framework. The random (variances) and fixed (mean values) elements of the model were statistically significant. Each truck type's mean intercept corresponded to the average shipment size in the reference year (2015) and the mean slope showed the average rate of change in cargo size over time (Figure 4). For all vehicle types, the slope or average growth ratings were negative, indicating a general decline in shipment size from the reference year. Moreover, truck types ranging in size from T-4 to ST-33 had larger negative slopes, with ST-23 and ST-33, in particular, showing a sharper drop in shipment size with time. Most significantly, these truck types transport various goods serving multiple economic sectors and can indicate the overall state of the economy.

The chi-square values ($\chi 2$) showed that the model fit the data reasonably well for all model estimates for each truck type. The intercept and slope variances were significant and reveal the presence of shipment size heterogeneity carried by each truck type in 2015 and afterwards. In essence, it shows the differences in shipment size between the truck types in 2015 (intercept) and the changes over time (slope). The covariance parameter estimate indicates a significant negative relationship between intercept and slope for all the truck types, which shows the negative growth rate of shipment size after 2015. Overall, the logistics decision related to shipment size exhibited a continuous decline after 2015, both at the system level and the level of each truck type.

Table 7. Latent growth (LG) model estimates of shipment size for each truck type.

	Truck type													
	LT-1		LT-2		T-2		T-3		T-4		ST-23		ST-33	
Parameter	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value
Mean intercept	1.91	6.99	4.34	18.16	5.56	16.23	14.56	21.58	22.81	68.87	33.59	33.13	39.56	88.67
Mean slope	−0.31	−1.51	−0.72	−3.68	−0.44	−1.41	−0.9	−1.94	− 2.7	−8.1	−4.81	−4.72	−3.47	−5.7
Intercept variance	0.78	1.31	0.85	1.27	4.14	1.37	2.95	1.71	3.2	2.23	64.51	4.65	6.8	1.15
Slope variance	0.67	1.95	0.61	1.48	3.17	1.53	5.38	1.73	2.57	2.15	51.86	3.53	5.24	0.85
Covariance (slope & intercept)	−0.77	−1.75	−0.68	−1.39	−3.59	−3.19	−4.64	−1.89	−3.5	−1.65	−55.03	−4.18	−3.32	−0.71
Error variances across shipment sizes	0.41	3.23	1.98	7.15	4.1	7.06	11.85	7.07	16.78	9.14	19.77	5.03	42.73	7.47
Fit indices: df∗, $\chi 2$∗, *p*-value	3; 14.38; 0.00		3; 23.74; 0.00		3; 36.73; 0.00		3; 20.35; 0.00		3; 13.69; 0.00		3; 21.64; 0.00		3; 4.31; 0.04	

Economic performance is interrelated with freight demand. Generally, the shipment size declines because of changes in inventory management or changes in the economy. Firms change their inventory management by reducing the shipment size and increasing the frequency. When there is a drop in the transport cost or fuel prices, firms reduce the shipment size while increasing the delivery frequency to lower inventory costs. However, the average transport cost per ton-kilometre for each truck type increased after 2015, as presented in Table A2. Therefore, our conjecture of shipment size decline is related to the second case due to the slowdown of economic activity.

The repeated cross-sectional datasets used to estimate the freight demand model in this study were from Ethiopia, which in the period 2010–2020 experienced a series of events that negatively affected the political environment and economic growth. To contextualise the discussion, some general background on political conditions and economic performance in the study area in 2010–2020 is provided below, with a discussion on the outlooks in relation to freight demand over time.

The country at focus, Ethiopia, is characterised by contrasting features of poverty and economic growth (Senbeta 2021). In this study, our interest lies in the economic growth conditions, particularly in the decade between 2010 and 2020. During this period, the government set bold and ambitious economic targets in Growth and Transformation Plans (GTP) covering 2010–2014 (GTP-1) and 2015–2020 (GTP-2). GTP-1 was considered to achieve most of the targets and to accelerate growth and transformation towards a middle-income level (Ethiopia-Planning-Commission 2016), but political volatility prevented the implementation of GTP-2. Figure A5 (in Appendix) indicates the timing of significant events in the period 2015–2020 in relation to the data collection years. For more information on the events covering these periods, see the recent literature (Senbeta 2021; Jima 2021; Woldesenbet, Gebreluel, and Bedasso 2022).

