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Managing household freight: The impact of online shopping on residential freight trips

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ABSTRACT

Freight transport management and planning traditionally relies on freight transport models. However, e-commerce has changed the way freight is transported and requires a paradigm shift in such models. In contrast to conventional purchases in physical outlets, there is a spatial and temporal disconnection between the purchase and the reception of goods bought online. While traditionally the shopper brings home the purchases, the courier, express and parcel (CEP) sector must bridge this leg for the online retail channel by delivering the parcel to the household. These new type of freight trips have been ignored in the literature on freight modeling. Given the increasing number of urban freight trips destined for households, this omission implies significant errors when demonstrating transport impacts, identifying potential innovations, or assessing policy initiatives with these models. Therefore, we develop a framework that demonstrates how households' online consumption translates into freight trips. Three key factors in this framework seem to determine the magnitude of freight traffic originated by household's online shopping: (i) consumer shopping behavior, (ii) the supplier network and distribution system designed by the online store, and (iii) the fragmentation of the CEP market and the density of the delivery network. The identification of these three key factors provides a framework for policy action to mitigate the impact of household freight.

Credit author statement

Conceptualization: Joris Beckers, Ivan Cardenas, Ivan Sanchez Methodology: Joris Beckers Formal analysis: Joris Beckers, Ivan Cardenas, Ivan Sanchez Data curation Ivan Cardenas Writing – Original Draft Joris Beckers Writing – Review & Editing Joris Beckers Visualization Joris Beckers.

1. Introduction

The rise of the on-demand economy is changing freight traffic patterns. Digital innovations have enabled the uberization of the service economy, which is centered around the immediate fulfillment of consumer demand for goods and services (Jaconi, 2014). This evolution, however, is carried by disruptions within the logistics sector (Dablanc et al., 2017; Perboli et al., 2021). The exponent of this evolution, business-to-consumer (B2C) e-commerce, for example, poses new constraints on freight transport now that online shoppers have gained the power to demand ever faster, cheaper, and more convenient deliveries that, ideally, are traceable from the warehouse to their doorstep. Compared to traditional retail freight trips, the on-demand nature of online orders results in a fragmentation of trips in time and space due to B2C orders consisting of a small number of items and the severe competition within the courier, express and parcel (CEP) sector. These effects reduce the potential degree of consolidation in contemporary commercial logistics, resulting in a surge in B2C freight trips. Preliminary estimates indicate that e-commerce could lead to three to five deliveries per 100 inhabitants per day (Allen et al., 2017; Dablanc, 2019; Gadrat et al., 2016).

Clearly, the changing geography of freight flows due to the popularity of the online shopping channel results in a greater impact of logistics activities (Cárdenas et al., 2017; Lin et al., 2016; Melo and Baptista, 2017). Residential areas now host a procession of parcel carriers during the day, while small corner shops without parking at the front door are turned into collection-and-delivery points (CDPs) (Simoni et al., 2020). And while the impacts have raised logistics on policy

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agendas, the attention paid to freight in Sustainable Urban Mobility Plans (SUMP), let alone the presence of their logistics equivalents, remains remarkably low (Fossheim and Andersen, 2017; Sanchez-Diaz and Browne, 2018). Nonetheless, mobility measures, such as the installation of dedicated freight parking spots or access restriction schemes, cannot ignore the demand for household freight trips.

Traditionally, the demonstration of transport impacts, the identification of potential innovations and the assessment of policy initiatives are carried out using models representing logistics and transport systems (Ortúzar and Willumsen, 2011). Such freight models consist of two components: freight generation (FG), describing the demand for goods in a study area, and freight trip generation (FTG), describing the transport flows that are used to supply this demand (Puente-Mejia et al., 2020; Sánchez-Díaz, 2017). Until recently, however, modeling efforts have focused primarily on establishments (i.e., business-to-business or B2B) and have largely neglected the freight trips generated by individual households. Consequently, the quantity, quality, and location of urban freight trips originating from household consumption patterns remain unclear. Although Jaller and Pahwa (2020) and Buldeo Rai et al. (2019) recently modeled household-generated freight in their attempts to quantify the environmental impacts of e-commerce, a thorough understanding of the link between online purchases and freight trips was beyond the scope of their more holistic analyses, which did include simulating passenger mobility.

