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Parcel Categorization for Freight Return Modelling: Implementing the Multiple Discrete-Continuous Extreme Value (MDCEV) Model

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Abstract

The increasing volume of e-commerce returns poses significant challenges for urban transportation systems. However, little attention is paid to e-commerce returns in transportation research. This study integrates return parcel volumes into freight demand modelling using the agent-based framework logiTopp. By categorizing parcel demand (e.g. fashion and electronics) through a Multiple Discrete-Continuous Extreme Value model and linking these categories to return probabilities, we estimate category-specific parcel order and return volumes for Karlsruhe, Germany. The results indicate that roughly one in five parcels is returned, corresponding to about 27,500 return parcels per week.This framework provides a foundation for assessing the impacts of return flows on urban logistics and for evaluating operational strategies such as parcel lockers, autonomous collection systems, or integrated pickup by delivery tours. The findings highlight the need for empirical data collection on return parcel drop-off behavior to enhance the modelling framework and enable a more comprehensive assessment of its transportation impacts.

Keywords: freight demand modelling; returns; parcel categorization; MDCEV

1. Introduction and related work

When customers purchase online, they have to sacrifice the benefit of a physical inspection of the product. Compared to traditional in-store shopping, this can increase the likelihood of a customer's desire to return the product (Yan, 2009). With the expansion of generous return policies offered by e-commerce retailers to promote sales, the volume of return parcels has grown substantially (Bower and Maxham, 2012; Shang et al., 2017). Despite various efforts to mitigate return rates through strategies such as improved product descriptions, these rates have remained

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persistently high in recent years. In Germany, for example, nearly half of all fashion shipments are typically returned (Asdecker and Karl, 2022; Cullinane et al., 2017).

Previous studies indicate that product types are a significant factor in determining return rates, with shipments of fashion items being particularly prone to high return rates. Bronson et al. (2023) highlight that a higher proportion of fashion and beauty items from online purchases strongly correlates with increased return rates. Additionally, the study also identifies socio-demographic and behavioral factors such as a higher overall volume of online purchases, access to delivery subscriptions, higher household incomes, and younger consumer age, all of which elevate the probability of returns. A systematic review by Asdecker et al. (2024) reinforces that age and gender significantly influence return behavior in e-commerce. Moreover, a recent online survey involving over 10,000 participants in the United States further emphasizes the dominant role of fashion in driving return rates, revealing that clothing, bags, shoes, other accessories and consumer electronics are the top five most frequently returned product categories in the past 12 months (Statista, 2024). A similar observation is reported by Mishra and Dutta (2024) in a study from India, which identifies significant variables impacting the parcel return probability, such as total order amount, product category, and cash-on-delivery charges, based on data of an e-commerce firm dealing with industrial equipment. Additionally, there exist return volume prediction studies that focus exclusively on forecasting the return volumes of a specific manufacturer. For example, Cui et al. (2020) developed and tested data-driven models that predict return volumes by accounting for retailer, product type, and time-specific factors, based on a dataset of operational and retailer-specific information.

However, the environmental and transportation-related impacts of returns remain largely unexplored, although attention to this issue has increased recently. Rossolov et al. (2024) analyzed how free and paid return delivery options influence mode choice for return trips. Their findings reveal that both male and female customers predominantly prefer using private cars to return their purchased items. Although microscopic freight models are well-suited for analyzing return flows, most commodity-based models, such as SimMobility Freight (Sakai et al., 2020), primarily focus on delivery processes, neglecting drop-off and collection operations. Furthermore, parcel shipments do not get further categorized, even though such distinctions could yield valuable insights for returns. This categorization is only found in empirical studies rather than in modelling approaches, such as the work of Silaen et al. (2024), who examined differences in the type of commodities and delivery methods among online shoppers using econometric and statistical analyses across eight commodity types. In contrast to commodity-based approaches, trip-based freight models, such as the MAG model by Livshits et al. (2017), are limited in addressing this specific case, as they model freight flows at an aggregate level and, if at all, and capture commodity types only through coarse classifications that are insufficient for return-specific analyses. Thus, modelling returns presents a unique challenge, as it occupies an intermediate position between passenger and freight travel demand models, depending on the customer's choice of return channel. For example, returns dropped off at a store or parcel locker generate trip patterns that are more consistent with passenger models, whereas parcels handed directly to a delivery driver contribute to trips typically captured within freight models. While passenger models may implicitly subsume return trips under general purposes such as "errands" or "personal business", they do not explicitly capture parcel drop-offs as a distinct category, limiting their ability to analyze return-related travel behavior. Overall, transportation research lacks a suitable modelling framework to adequately quantify the impact of return shipments.

