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Delivery time-period choice modeling considering time-of-day network performance

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Abstract

Cities generate enormous freight delivery demand and the resulting freight vehicle traffic. Although various freight-related traffic problems exist, growing attention in land-constrained urban areas has shifted toward logistics policies that disperse freight demand such as time-based traffic regulations and the promotion of off-peak deliveries rather than relying solely on infrastructure expansion. Understanding delivery time-period choice behavior is essential for evaluating such policies. Kodera et al. (2025) developed a delivery time-period choice model using pseudo-shipment data derived from GPS data; however, network characteristics such as congestion and toll road charges were not considered. Research explicitly linking changes in traffic network performance due to congestion and other factors to delivery time-period choice remains limited. This study focuses on the Tokyo Metropolitan Area and use a vehicle trip diary dataset. Shipment data were constructed from individual vehicle tour diaries, and a delivery time-period choice model was estimated. Explanatory variables include deviation from the shortest travel time, travel time, land-use zoning characteristics around delivery destinations, and receiver attributes. Travel time was calculated using average speeds by time period, enabling examination of how changes in traffic network performance influence delivery time-period choice. Furthermore, a sensitivity analysis targeting Tokyo's 23 wards was conducted to quantitatively assess the impact of traffic condition changes. The results clarify the influence of road network performance on delivery time-period choice and provide empirical evidence and policy implications for off-peak delivery measures and urban freight demand management.

Keywords: time-period choice; shipment; freight modelling; urban freight; off-hour delivery

1 Introduction

Diverse industries and large populations concentrate within cities. The activities in cities generate a high volume of goods delivery demand, which in turn leads to externality such as congestion and emissions. Interest has been growing in urban freight policies that shift and freight trip demand—such as off-peak deliveries and congestion pricing—in cities around the world (e.g., New York and Singapore). Designing such effective policies requires a clear understanding of the factors determining the delivery time. However, existing research that explicitly models delivery time choice is limited largely because of the difficulty of obtaining the shipment records together with its delivery time. Kodera et al. (2025) used pseudo-shipment data from GPS trajectory data to estimate a delivery time choice model, but due to data limitations, their study could not sufficiently incorporate road network performance that vary by time of day. To overcome their limitation, we use the GPS data collected through a next-generation in-vehicle communication system, ETC2.0. We construct shipment records based on trip diaries collected in a public survey and assign time-of-day travel times between each shipment's origin and destination using link speed information derived from the ETC2.0 data. Using this data, we estimate a delivery time-period choice model to clarify how changes in network performance affect delivery time choice.

2 Literature review

While many studies focus on passengers' travel time choice, only a very small number of papers model delivery time choice. Discussion of delivery time choice has mainly developed in the field of demand management for urban freight transport. Holguín-Veras et al. (2007) analyze how measures such as tax credits and delivery-fee discounts for firms accepting off-peak deliveries influence the acceptance rate of off-peak deliveries. Holguín-Veras et al.

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(2008) analyze both the share of receivers who are willing to accept off-peak deliveries and the share of carriers willing to provide off-peak deliveries in response to incentives. Building on these two studies, Silas and Holguín-Veras (2009) conduct policy simulations of off-peak deliveries using the models developed in the earlier work. These studies provide important insights into predicting receiver participation in off-peak delivery programs; however, because they mainly focus on commercial areas and retail stores and use coarse time-of-day classifications, they have limitations in reproducing the fine-grained variation in delivery time periods observed across an entire city. As for the delivery time choice modelling, de Jong et al. (2016) estimate a logit model using a stated preference (SP) survey of receiver firms in Flanders, Belgium, with travel time and cost as explanatory variables. Although this is one of the few studies that use a fine time classification, receiver attributes were limited to three categories due to a small sample size, making it difficult to capture in detail the heterogeneity of receivers, commodity types, and vehicle types. Kodera et al. (2025) leverage large-scale datasets to estimate delivery time-period choice at the metropolitan scale. They generate pseudo-shipment data from goods vehicle GPS trajectory data in the Tokyo Metropolitan Area (TMA) and estimate a delivery time-period choice model using shipment distance, shipment size, and destination attributes as explanatory variables. However, due to the nature of the data, they do not incorporate time-varying road network performance. This is a key limitation because many urban freight policies aim to ease congestion at specific time-of-day, especially peak hours, and delivery time choices are partly driven by the time-dependent delivery costs. Therefore, without this consideration, policy-induced shifts in delivery time cannot be reliably estimated.