The political conditions were reflected in the economic outputs of the country, as evidenced by our case study, the economic decline caused by political instability. For measuring economic activity, several metrics were used, including GDP, inflation, growth rate of the main economic sectors, import and export real growth, and merchandise imports and exports as percentages of GDP. Figure 5a shows the GDP, inflation, and growth rate of the main economic sectors in Ethiopia over the decade 2010-2020. The first half of the decade was characterised by lower inflation (less than 15%) and an average real GDP growth rate of 10.1%. The second half was characterised by higher inflation, reaching more than 20%, and a decline in GDP growth, with an average rate of 7.2%. Peak inflation increased from 6.1% in 2015/16 to 20.2% in 2020/21. Moreover, real GDP growth declined sharply, from 10.1% in 2016/17 to 2.3% in 2020/21. The individual sectors also exhibited variable growth rates over the first and second halves of the decade (positive and negative growth, respectively). Figure 5b shows trade activity, which includes import and export real growth and merchandise imports and exports as percentages of GDP. All these metrics showed declining patterns from the first to the second half of the decade. Overall, the economy vastly underperformed, or there was an economic slowdown in 2015/16–2020/21 compared to 2010/11–2014/15.

The data collection years represent two different realities, as the 2015 data were collected in the decade's first half, while the 2017 and 2019 datasets were collected in the second half. The shipment size decreased after the reference year 2015 at the overall freight