The approach introduced in this study extends commodity-based freight modelling frameworks by explicitly incorporating return parcels as a complement to parcel delivery. Utilizing logiTopp, an agent-based framework designed for simulating urban courier, express, and parcel (CEP) deliveries to residents and establishments over a one-week period (Barthelmes et al., 2023; Reiffer et al., 2023), we implement a two-step approach. First, the parcel demand generation module for agents within logiTopp is enhanced by incorporating parcel categories such as fashion and electronics to each generated parcel. To this end, a Multiple Discrete-Continuous Extreme Value (MDCEV) model is used, leveraging data from a German online shopping survey in which respondents provided insights into their ordering patterns across various product categories. Second, we estimate return parcel volumes by linking these parcel categories with their associated return probabilities from the literature.

The research is structured as follows: The next section outlines the data for model estimation and forecasting. The methods section covers the MDCEV model's theoretical foundations and returns volume derivation. The results and discussion section presents the model estimation and application. Finally, the conclusions are given.

2. Data

The data for this study was collected as part of the research by Reiffer et al. (2023) to analyze and model e-commerce behavior. The sample consists of 1,089 respondents from Baden-Wuerttemberg, Germany, and is representative of the population in terms of age, gender, income, and city size of one's place of residence. In addition to single-choice questions about e-commerce behavior, socio-demographic information such as age, gender, household income, employment status, and household size was gathered. Although our study focuses exclusively on online shoppers due to their role in generating return parcels, non-online shoppers are included in Table 1 to provide a more comprehensive view of the sociodemographic characteristics.

Table 1: Sample characteristics differentiated by online shopping behavior

	Full sample (N = 1,089)	**Online shopper (n = 1,044)**	**Non-online shopper (n = 45)**
Gender			
female	48.0 %	47.0 %	40.0 %
Age			
18 – 29 years	15.6 %	15.8 %	8.9 %
30 – 49 years	31.6 %	32.4 %	13.3 %
50 – 69 years	44.4 %	44.0 %	55.6 %
> 70 years	8.4 %	7.8 %	22.2 %
Net household income			
< 2,000 €	31.2 %	30.8 %	42.2 %
2,000 € – 3,000 €	29.2 %	29.3 %	28.9 %
3,000 € – 4,000 €	21.5 %	21.5 %	15.6 %
4,000 € – 5,000 €	10.3 %	10.5 %	4.4 %
> 5,000 €	7.8 %	7.9 %	8.9 %
Car ownership			
yes	72.5 %	72.9 %	64.4 %
Child(-ren) in household			
yes	27.4 %	28.2 %	20.0 %
City size			
< 20,000 inhabitants	39.1 %	39.0 %	42.2 %
20,000 – 99,999 inhabitants	27.6 %	28.0 %	20.0 %
100,000 – 499,999 inhabitants	15.6 %	15.4 %	17.8 %
> 500,000 inhabitants	17.7 %	17.6 %	20.0 %
Online shopping frequency			
> 1 purchase/week	15.9 %	16.6 %	-
> 1 purchase/month	44.9 %	46.8 %	-
> 1 purchase/year	35.1 %	36.6 %	-
< 1 purchase/year	4.1 %	-	100.0 %

The dataset specifically provides detailed e-commerce purchasing behavior across product categories, with each respondent indicating the percentage share of each category in their total online orders. Table 2 shows the selection and consumption rates: the selection rate reflects the proportion of respondents shopping in a category, while the consumption rate indicates the average share of that category in total orders, both for all respondents (total) and those who make purchases in the category (only selected).