To address this research gap, the current study estimates a delivery time-period choice model for the TMA by adding time-of-day travel times as explanatory variables, thereby clarifying how temporal variations in network performance, due to congestion and other factors, affect delivery time-period choice.

3 Study area and data

This study target shipments within the TMA (Figure1). The TMA is a broad region comprising a high-density urban core and multiple suburban cities. While commercial and business activities are highly concentrated in the central urban core, distinct freight demands emerge in surrounding cities like Yokohama and Saitama, as well as other suburban centers. This region features the ongoing development of three ring roads: the Metropolitan Expressway Central Circular Route, the Tokyo Outer Circular Road, and the Metropolitan Expressway Central Link. Numerous factories and logistics facilities are located along these routes. Major logistics facilities such as Tokyo International Airport, Narita International Airport, Tokyo Freight Terminal Station, and port facilities along Tokyo Bay are also located here, forming diverse freight movement patterns within the metropolitan area. According to the 5th Tokyo Metropolitan Area Freight Transport Survey, the daily freight volume within the region is approximately 2.8 million tons, while the daily flow of goods to and from the region is approximately 1.6 million tons.

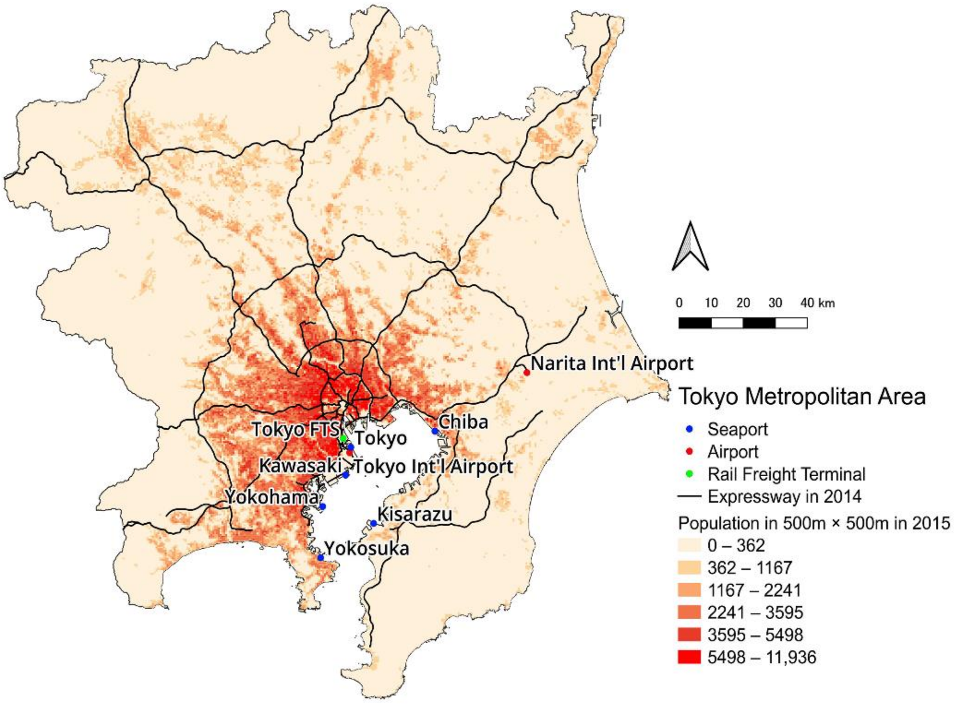

Fig. 1. Tokyo Metropolitan Area (Kodera et al., 2025).