Thus, the impact of consumer behavior on urban freight remains strongly based on assumptions. This calls into question the validity of existing modeling efforts and prevents effective policy making on this topic. The purpose of this paper is therefor to quantify how households' online consumption translates into freight trips. In order to achieve this, we propose a set of models to quantify household FG as a function of socioeconomic characteristics. In doing so, this paper contributes to the quantification of household FG based on household surveys and thus realigns the FTG literature with the recent developments in the logistics sector. This increases the application of such models for infrastructure planning and logistics-related policy measures. In the next section, we first introduce the different components of the B2C freight system. In the Methodology section, we combine these components into a framework suitable for analyzing freight transport demand in the age of e-commerce. This framework is applied to a case study in the fourth section. Finally, we reflect on the value of its application in the concluding section.

2. Literature

The emergence of the internet opened up a new retail channel for consumers: apps and websites now provide new touchpoints connecting retailers and consumers. With pure online players such as Amazon as early adopters, retail chains swiftly followed in the adoption of online offerings, pursuing a multichannel strategy (Reynolds, 2002). Profound integration between channels over time allowed for omnichannel shopping, with the possibility to move between physical and online retail touchpoints, and it reshaped the consumers' perceived shopping value (Huré et al., 2017). As different channels are linked to different steps in the consumer's path to purchase, consumers now expect a consistent offer and a seamless transition from one channel to another (Melero et al., 2016). These new requirements are reshaping the urban landscape in terms of infrastructures and transport flows, as conventional shopping trips are now complemented with a new, direct connection between the distributor and the consumer (see Fig. 1) (Hagberg et al., 2016).

This evolution puts pressure on conventional retail and logistics processes. While in the conventional setup (i.e., physical shopping) the shopper receives the goods directly after purchase, online shopping results in a spatial and temporal disconnection between the purchase and the reception (Gadrat et al., 2016). These goods are delivered at home, at work, or in a CDP hours or days after the moment of purchase. Gadrat et al. (2016) refer to these goods as 'deferred purchases and receptions', emphasizing that the delivery process is put off until a later time. Deferred deliveries constitute a paradigm shift in the way we approach urban transport related to commercial activities (see Fig. 1). In the conventional setup, these commercial trips are considered in two separate classes: (i) inter-establishment movements where a freight vehicle moves the goods into the city from a depot to a retail business and (ii) end-consumer (i.e., household) movements where the final consumer moves to the retail point to acquire the goods (Gonzalez-Feliu and Peris-Pla, 2017). The former movements are viewed as freight transport and the latter as passenger transport. Yet, in the e-commerce setup, the last part of the retail chain has now become a mix of freight and passenger transport (Beckers, 2019).

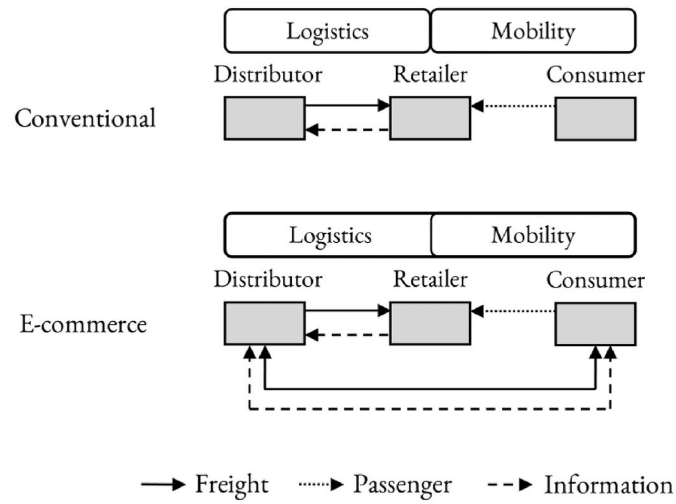


Fig. 1. The evolution of transport flows associated to the retail sector. Adapted from (Dicken, 2015).

This observation demands a reconsideration of the relationship between urban transport and commercial activities. Transport sciences traditionally use modeling techniques to explain and predictgain insights in the use of transport in specific situations. As more robust data and calculation capacity became available, transport models have evolved to higher levels of disaggregation (Ortúzar and Willumsen, 2011). Since transport is a derived demand from other activities, disaggregated models try to capture the decision-making process of transport agents to predict trips. As such, passenger transport is mostly studied using activity-based models (e.g., Adler and Ben-Akiva, 1976; Bhat and Steed, 2002).

In the case of freight, the variety of stakeholders in a complex environment poses additional challenges. In the conventional urban commercial context, FTG models consider three main agents when modeling the number of freight trips that take place (Russo and Comi, 2010). The *shipper* decides the origin of the shipments, the degree of bundling (i.e., how many items, parcels, or pallets per receiver) and the delivery consolidation (i.e., how many orders per shipment). The *receiver* is the shop owner who decides the destination, the specific items and types of products, and the frequency of the shipments. The *carrier* transports the shipments from the shipper to the receiver, deciding on the vehicles used to transport the shipments and how those shipments are divided into trips. Additional stakeholders are *public authorities,* whose prime concern is a livable city, and *households,* who influence the receiver's demand. As mentioned, a household's shopping trip to acquire these goods is normally not considered part of the freight chain.