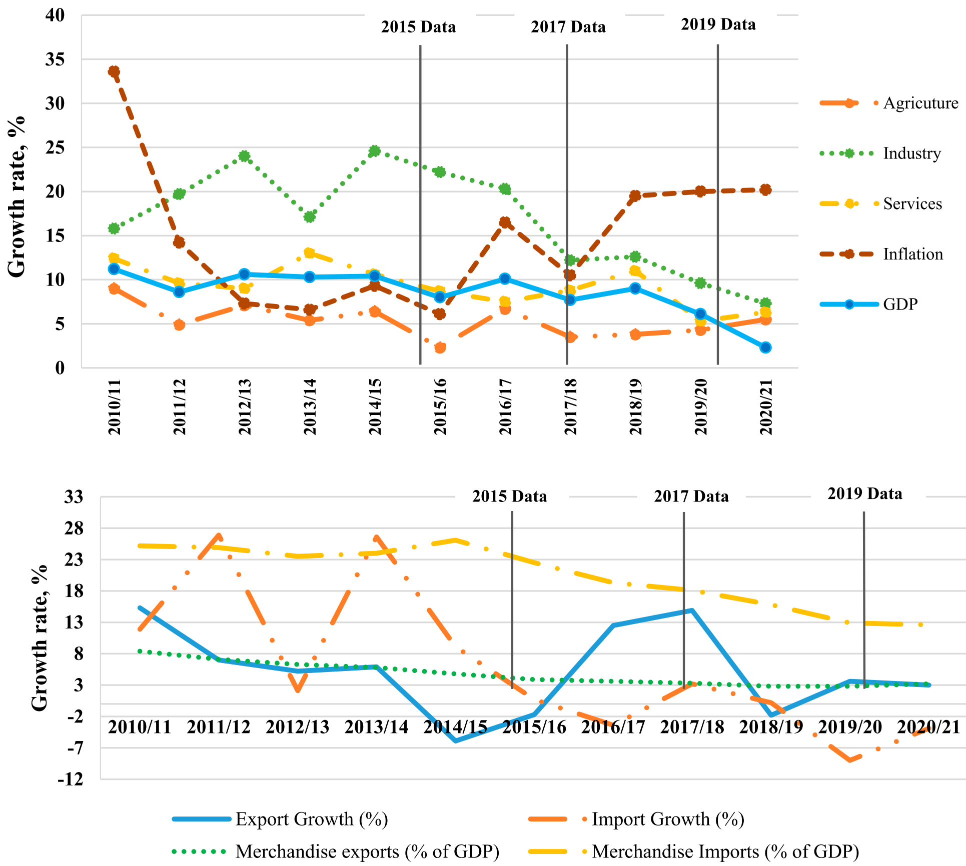

Figure 5. Economic metrics for Ethiopia, 2010/11–2020/21. (a) GDP, inflation, and growth of main sectors, and (b) trade growth and merchandise trade. (Data source: World-Bank (2022)).

transport level (Table 4) and individual truck type level (Table 5). Shipment size as an important decision in freight transport exhibited a similar pattern to different metrics of economic activity (Figure 5).

Other studies on the internal relationship between freight transport and economic growth have also encompassed different economic decisions and events. A study by US-DoT (2017) found that freight transport services declined in the USA during the great recession between 2007 and 2009, and the recovery afterwards had a similar pattern to the pace of GDP growth. Similarly, the 2009 economic crisis in Greece negatively impacted the transport sector (Moschovou 2017). Consequently, it was evident that the relationship between economic development and demand for freight transport has a time-dynamic behaviour. The study's results can help to develop more accurate forecasts of freight demand due to its essential link to logistics decisions, such as shipment size, while accounting for time-dependent patterns.

5. Conclusions

The study examined the temporal stability of shipment size decisions interrelated to the choice of truck type using repeated cross-sectional data collected from truck trips and businesses in Addis Ababa, Ethiopia, in 2015, 2017, and 2019. The combined dataset was used to create joint freight truck-shipment size choice models using the integrated choice and latent variable (ICLV) method and the latent growth (LG) method and evaluated the changes in shipment size over time. The temporal changes in shipment size were examined at two levels: with binary variables in the ICLV model at the overall system level and at the level of each truck type with the estimation of the LG models.

The results revealed that commodity type, haulage, and shipment characteristics significantly affected shipment size, but to varying degrees. Shipment size changed significantly over time at the system level, with a diminishing pattern (shrinkage) from the reference year (2015) and an average slope decline from the reference year for all truck types according to the LG model. The highest rate of decline was observed for truck types T-4, ST-23 and ST-33, which serve a range of industry sectors and generally carry different commodity types. The variations in shipment size with time can significantly affect the quantification and forecasting of traffic volume and composition, which may translate to large differences in estimated traffic externalities produced by policy decisions.

The temporal stability of shipment size was discussed in close connection with the case study location using the correlation between freight transport demand and economic growth in Ethiopia in the decade 2010-2020, which was split into two halves for analysis of economic performance and freight demand. The country's economic performance declined from the first to the second half of the decade, as indicated by various economic growth metrics. Also, the freight demand shows a decreasing trend, as explained by the shipment size choices.

These findings have the following key implications for freight demand modelling and related policy analysis: (i) Choice of freight truck type is temporally unstable due to the time-varying nature of influencing shipment size decisions. (ii) Planning decisions and policies intended to influence truck type choices and related shipment sizes need to consider economic conditions over time. (iii) The elasticity of choice estimates indicated that choices of smaller trucks are sensitive to changes in operating costs and that utilisation of spare loading capacity influences the choice of trucks with larger loading capacity. These results could be indicative of the expected success of policy measures. For example, imposing toll costs could influence the choice for smaller truck types, while regulations targeting loading levels such as weight or axle load limits would be more effective with larger trucks. We recommend more extensive studies on the policy implications of our findings to validate these expectations with other models and real-world observations.

Until now, behavioural studies on freight mode choice used cross-sectional datasets assuming the stability of preferences over time. Our analysis reveals that these preferences can be strongly time-dependent. This opens a new direction for behavioural analysis of freight mode choice to account for the time-dependent effects of the joint decision of freight mode and shipment size. In modelling the temporal patterns of freight mode choices, the linkage between freight activity levels with the changes in the overall economy or other exogenous factors is imperative to consider together with the use of periodically collected freight data.