Table 1 summarizes the data sources. We prepare shipment data from goods vehicle trip-diary data. Here, a "shipment" refers to the movement of goods from an origin to a destination that implemented at a time. We then estimate time-of-day travel times for each shipment's origin–destination pair and append them to the shipment dataset. Specifically, we identify the route between the origin and destination on a road network, compute link travel times using time-of-day link speeds derived from ETC2.0 data (MLIT,2025b) and obtain time-of-day travel times for each OD pair. Moreover, destination facilities within the shipment dataset were classified into end receivers and others. In this study, end receivers refer to locations where goods are consumed or purchased, such as residences, offices, and supermarkets.

Furthermore, we compute the shares of different zoning types within each shipment destination zone and use them as shipment characteristics. In the tour-diary data, origins and destinations are recorded at the B-zone level. B-zone is traffic analysis zone used in the survey to represent sub-municipal areas. Zoning data are obtained from the National Land Numerical Information (MLIT, 2025c) and overlaid with B-zone boundaries to calculate zoning shares.

Table 1. List of data used.

Dataset	**Source**	**Preparation method/usage**
Goods vehicle tour-diaries tours	Owner Interview OD Survey in the FY2021 Road Traffic Census (MLIT,2025a)	For the Tokyo Metropolitan Area, loading and unloading locations were inferred from increases/decreases in on-board load within tours; shipment data were created by extracting only cases with clearly identified origins and destinations.
Road network	Digital road map managed (Japan Digital Road Map Association,2025)	The nearest road to each B-zone centroid was assigned; shortest paths between shipment origins and destinations were searched; distances were computed.
Time of day travel time by road segment	Link speed data created by map-matching road network data with ETC2.0 probe data managed (MLIT,2025b)	For each link on the shortest path, link travel time was computed as "link length ÷ speed," then summed to obtain time-of-day travel time
Zoning shares within destination B-zone	National Land Numerical Information (MLIT,2025c)	Zoning data was overlaid with B-zone polygons to compute zoning shares for each destination B-zone.

Figure 2 shows the average hourly travel time for all shipments. Average travel times fluctuate depending on the time of day. While average times are short between midnight and 5 a.m., they surge during the morning hours from 6 to 8 a.m. and then remain at a high level from 8 a.m. to 4 p.m. They peak again between 5 and 6 p.m., decline after 7 p.m., and become shorter once more during the night.