The new reality depicted in Fig. 1 implies changes in the roles of and interactions among freight agents for the deferred deliveries. First, for these parcels originating from online purchases by consumers, the number of carrier responsibilities increases. As the integration of logistics processes has become more common, an increasing share of fulfillment activities has shifted from the shipper to the carrier offering third-party logistics services (Mortensen and Lemoine, 2008). This is largely due to the decrease in basket size and the fragmentation of basket content (Van Loon et al., 2015). Online non-food baskets typically consist of few but diverse items. The small quantity limits the potential for the retailer to achieve economies of scale, and the diversity implies that items in one order might be stored in different places. As shippers see a fragmentation of their shipments, carriers now engage more in consolidation, thus affecting the origin of freight movements.

However, the most significant change is taking place at the other end of the freight chain. There, the household is being promoted to a more important freight actor with a direct demand for freight, deciding on frequency, destination, size of shipments, and so on. E-commerce has made the household a core actor in the supply chain (Kiba-Janiak et al., 2021; Marcucci et al., 2021), which has led some authors to coin the term *consumer logistics* (Beckers, 2019; Rimmer and Kam, 2018). Yet, in the transport sciences literature, freight transport remains restricted to B2B flows (Alho et al., 2018; Sánchez-Díaz, 2017), usually ignoring their B2C counterparts. Since a correct understanding of freight agents' interactions and behavior is paramount for a contemporary assessment of urban freight transport (Marcucci and Gatta, 2014; Sánchez-Díaz, 2017), this paper attempts to identify how consumers influence the way freight related to online purchases moves in the city.

Household demand for freight originates from consumer purchasing behavior. The growing body of literature on consumer behavior has thus paved the way for our proposed effort. Significant relationships between the socioeconomic variables age, income, and gender and the amount of online ordering have been found frequently, but these seem to be context-specific (Clarke et al., 2015; Farag et al., 2006; Mortimer et al., 2016, see Table 1). These socioeconomic findings are often linked to the innovation diffusion theory, which predicts higher e-commerce usage and more deliveries among more technology-savvy households (W. P. Anderson, Chatterjee and Lakshmanan, 2003). Other scholars have proven the prevalence of the efficiency theory, finding higher online purchasing frequencies in more remote areas due to lower retail accessibility (Kirby-Hawkins et al., 2019; Motte-baumvol et al., 2017), although this effect has also been disputed (Lee et al., 2015). Recent studies have applied similar models to delivery preferences, for example by linking socioeconomic and product characteristics to the use of CDPs.

Table 1
Overview of the most recurrent predictors and dependent variables concerning online consumers.

Predictor	Dependent variable	
	Purchase frequency	Delivery location
Age	4, 5, 6, 7, 11, 13, 14, 16, 17, 18, 20, 21, 22	9, 15
Car ownership	4, 21	15
Credit card ownership	6, 8, 21	
Education	1, 6, 17, 18, 22	
Gender	1, 4, 5, 6, 7, 8, 11, 13, 16, 19, 20, 21	9
Household size	4, 6, 11, 16, 22,	
Income	1, 4, 5, 6, 7, 11, 14, 17, 18, 19	9, 15
Internet propensity	4, 5, 6, 7, 8, 16, 19, 21	
Product type		14, 15
Sustainability		2, 10
Urbanization rate/ Accessibility	3, 8, 12, 16, 17, 18, 19, 20	9, 10, 15

Note: [1](Beckers et al., 2018); [2](Buldeo Rai et al., 2021) [3](Cao et al., 2013); [4](Clarke et al., 2015); [5](Crocco et al., 2013); [6](Dominici et al., 2021) [7](Farag et al., 2006a); [8](Farag et al., 2006b); [9](Hood et al., 2020); [10](Iannaccone et al., 2021) [11](Jaller and Pahwa, 2020); [12](Kirby-Hawkins et al., 2019); [13](Mortimer et al., 2016); [14](Motte-baumvol et al., 2017); [15](Pernot, 2020); [16](Ren and Kwan, 2009); [17](Shao et al., 2022); [18](Shi et al., 2021); [19](Song, 2021);[20](Vrechopoulos et al., 2001); [21](Weltevreden, 2007); [22](Zhou and Wang, 2014)

They found that gender, age, income, and product perishability also appear to influence the probability of using alternatives for home delivery (Hood et al., 2020; Pernot, 2020).