Table 2: Distribution of e-commerce demand by category

Category	Selection rate	Consumption rate	
		Total	Only selected
fashion	79.46 %	25.83 %	32.50 %
electronics	70.35 %	15.98 %	22.72 %
furniture	41.73 %	5.22 %	12.52 %
household	48.23 %	6.49 %	13.46 %
books	51.86 %	11.05 %	21.31 %
hobby	49.07 %	8.31 %	16.94 %
groceries	30.95 %	7.87 %	25.41 %
health and beauty	46.65 %	7.54 %	16.17 %
jewelry	19.89 %	1.82 %	9.17 %
do-it-yourself (DIY)	27.97 %	3.49 %	12.48 %
others	28.07 %	6.38 %	22.74 %

The data reveals that fashion (including shoes) is the most popular e-commerce category, with a selection rate of 79.46%, followed by electronics at 70.35%. Both categories show above-average consumption rates. Books, hobby items, and household goods also show high selection rates of around 50 %, with consumption rates similarly exceeding the average share. While the group of online grocery shoppers is relatively small, they account for a significant portion of consumption, indicating frequent purchasing behavior. Jewelry and DIY products have comparatively lower selection and consumption rates, suggesting a more specialized demand in these categories. Reiffer et al. (2023) used this survey data, supplemented by information from the national household travel survey provided by infas et al. (2018), to develop three models within the logiTopp framework. This framework is a logistical extension of mobiTopp, an agent-based travel demand model applied over a period of one week, which is a distinctive feature of the approach (Mallig et al., 2013). The dataset underlying the simulation is representative of the population composition in the urban area of Karlsruhe, Germany. The models simulate e-commerce participation, the number of parcels ordered, and the choice of delivery locations (home, workplace, or parcel locker). The output of the models, particularly the number of parcels ordered, is modeled using Poisson regression, with independent variables such as age, job status, and the frequency of leisure activities. The resulting parcel data per agent forms the basis for estimating return volumes by assigning product categories to all parcels.

3. Method

This research aims to model the distribution of parcel demand across various product categories in order to estimate the occurrence of returns. Since the survey data is limited to household demand, we restrict the model's application to household parcel demand, excluding shipments to business recipients. For each agent in the simulation, the model determines selection probabilities for product categories and the proportions of each category relative to the agent's overall parcel demand. This decision-making process involves choosing from a set of discrete alternatives (i.e., product categories) while simultaneously deciding on a continuous quantity for each selected category. To capture this discrete-continuous nature of the decision, the MDCEV model is employed based on the dataset presented earlier (see Table 2). Originally proposed by Bhat (2005) for modelling time-use decisions, the MDCEV model is particularly suited for situations where agents allocate resources (such as time, money, or, in this case, parcel quantities) across multiple alternatives. It has been applied in various other fields (e.g., Wörle et al. (2025)). The developed model addresses the utility maximization problem under a budget constraint, as formulated by Palma et al. (2021):

$$max_{x_m} \sum_{m=1}^{M} \frac{\gamma_m}{\alpha} \psi_m \left(\left(\frac{x_m}{\gamma^m} + 1 \right)^{\alpha} - 1 \right) \quad (1)$$

$$s.t. \sum_{m=1}^{M} x_m = B \quad (2)$$

where x_m is the amount of alternative m consumed, γ^m is the satiation parameter for each alternative m, ψ_m is the marginal baseline utility of each alternative m, α is the further satiation component and B is the budget. The parameters γ^m and ψ_m are linear combinations of attributes, linking utility and satiation to the decision-maker and their alternatives. Higher values indicate lower satiation and greater utility. While α adds a second satiation component, its estimation alongside γ^m often leads to identification issues (Bhat, 2008). This study uses the γ^m-profile, with a single α across all alternatives. For implementation, the Apollo R package (Hess and Palma, 2019) is used. The model specification includes two key components: 1) category-specific baseline utilities, reflecting the inherent attractiveness of each product category, and 2) category-specific satiation parameters, which control the rate of diminishing marginal utilities for ordering larger quantities of a product category.

To incorporate return dynamics, we first classify each parcel based on logiTopp's output, using a stochastic assignment that accounts for both discrete and continuous decision levels. We then apply category-specific return rates from Asdecker and Karl (2022), aligning these rates with the product categories identified in the survey data. For each parcel, a probabilistic decision is made to determine whether it will be returned based on the assigned category's return rate. Table 3 presents the assigned return rates.