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Authorship Contribution

Abel Kebede Reda: Conceptualisation, Methodology, Formal analysis, Writing – original draft. Jose Holguin-Veras: Conceptualisation, Methodology, Formal analysis. Lori Tavassy: Methodology, Writing – review & editing. Girma Gebresenbet: Methodology, Writing – review & editing, Project administration. David Ljungberg: Methodology, Writing – review & editing.

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Appendix

Table A1. The distribution of establishment categories in the freight flow (intercity trips).

	2015, Sample = 530				2017, Sample = 1203			
Sectors	Retail	Wholesale	Manufacturer	Others	Retail	Wholesale	Manufacturer	Others
Retail	4.8%	1.4%	1.8%	0.0%	3.9%	2.0%	2.3%	0.0%
Wholesale	8.3%	5.4%	4.6%	0.2%	8.7%	3.7%	4.3%	0.8%
Manufacturer	11.7%	13.0%	8.7%	7.0%	13.1%	11.6%	10.6%	8.8%
Others	7.8%	10.0%	12.6%	2.5%	7.6%	9.2%	11.2%	2.2%
Sectors	2019, Sample = 229							
	Retail	Wholesale	Manufacturer	Others				
Retail	7.1%	4.0%	3.6%	0.8%				
Wholesale	6.8%	3.7%	3.3%	0.7%				
Manufacturer	14.9%	14.6%	12.2%	9.4%				
Others	4.3%	6.2%	7.7%	0.7%				

Table A2. Average transport cost per ton-kilometres for each truck type over the years (in US$).

	Transport cost (US$ per ton-kilometres)		
Truck types	2015	2017	2019
LT-1	1.39	2.89	2.53
LT-2	1.01	1.50	1.58
T-2	0.85	1.11	0.93
T-3	0.54	0.82	0.85
T-4	0.26	0.58	0.45
ST – 23	0.14	0.15	0.16
ST – 33	0.05	0.11	0.09

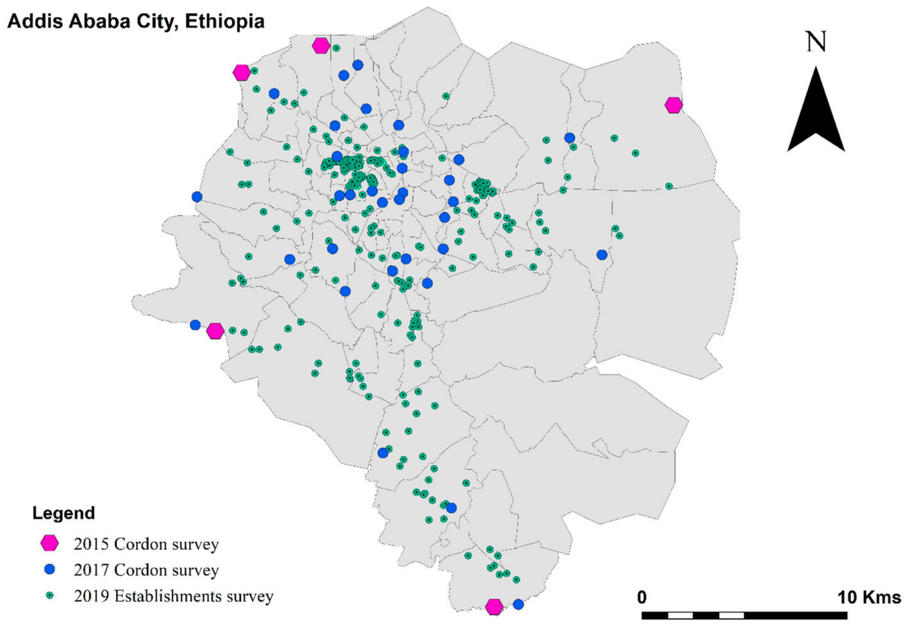

Figure A1. Map of Addis Ababa city showing locations used for data collection in the three surveys.