Recently, attempts have been made to study B2C freight trips based on receiver characteristics, as depicted in Table 1. Yet the household FG models are still in their infancy, especially when compared to the larger B2B FG literature. Jaller and Pahwa (2020), for example, linked shopping preferences to household freight trips, but they did not address the complexity of different delivery location alternatives for goods purchased online. Buldeo Rai et al. (2019) did include different delivery options but modeled this for a set of six shopper archetypes using a case study approach. Although both attempts are in line with the suggestion of Dias et al. (2020), who claim that travel forecasting models should consider freight and passenger trips to ensure a holistic perspective on the topic, this holistic perspective implies a large set of assumptions. In contrast, Wang and Zhou (2015) proposed a model to estimate household freight demand in the US. Their model links household characteristics to the frequency of home deliveries. However, demand frequency is only one of the freight dimensions that households can influence, as elaborated in the next section. These attempts to model household FTG are noteworthy and demonstrate the timeliness of the topic, yet in our opinion they fall short in providing the comprehensive framework necessary for the disaggregated analysis of household FTG.

Acknowledging the role of socioeconomic characteristics is key to account for the spatial variations of household FTG in urban areas. Moreover, the increased use of alternative locations (e.g., CDPs, deliveries at work, etc.) creates an additional mismatch in the estimations. In this paper, we took up the challenge to provide a more comprehensive framework for the inclusion of households in freight models. We distinguished our work from previous studies by explicitly establishing the consumer as an independent freight agent. More specifically, the paper focuses on how the socioeconomic characteristics of consumers influence the generation of freight demand. The demand considered here consists of two parts. First, we studied the profile of online consumers and their shopping frequency. In particular, we examined whether previous findings (Table 1) hold. Next, we assessed the delivery location of these orders. Finally, we tried to link orders to freight trips, and hence we modeled the household FTG in our study area. The transformation of online orders to physical parcels and trips will require some assumptions as it depends on the logistics and transport decision-making processes by carriers and shippers. This point will be elaborated below.

3. Methodology

Fundamental to the construction of any freight model is the identification of the key actors whose interactions transform an online purchase into a residential freight trip. As stated in the previous section, these key actors are (i) consumers, who play the role of buyers and receivers of goods, (ii) retailers and wholesalers, who play the role of shippers and buyers of transport services, and (iii) transport operators, who play the role of carriers. The interactions between these actors are shown in Fig. 2.

As shown in Fig. 2, consumer behavior generates freight, while the interactions between the shipper and carrier eventually lead to freight trips. First, household FG is a result of online shopping behavior. In particular, consumers now directly influence the different FG dimensions: frequency of orders, the number of items purchased per order, the type of goods and the delivery location (Sánchez-Díaz et al., 2016). After deciding on the freight to be transported, the shipper and carrier decide on the generation of a freight trip to fulfill the demand, as is the case in traditional freight models. The shipper, meaning a wholesaler or online store, makes the logistics decisions. The carrier, which is a different transport operator if transport services are outsourced by the retailer, makes the transport decisions. Logistics decisions include order fulfillment, delivery consolidation and the origin of the freight trip.

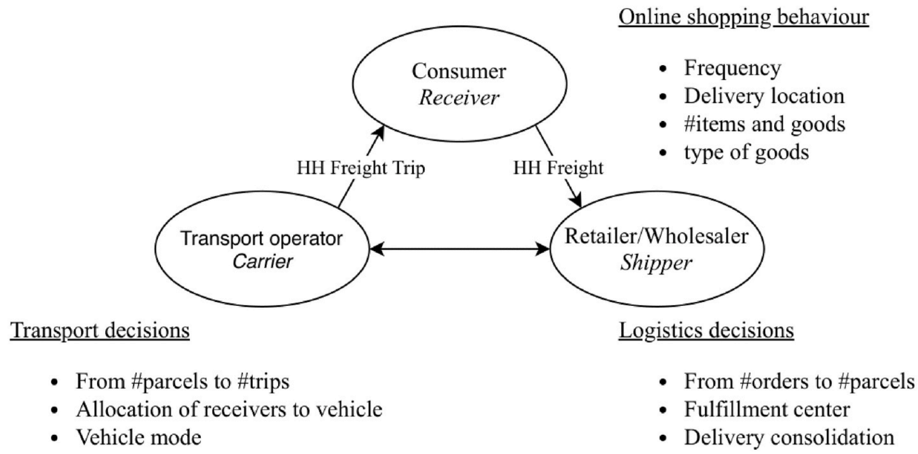


Fig. 2. Relationship between online shopping behavior, household FG and FTG.