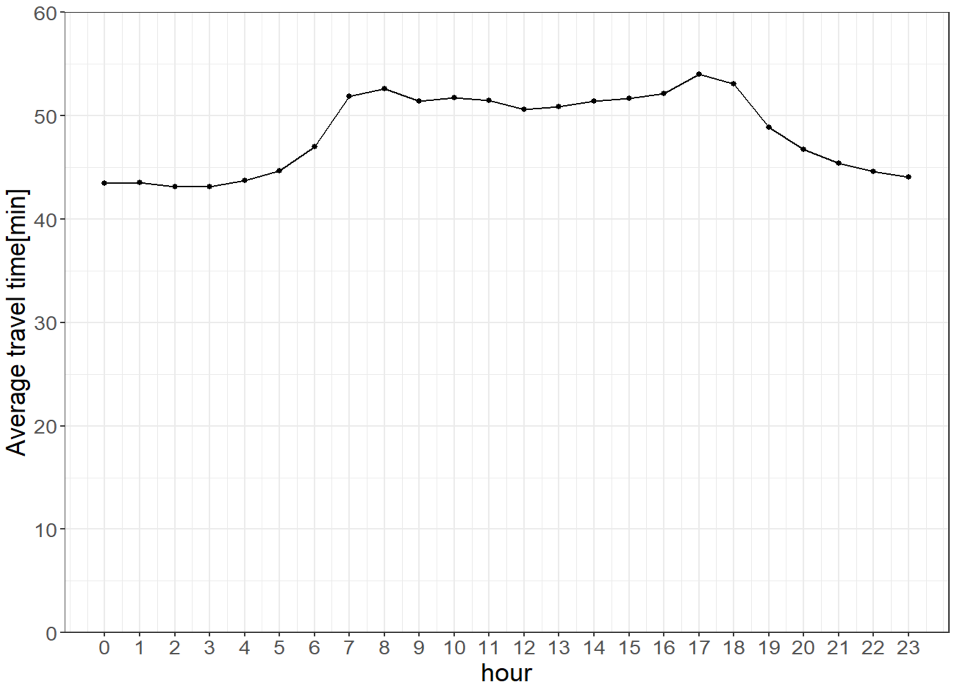

Fig.2 Average hourly travel time (all shipments)

4 Delivery Time-Period Choice Model

This section describes the specification of the delivery time-period choice model. The variables used in model estimation are shown in Table 2. The dependent variable is the delivery time period, and all other variables are explanatory variables. Models are estimated separately by commodity type. Drawing on de Jong et al. (2016) and Kodera et al. (2025), we define delivery time periods by integrating elements from both classifications.

Table 2. Description of variables

Variables	Definition	Notation
Difference from the shortest travel time	Difference between travel time in each time period and the shortest travel time	$\Delta time$
Shortest travel time	Minimum travel time among all time periods for a shipment	$time$
Zoning shares within destination B-zone	Four categories: residential, commercial, industrial, and other	$share\_com$(commercial zone) $share\_ind$(industrial zone) $share\_other$(other)
End receiver	A dummy variable. 1 if shipment is to an end receiver; 0 otherwise.	dum_end
Delivery time-period	Goods delivery time-period (categorical variable) ● Early morning (5:00–7:00) ● Morning peak (7:00–9:00) ● Late morning (9:00–12:00): base category ● Afternoon (12:00–16:00) ● Evening peak (16:00–19:00) ● Night (19:00–22:00) ● Late at night (22:00–5:00)	

Let $time_{i,j}$ denote the travel time for shipment i in time period j, and let $time_{min}^{i}$denote the shortest travel time among all time periods for shipment i. We define:

$$\Delta time_{i,j} = time_{i,j} - time_{min}^{i} \qquad (1)$$

Because this is the difference relative to the minimum travel time, it serves as an indicator of extra travel-time due to congestion and other factors. A common explanatory variable across all commodity-category models is $\Delta time$, i.e., the difference between each period's travel time and the shortest travel time. If the coefficient for $\Delta time$ was positive, the coefficient of $\Delta time$ was fixed to zero and the model was re-estimated.

We use a multinomial logit (MNL) model and estimate parameters using the maximum likelihood method. In this model, the decision-maker is the receiver, and the receiver chooses the alternative which provides the highest utility. The utility function is specified as follows.

$$U_{i,j} = V_{i,j} + \varepsilon_{i,j} \qquad (2)$$

where $U_{i,j}$ is the utility of alternative i for receiver j, $V_{i,j}$ is the systematic component of the utility, and $\varepsilon_{i,j}$is an error term that follows a Gumbel distribution ($\varepsilon_i \sim$ Gumbel(0,1)). The reference alternative is late morning (9:00–12:00) ($j = 1$). The systematic component is specified as follows:

$$V_{i,1} = \beta_{\Delta time}\, \Delta time_{i,1} \qquad (3)$$

$$V_{i,j} = \beta_{constant}^{j} + \beta_{\Delta \mathrm{time}}\, \Delta time_{i,j} + \beta_{time}^{j}\, time_i + \beta_{share\_com}^{j}\, share\_com_i + \beta_{share\_ind}^{j} share\_ind_i + \beta_{share\_other}^{j} share\_other_i + \beta_{dum\_end}^{j}\, dum\_end_i \qquad (4)$$

$\beta_{constant}^{j}$, $\beta_{\Delta \mathrm{time}}$, β_{time}^{j}, $\beta_{share\_com}^{j}$, $\beta_{share\_ind}^{j}$, $\beta_{share\_other}^{j}$, and $\beta_{dum\_end}^{j}$ are the parameters to be estimated.