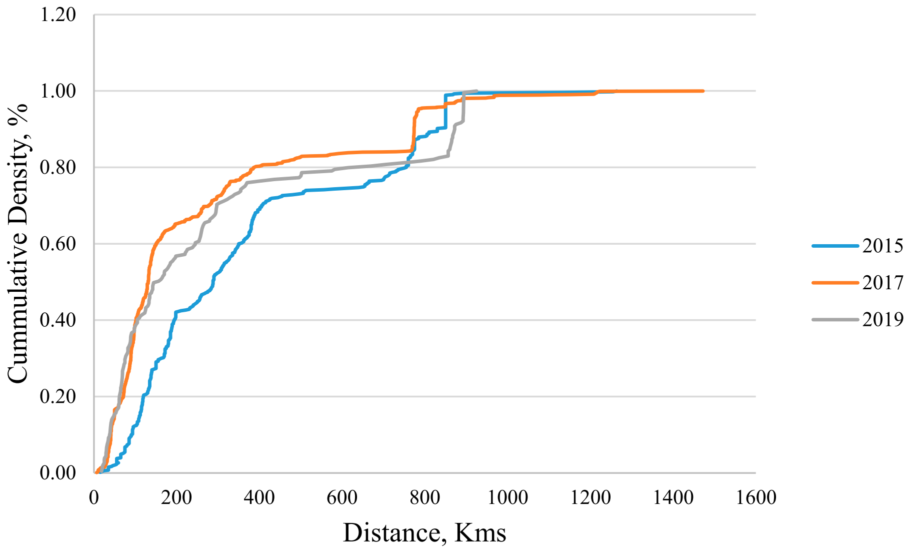

Figure A2. Cumulative distribution of three datasets with travel distance.

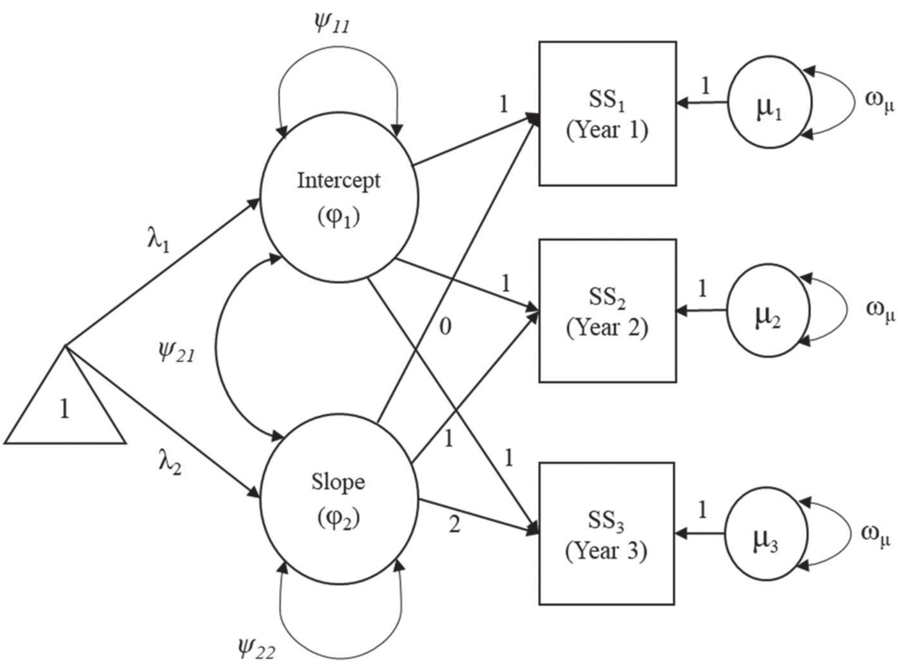

Figure A3. Complete path diagram of the shipment size growth curve model.