Transport decisions allocate destinations to routes and lead to vehicle selection. The interactions between those two actors lead to the occurrence of freight trips. An important note, as mentioned in the previous section, is that the line between transport and logistics decisions is blurred in the B2C context, as some third-party logistics providers (3 PL) manage both logistics and transport. This is especially the case for smaller retailers.

This paper attempts to quantify how many freight trips are generated by online shopping behavior. To achieve this, we first used discrete choice models to estimate the number of online orders in a spatial unit, which represents the demand for freight. The number of online orders was modeled using two FG dimensions: shopping frequency and delivery location. The former FG dimension is the key component and the most studied element in the model. The frequency at which people shop online is traditionally presented as an ordinal variable with a set of response levels. An ordinal logit regression was applied to assess the relationship between the predictors ($x_1, x_2 \dots x_n$) and the frequency. The ordinal regression calculates the log odds of $P(frequency \leq i)$, the cumulative probability of the frequency being level i at most, as follows:

$$ln\left(\frac{P(frequency \leq i)}{P(frequency > i)}\right) = \beta_0 + \beta_1 x_1 + \dots \beta_n x_n \quad (1)$$

with β_n the regression coefficient to be estimated for predictor x_n.

The second FG dimension in the B2C context is the location where parcels are delivered (e.g., at home or at a pickup point). Again, in the limited number of attempts, the delivery location was modeled based on survey data (e.g., Hood et al., 2020; Pernot, 2020). In addition to the influence of socioeconomic characteristics, product type also seems to be an important predictor for this dimension (cfr. Table 1). The proposed household FG model assesses the combined impact of socioeconomic variables attributed to the respondents and the types of goods bought on the preferred delivery location. Modeling the combined impact of socioeconomic variables and product characteristics on the decision between a set of distinct delivery locations is possible using a multinomial logistic regression. In essence, this technique is similar to the ordinal logistic regression applied in step 1, but with a categorical rather than an ordinal dependent variable. The log odds of each delivery location j were compared to a reference category (home deliveries) as follows:

$$ln\left(\frac{P(delivery\ location = j)}{P(home\ delivery)}\right) = \beta_{j0} + \beta_{j11} x_{11} + \dots \beta_{jmh} x_{mh} \quad (2)$$

with β_{jmh} the regression coefficient of delivery location j to be estimated for level h of predictor x_m.

The combination of the two models allows for a detailed view of consumer delivery preferences. While this is certainly valuable for various stakeholders, especially the shippers, it is only the first step in quantifying household FTG. Our overall objective requires predictor values to be available at a detailed spatial unit. This is often the case for socioeconomic variables through census data, but rarely is it the case for other categories of variables. The strength of census data lies in their accessibility, geographical detail, and spatial coverage, which explains their wide use in geographical and planning studies (Bracken and Martin, 1989; Shultz and King, 2001; Subramanian et al., 2001). Given these advantages, we developed a forecasting model in addition to the explanatory model, containing only predictors typically captured in censuses.

In the final step of the analysis, the generated freight demand (in orders per spatial unit, see Fig. 3) was converted into freight trips (in trips per spatial unit). This step was necessary to evaluate the freight transport impacts derived from household demand. To estimate the number of trips, we resorted to the microsimulation of e-commerce trips proposed by Cárdenas et al. (2019). This model uses the generated freight demand of the most detailed spatial unit possible and simulates delivery tours using the Clarke and Wright heuristic procedure (Clarke