The choice probabilities are as follows.

$$P_{i,j} = \frac{e^{V_{i,j}}}{\sum_{j=1}^{J} e^{V_{i,j}}} \qquad (5)$$

Commodity types with too few samples or with highly skewed time-period distributions are excluded from modeling. The model is applied to the following commodity types: food products, agricultural products, daily goods, parcels, chemical products, machinery, metal products, and transport containers.

5 Results

Some estimated models are shown in Tables 3–5. First, the coefficients of $time$ for *night*, *late night*, and *early morning* for parcels and daily goods are positive and statistically significant. This suggests that deliveries with long minimum travel times, i.e., long-distance deliveries, are more likely to be scheduled during *late at night* and *early morning*. In particular, the coefficient of $time$ for *late at night* for parcels is high (1.58). One explanation for this is that in the parcel delivery service industry, shipments between regional logistics hubs are often implemented during nighttime. This is consistent with the findings of Kodera et al. (2025), who found that longer-distance deliveries tend to be delivered during off-peak hours such as late night.

Next, for parcels and daily goods, the coefficient of $share\_com$ for *night* and *late at night* is negative and statistically significant. This indicates that the higher the proportion of commercial areas, the less likely *night* and *late at night* are selected. This result can be interpreted as reflecting constraints on the recipient's ability to receive deliveries outside of business hours in commercial areas, such as store closures and noise considerations. On the other hand, the coefficient of $share\_ind$ for *night* for parcels and daily goods is positive and statistically significant. This indicates that the higher the proportion of industrial areas, the more likely nighttime hours are selected. This is partially due to the fact that warehouses and logistics centers, which have well-established cargo handling facilities and nighttime receiving systems, making after-hours deliveries possible, are concentrated in industrial area.

Furthermore, the coefficients of dum_end for *evening peak* and *night* are negative and significant for agricultural products and daily goods. This indicates that when the business type of the destination is an end receiver, *evening peak* and *night* are less likely to be selected than before noon. This may be due to the fact that many recipients are small stores or offices and are unable to receive deliveries outside of business hours. The coefficient of dum_end for agricultural products at *night* is particularly small (-1.83). This suggests that because agricultural products cannot be stored for long due to their product lifespan, recipients are more likely to choose to receive them just before store opening, such as during *morning peak*. The estimated coefficients reflect the supply chain characteristics of different commodity types.

Table 6 compares $\Delta time$ coefficients by commodity type. The $\Delta time$ coefficients for agricultural products and parcels are negative and statistically significant. This suggests that these two categories are less likely to be delivered during periods with larger $\Delta time$—that is, periods with heavier congestion. In contrast, other commodity types show no statistically significant effects, implying that they are not influenced by congestion-related travel-time increases. This can be interpreted as reflecting strong constraints that compel deliveries to occur during specific time periods even if traffic is heavy. For such commodities, congestion pricing or vehicle type restrictions may have limited effects. Therefore, to disperse freight demand for these commodities, policies other than those directly related to traffic network conditions may be required.