Table 3: Assignment of return rates based on Asdecker and Karl (2022)

Cluster	Original description	Assigned categories	Return rate
entertainment	PC & accessories, books, games, CDs, electronics	electronics, books	5.38 %
fashion	clothing & accessories, shoes	fashion, jewelry	46.46 %
interior	furniture, lamps, home textiles, household	furniture, household	5.45 %
leisure	DIY, flowers, toys, hobby, car accessories	health and beauty, DIY, and hobby	10.30 %
others	anything else	groceries, others	5.66 %

4. Results and discussion

Initially, a baseline model containing only alternative-specific constants (ASCs) was estimated to establish a reference for model estimation. The extended model incorporates socio-demographic parameters and was evaluated using a likelihood ratio (LR) test. The null hypothesis was rejected, indicating a significant improvement in the model fit (LR test: $\chi^2 = 242.42$, $df = 24$, $p < 0.001$). The findings reveal that gender, age, income, city size, household composition (e.g., presence of children), car ownership, and frequency of online shopping significantly influence the discrete-continuous selection of the parcel categories.

The estimation results, with the fashion category as the reference, confirm the distribution of the input data in terms of the ASC specification, particularly with the higher baseline utility for electronics and fashion. Additionally, the lower satiation for groceries and others indicates that, when these categories are selected, they are consumed more intensively. The results also indicate notable gender-based differences in preferences for online product categories. Women are less likely to make online purchases from categories such as electronics, DIY, groceries, household, hobbies, and furniture, but exhibit a stronger preference for fashion, health and beauty, books, and jewelry. Additionally, households with children are less inclined to purchase groceries through online channels. This can likely be attributed to the complexity and larger scale typically involved in grocery purchases for such households. Car owners are more likely to purchase DIY products and jewelry online but less likely to buy books. Other factors influencing online purchasing behavior are age, income, and the size of the city of residence, although these correlations are generally weaker than those mentioned earlier. Specifically, older consumers are less likely than younger ones to purchase jewelry and furniture online but are more inclined to buy books and health and beauty items.

Higher income levels are associated with an increased likelihood of purchasing books and hobby-related items online. Consumers who frequently engage in online shopping are generally more likely to purchase household, health and beauty, and jewelry categories, thus extending beyond occasional or necessity-driven online purchases. Lastly, individuals living in urban areas tend to purchase household goods and books online more frequently than those living in rural areas. The results of the model estimation are presented in Table 4.

Table 4: Estimation results of MDCEV

Parameters		Estimate	Parameters		Estimate
α		-21.120***		female_electronics	-0.780***
	fashion	8.540***		female_furniture	-0.348***
	electronics	6.328***		female_household	-0.402***
	furniture	5.587***		female_hobby	-0.371***
	household	5.880***		female_groceries	-0.438***
	books	8.584***		female_DIY	-0.722***
γ	hobby	7.040***		female_others	-0.578***
	groceries	14.640***		income_books	0.046***
	health and beauty	6.940***		income_hobby	0.046***
	jewelry	4.602***		city_size_household	0.060*
	DIY	6.911***		city_size_books	0.064*
	others	13.093***		age_jewelery	-0.017***
	electronics	0.160**	δ	age_furniture	-0.020***
	household	-0.841***		age_books	0.010***
	books	-1.518***		age_hobby	-0.008**
	hobby	-0.633***		age_health_and_beauty	0.010***
δ	groceries	-1.465***		childinhousehold_groceries	-0.281**
	health and beauty	-1.484***		childinhousehold_others	0.270**
	jewelry	-1.561***		car_ownership_books	-0.277***
	DIY	-1.706***		car_ownership_jewelry	0.316**
	others	-1.432***		car_ownership_DIY	0.348***
	-	-		onl_shop_freq_household	0.305***
	-	-		onl_shop_freq_healthbeauty	0.275***
	-	-		onl_shop_freq_jewelry	0.364***
	-	-		onl_shop_freq_DIY	0.440***

*LL = -22,398.15; BIC = 45,117.98; Number of parameters = 46; Level of significance: *** = 1 %, ** = 5 %, * = 10 %;* $\alpha = 1/(1+\exp(-\alpha_{base}))$

The estimated model was applied to the logiTopp simulation output based on the urban inhabitants of Karlsruhe, Germany. The dataset includes 141,666 parcels delivered to 121,598 agents who participate in online shopping (out of a total of 304,886 agents) within one week. The forecasting results offer insights into the distribution of parcel demand across product clusters and the corresponding return volumes, which are determined based on the assigned return rates (see Table 3) and a subsequent random draw that decides whether a parcel is returned.