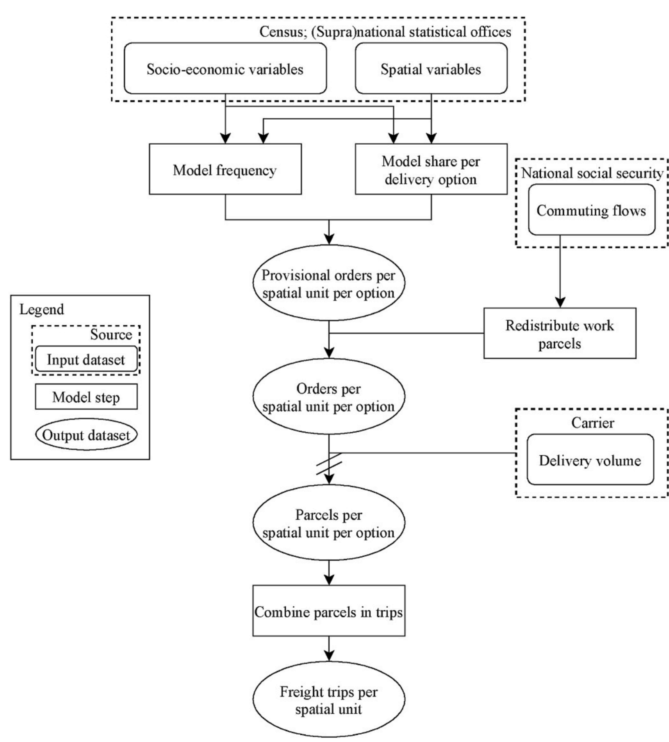


Fig. 3. Flowchart of the generic forecasting mode.

and Wright, 1964). This simulation takes into consideration various characteristics of the transport supply, such as the size of the different carriers, the origin of the trips, the vehicle capacity, and the characteristics of the road network.

The flow of the analytical part of this paper is summarized in Fig. 3. As input for the two statistical models, one for each FG dimension, we used the socioeconomic data coming from census data and spatial variables – the morphology in this case – derived from other sources. The modeled order frequency results were combined with the modeled probability for the different delivery options, resulting in a provisional number of parcels for each delivery option in each spatial unit. The number of workplace deliveries for a given spatial unit was then redistributed over the study area using commuting patterns. For example, if X % of the residents in spatial unit A work in spatial unit B, X% of the number of workplace deliveries of unit A are subtracted from the total number of parcels destined for spatial unit A and added up to the amount of home deliveries for unit B. Such patterns can be found in data from the Social Security Administration (i.e., when linking residential and work addresses for individuals) or through traffic analysis zone (TAZ) counts. Finally, this yielded an estimate of the number of online orders destined for each spatial unit. The conversion of the order frequency into parcels depends on decisions regarding purchasing (i.e., the number of items per order), logistics (i.e., the number of shipments and parcels per order) and transport (i.e., the number of shipments that can be combined in one stop). This process, which effectively bridges the gap between retail and logistics decision-making, is beyond the scope of this paper, but we consider it a key issue to address going forward. To avoid relying on a series of assumptions for these different components, we illustrate the final steps through a case study, for which parcel data were available through the R!sult project, a two-year project funded by the Flemish institute for logistics (VIL).[1]

In the following section, we present the application of the forecasting model in the case of Belgium. We started from the findings of Beckers et al. (2018), who only constructed the first model of Fig. 3. Next, the delivery location was modeled and refined with commuting data to predict actual freight demand at a highly detailed level. Census data of 2011 and the annual publication of various tax statistics at the same geographical level were used, as well as commuting patterns from social security data (Statistics Belgium, 2014, 2018; Verhetsel et al., 2018). Finally, the freight demand was translated into a total number of occurring freight trips based on the model proposed by Cárdenas et al. (2019).

4. Application of the model in a case study

The forecasting model was applied to the case of Belgium. With a slower adoption compared to its immediate neighbors, the share of the Belgian population familiar with online shopping is similar to the European average (75% vs 73%; Eurostat, 2019). This is partly due to Belgian's nebular structure, where 83% of the population lives in urban or urbanized areas (Dijkstra and Poelman, 2014; Statistics Belgium, 2014). Still, home delivery costs due to e-commerce vary significantly across the country, with an estimated difference of magnitude 10 between the most urban and rural areas (Cárdenas et al., 2017a). Delivery alternatives, such as CDPs, are also widespread. The country scores relatively high compared to other European countries with 6.6 CDPs per 10,000 inhabitants, but the installation of parcel lockers is still in its infancy (Beckers, 2019).

The model was applied at the statistical sector level. This is the most detailed spatial unit available, with an average area of 1.54 km[2] (Jamagne, 2001). In the statistical analysis, we first explored the relationships between a set of socioeconomic predictors and the FG dimension. Next, the statistically significant predictors were retained to build the FG prediction model. The significance of the relationships was tested based on household surveys originating from the "E-commerce in Belgium 2016) questionnaire" commanded by the Belgian retail federation Comeos to identify the online shopper. This questionnaire surveyed 1,600 respondents about their online shopping frequency and preferred delivery location, while also surveying their socioeconomic characteristics (*income*, *gender*, *age*, *education*, *number* of *children*, *zip code*). Beckers et al. (2018) used the same dataset to detect the online shopping propensity in Belgium from a regional economics perspective. This paper builds on that work but applies a transport engineering point of view. A detailed description of the variable levels can be found in that paper.