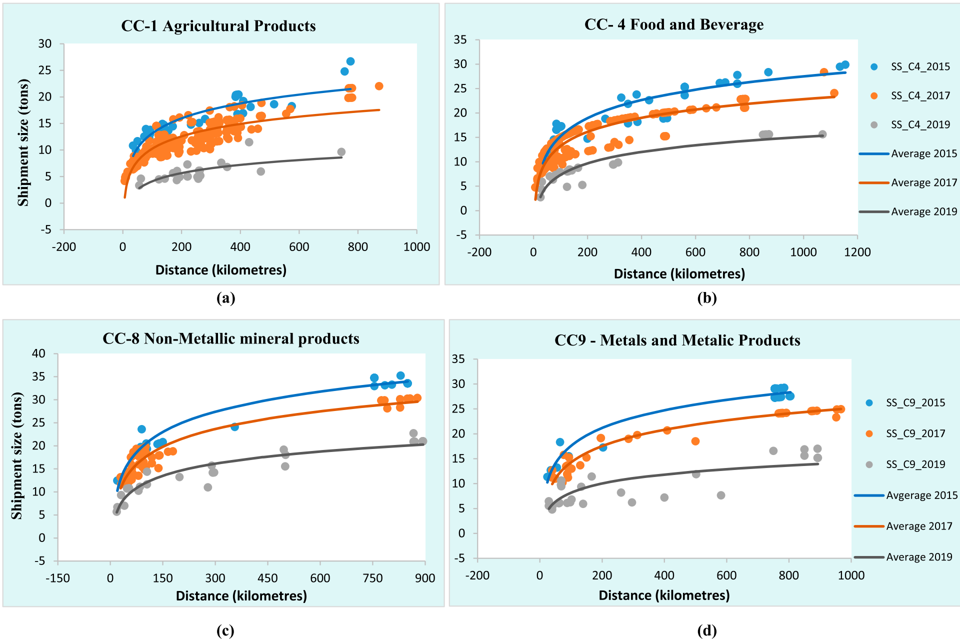

Figure A4. Commodity-specific shipment size trends with travel distance over data collection years 2015, 2017 and 2019. Note: the bars only indicate the time of major events and do not represent any scale.

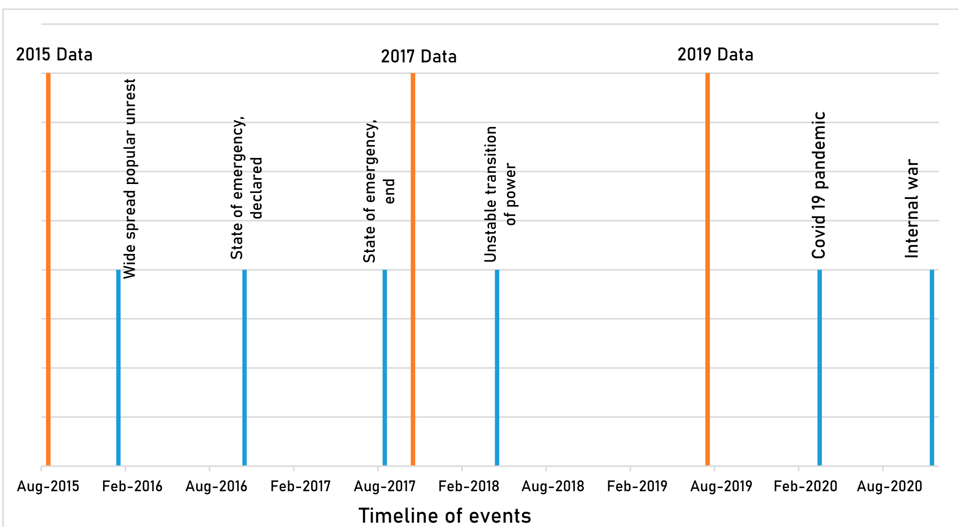

Figure A5. Ethiopia's major socio-political events with a timeline between 2015 and 2020 (own depiction).