The distributions reflect that fashion (clothing and jewelry) exhibits the highest return volume driven, by its higher consumption and return rate. This is followed by leisure (hobby, DIY, health and beauty), which also shows notable return volumes. In contrast, interior (furniture and household goods) and entertainment (electronics and books) have significantly lower return rates, as these items are less affected by fit uncertainty or involve higher return barriers. In total, we obtain 27,492 return parcels for the city of Karlsruhe, which means that approximately 19.4 % of all delivered parcels are returned. Fig. 1 illustrates these results.

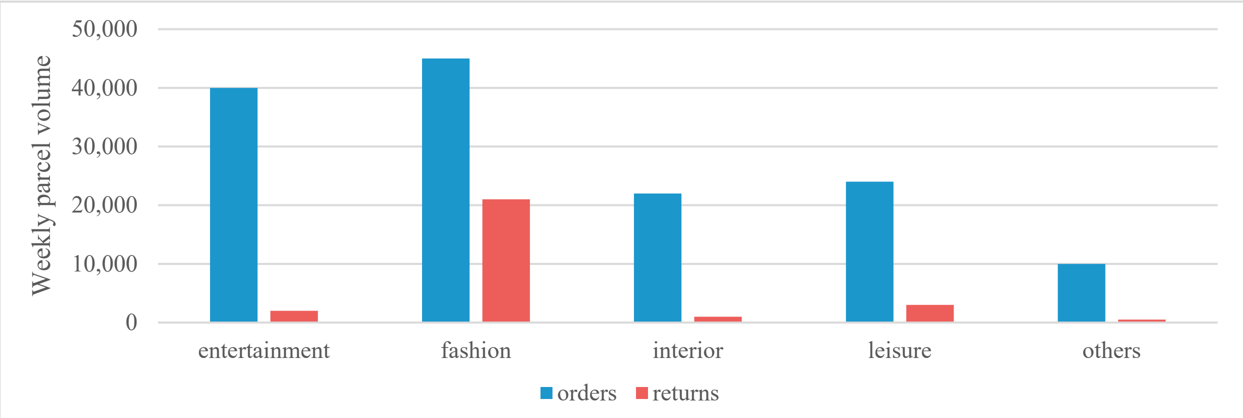

Fig. 1: Weekly parcel order and return volumes by clusters

5. Conclusion

This research is motivated by the growing need to integrate return parcels into urban freight models to enable a more comprehensive assessment of transportation and environmental impacts. The paper addresses this challenge by introducing an MDCEV model, which categorizes parcels based on the product type. The empirical correlation between product types and return probabilities highlights the significance of this classification. The results reveal that various sociodemographic factors, such as gender, age, income, city size, household composition (e.g., the presence of children), car ownership, and online shopping frequency, significantly influence the discrete-continuous selection of product categories by online shoppers. The estimated model is applied to the logiTopp simulation output to categorize ordered parcels and derive return volumes. The findings estimate approximately 27,500 return parcels per week, implying that about one in every five parcels is returned.

Despite these insights, several limitations should be acknowledged. Firstly, no additional dataset was available for independent model calibration or validation, which may impact the robustness and generalizability of the findings. Secondly, the underlying data may no longer fully reflect current consumer behavior, especially considering recent shifts in online shopping patterns, such as the increased relevance of non-fashion product categories. Thirdly, the behavioral results obtained in this study may be context-specific and not easily transferable to other countries, as ordering and return practices can vary significantly across regional and cultural settings.

Future research should focus on collecting additional data on attributes that influence return probabilities and integrating them into the existing framework. Additionally, modelling return drop-off trips by identifying factors that affect drop-off choices and mode selection represents the next step towards a comprehensive assessment of the impacts of return parcels on urban transportation systems. Building on this framework, the approach facilitates the evaluation of both operational efficiency (e.g., vehicle capacity utilization) and user accessibility (e.g., ease of access to return locations) across different return options. This enables the assessment of solutions such as parcel lockers, autonomous delivery and collection systems (e.g., delivery robots), or the collection of return parcels by delivery personnel during regular tours. Extending this framework, future studies could link the proposed model to empty trip models (Holguín-Veras and Thorson, 2003) to investigate whether representing return flows and integrating corresponding pick-up stops into carrier tours can reduce empty trips and achieve overall transport efficiency gains. Beyond return flows, the proposed parcel categorization model can also enhance the representation of parcel sizes, thereby improving the accuracy and applicability of existing urban freight models.

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