Finally, results were validated with data from parcel carriers. These data were obtained at street level for a period of three months. For the purpose of this paper, we aggregated the data within the spatial unit and calculated the daily average.

4.1. From socioeconomics and product characteristics to online orders (explanatory)

Bootstrapping was used to identify the relevant predictors of online shopping frequency. This is a resampling method where we ran the analysis on a random subset of observations in order to infer variance in the model estimations, providing an additional quality control. In this test, we iterated the ordinal logistic regression 1,000 times on a random subset of 80% of the total sample size. Fig. 4 shows the share of iterations for which each predictor has a statistically significant impact on the shopping frequency at the 95% confidence interval. First, the significance of the threshold parameters for the ordinal variable (*Monthly|Weekly; Every 1–3 Months|Monthly; …*) indicates the relevance of the different levels. Second, *education* and *income* show a strong relationship with online shopping frequency. *Family size* and *type of goods* show a very weak relationship, while *age*, *gender,* and *morphology* do not seem to affect online shopping frequency.

Table 2 shows the averages of the model coefficients for the individual variables in the 1,000 iterations. The odds ratio has been included

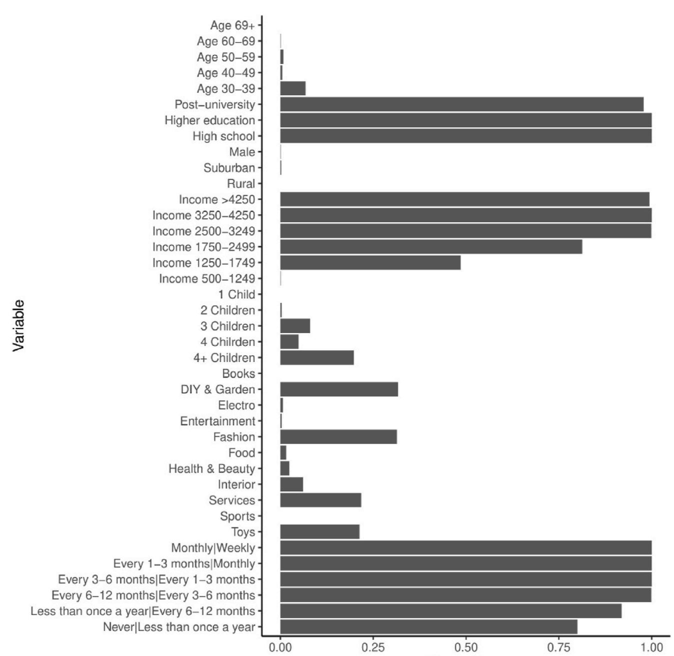


Fig. 4. Percentage of iterations for which the predictor is statistically significant at the 95% confidence interval. The ordinal logit regression was iterated 1,000 times on a random subset of 80%.

[1] https://vil.be/en/project/rsult-responsive-sustainable-urban-logistics/.
[2] https://www.mechelen.be/convenantduurzamelogistiek.

Table 2
Average model coefficients, their variance, and the average odds for the 1,000 iterations of the ordinal logit.

	Coefficient (variance)	Odds
Income 500–1,249	−0.06 (0.034)	0.945
Income 1,250–1,749	0.14 (0.035)	1.150
Income 1,750–2,499	0.19 (0.035)	1.207
Income 2,500–3,249	0.34* (0.038)	1.410
Income 3,250–4,250	0.46* (0.04)	1.586
Income >4,250	0.94* (0.065)	2.548
Gender Male	0.6 (0.003)	1.814
Age 30-39	0.24 (0.007)	1.269
Age 40-49	0.22 (0.006)	1.249
Age 50-59	−0.03 (0.004)	0.968
Age 60-69	−0.1 (0.006)	0.901
Age 70	0.04 (0.232)	1.044
Higher secondary	0.48* (0.005)	1.618
Higher education	0.52* (0.007)	1.674
Post-university	0.35* (0.042)	1.423
1 child	−0.14 (0.007)	0.872
2 children	−0.13 (0.005)	0.880
3 children	0.34 (0.028)	1.403
3+ children	−1.6 (0.079)	0.202
Suburban	−0.1 (0.003)	0.901
Rural	−0.01 (0.004)	0.985
Books	0.87 (0.005)	2.395
DIY_garden	0.44 (0.011)	1.552
Electronics	0.8 (0.005)	2.221
Entertainment	0.37 (0.007)	1.444
Fashion	1.47 (0.004)	4.348
Food	0.56 (0.026)	1.750
Health_beauty	0.7 (0.006)	2.021
Interior	−0.06 (0.012)	0.943
Services	2.16 (0.005)	8.677
Sports	0.5 (0.011)	1.647
Toys	0.37 (0.006)	1.445
Never|Less than once a year	2.00 (0.052)	
Less than once a year|Every 6–12 months	2.25* (0.052)	
Every 6–12 months|Every 3–6 months	3.08* (0.050)	
Every 3–6 months|Every 1–3 months	4.04* (0.053)	
Every 1–3 months|Monthly	5.70* (0.056)	
Monthly|Weekly	8.10* (0.065)	