Next, we conducted a sensitivity analysis assuming daytime congestion within Tokyo's 23 wards worsens further (Fig.3). Specifically, Δtime was increased by 10%, up to 100% during daytime periods (*morning peak*, *late morning*, *afternoon*, and *evening peak*). Figure 3 shows the change in choice probability as Δtime increases for agricultural products and chemical products. As Δtime increases for agricultural products, the proportion of daytime deliveries decreases and the proportion of off-peak deliveries (*night*, *late at night*, and *early morning*) increases. A 100% increase in Δtime increases the off-peak choice rate by approximately 11%. In contrast, for chemical products, the increase is only 2%. These results demonstrate that agricultural products are sensitive to changes in Δtime. These results highlight the heterogeneity in flexibility of delivery time choice across commodity type.

Table 3. Estimation results of the delivery time-period choice model (parcels)

Variables	**Coef.**						
$\Delta time$	-3.284***						
	Late morning	**Afternoon**	**Evening peak**	**Night**	**Late at night**	**Early morning**	**Morning peak**
constant	0	-0.021	-0.988***	-1.649***	-2.228***	-2.412***	-1.990***
time	0	0.267	-0.419	0.723***	1.576***	1.187***	1.004***
share_com	0	-0.170	-0.243	-1.499*	-1.300*	-0.850	0.153
share_ind	0	0.224	1.413***	1.759***	1.302***	-0.013	0.054
share_other	0	0.035	0.525*	0.424	-0.013	0.358	-0.191
dum_end	0	-0.104	0.202	-0.202	-0.149	-1.040***	-0.096
Rho-squared: 0.153							
No. of samples: 2803							

Significance levels: ***(p < 0.001), **(p < 0.01), *(p < 0.05)

Table 4. Estimation results of the delivery time-period choice model (agricultural products)

Variables	**Coef.**						
$\Delta time$	-3.467***						
	Late morning	**Afternoon**	**Evening peak**	**Night**	**Late at night**	**Early morning**	**Morning peak**
constant	0	0.843***	-1.194***	-0.874*	-0.800**	-1.014***	-1.031***
time	0	-0.187	0.175	0.314	-0.137	0.203	0.481**
share_com	0	-1.674**	-0.993	-1.418	-0.169	-0.896	-0.940
share_ind	0	-0.510	0.679	-1.099*	-0.215	-0.507	-0.020
share_other	0	-0.226	0.231	-0.577	-0.468	-1.109***	-0.259
dum_end	0	-0.716***	-1.248***	-1.827***	-0.858***	0.303	0.378
Rho-squared: 0.122							
No. of samples: 1681							
Significance levels: ***($p < 0.001$), **($p < 0.01$), *($p < 0.05$)							

Table 5. Estimation results of the delivery time-period choice model (daily goods)

Variables	**Coef.**						
$\Delta time$	0						
	Late morning	**Afternoon**	**Evening peak**	**Night**	**Late at night**	**Early morning**	**Morning peak**
constant	0	0.060	-1.354***	-2.005***	-1.140***	-2.199***	-1.764***
time	0	-0.073	-0.164	0.804***	1.203***	1.003***	0.574***
share_com	0	-0.213	-0.934*	-1.582**	-2.770***	-0.440	0.336
share_ind	0	0.496**	1.584***	1.999***	0.081	-0.098	0.315
share_other	0	0.144	0.585*	0.314	-0.579**	0.141	0.194
dum_end	0	-0.054	-0.270*	-0.493***	-0.189	-0.443**	-0.112
Rho-squared: 0.144							
No. of samples: 4781							
Significance levels: ***($p < 0.001$), **($p < 0.01$), *($p < 0.05$)							

Table 6. ΔTime coefficient by commodity type

	agricultural products	parcels	machine products	chemical products	daily goods	food products	Light industrial goods	Metal products	Transport container
$\Delta time$	-3.467***	-3.284***	-0.511	-0.728	0	0	0	0	0

Significance levels: ***($p < 0.001$)

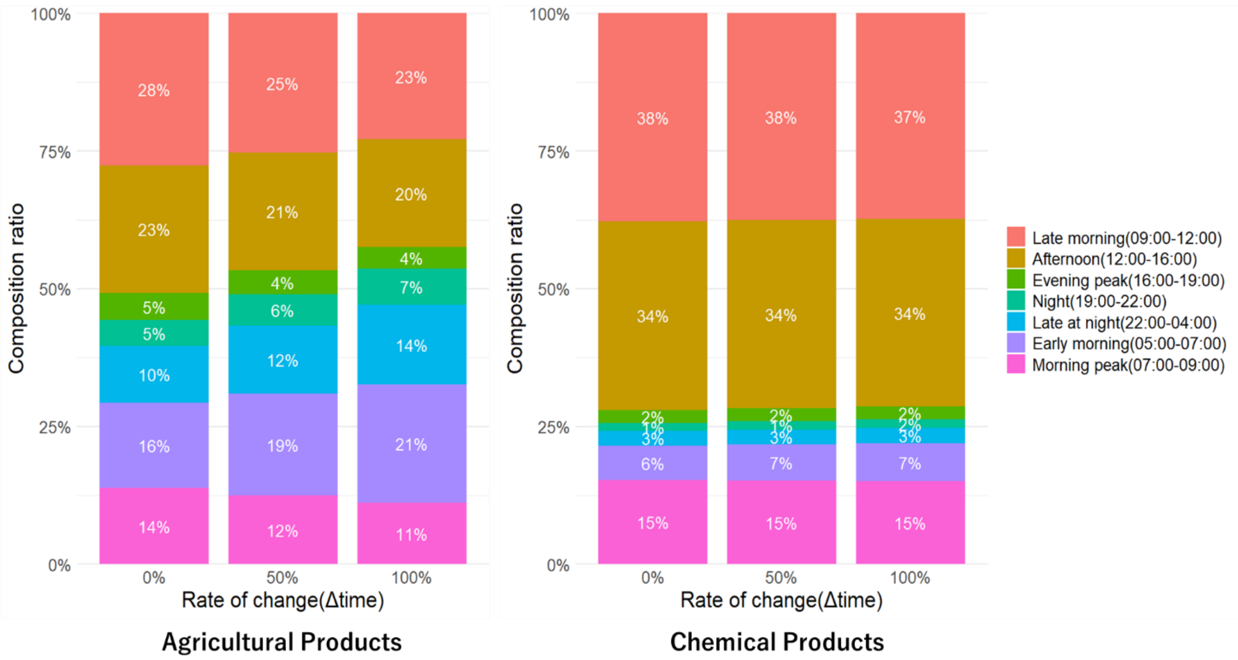

Fig. 3. Change in selection probability due to Δtime increase

6 Conclusion

This study estimated a delivery time selection model incorporating time-varying traffic network performance by creating shipment-level delivery data from large-scale trip diary data for the TMA and assigning time-of-day travel times based on road network data. The results indicate that the response to Δtime varies by commodity type. Some goods, such as agricultural products and parcels, tend to avoid increased travel time due to congestion, while others, such as machine products and chemical products, are largely unaffected by congestion. Sensitivity analysis showed that Δtime increases with a shift from daytime to off-peak time slots, particularly for agricultural products. Overall, the effectiveness of traffic network-related policies is limited by commodity type. For goods unaffected by congestion, policies impacting recipient acceptance capacity and related arrangements are necessary. These findings provide useful insights for demand management policies in urban freight transport.

The main limitation of this study is that, due to data constraints, transportation costs such as expressway tolls could not be directly incorporated into the estimation model. The dataset used in this study does not record the actual route choices for each shipment, the expressway entrance and exit interchanges used, or toll information. Therefore, it is difficult to calculate costs based on the actual toll structure using only the shortest routes inferred from the road network. Future research should employ more detailed route estimation, calculate expressway usage distances, and estimate shipment-level costs based on actual toll structures. These should then be incorporated into the model as time-of-day cost variables. This would enable policy evaluation, including toll-based measures.

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