Note:*$p < 0.05$ in at least 80% of the iterations in Fig. 4.

to enhance readability. In line with previous literature (e.g., Beckers et al., 2018; Graham Clarke et al., 2015; Zhou and Wang, 2014), we found that higher incomes and a higher level of education generally increase the probability of someone shopping online more frequently. For example, for someone with a monthly income in the range of €2, 500-€3,249, the odds of buying online more frequently (i.e., *Every 3 to* 6 months compared to *Every 6 to* 12 months, or *Weekly* compared to *Monthly*) are 1.410 times that of someone who's monthly income is <€500, holding constant all other variables. Similar to what Beckers et al. (2018) and Clarke et al. (2015) found for shopping propensity, age shows a more complex relationship with shopping frequency, with the highest probability for people in their thirties and forties. This is probably related to higher income levels. The higher odds for the oldest age category are due to the limited sample size in this category (note the large variance). Men seem more likely to buy online, which contradicts the findings of Wang and Zhou (2015), who found higher home delivery rates for women, and Jaller and Pahwa (2020) who also found women more easily switch to the online channel. The relationship between family size and shopping frequency is not straightforward. Both suburban and rural residents are less likely to shop online frequently than their urban counterparts, indicating that the efficiency hypothesis might not play a very significant role in our study area. This may be related to the high number of stores due to significant urban sprawl across the entire country. *Services* are most likely to be purchased online frequently, followed by *Fashion*, *Books,* and *Electronics*.

Since not all orders were delivered at home, the delivery location was assessed in a subsequent step. Each of the 1,600 original survey respondents could indicate the types of goods they bought and their preferred delivery location for each type of good. As could be derived from the model coefficients, the types of goods that respondents most often bought online were *Fashion* (52%) and *Electronics* (45%). Fewer people bought *Books* online (22%), while the goods in the categories *Do-it-yourself (DIY)*, *Entertainment*, *Health*, *Interior* (i.e., furniture and home decoration), and *Toys* were all in the region of 10–15%. Finally, the types *Food* (groceries) and *Sports* were bought by the fewest people. Fig. 5 plots the preferred delivery location according to the different types of items purchased.

On average, 75% of the respondents indicated they prefer home deliveries. However, Fig. 5 demonstrates that this average clearly depends on the type of goods. *Sports* and *Interior* were the categories with the highest percentage of home deliveries, exceeding 80%. The high share of *Interior* goods delivered at home can be explained by the typical size and weight of the items, which are often large. For *Sports* goods, the reason is not evident. The home delivery rates for *Books*, *DIY*, *Entertainment*, *Electronics,* and *Health* were between 69% and 80% and thus align with the average Belgian home delivery rate. *Fashion* had a slightly lower home delivery rate at 62%. In contrast, a high percentage of its orders (26%) were delivered to a pickup point or locker. One reason that people prefer this type of goods to be delivered at pickup points may be the possibility of a quick return in case the goods do not fit. Remarkably, the preference for home delivery for *Toys* was only 50%. Collection at the store and at a pickup point made up most of the remaining half of these deliveries. Finally, *Food* deliveries clearly show a different delivery pattern than the other types of goods. The preferred delivery location for this type of goods was the store itself (40%). This may be due to the high costs associated with home delivery and the type of services that supermarkets offer online.

Finally, a multinomial logit model was applied to assess the relationship between respondents' characteristics and the type of goods on the one hand and the delivery location on the other. The choice for a multinomial logit implies we model coefficients for 'average consumers' to explain the choice of delivery location. The model produced a McFadden pseudo R^2 of 0.11. Note that the values of the pseudo R^2 tend to be considerably lower than those of the traditional R^2 and that values of 0.2–0.4 are considered excellent fits (McFadden, 1974). The quality of the model was confirmed in the forecasting model, as elaborated in the next section (Table 4). The parameters β for the different predictors with their significance levels are shown in Table 3. These parameters represent the impact a certain predictor has on the log odds for a certain type of delivery compared to the reference level, meaning home deliveries. For example, if the goods bought online belong to the type *Interior*, the

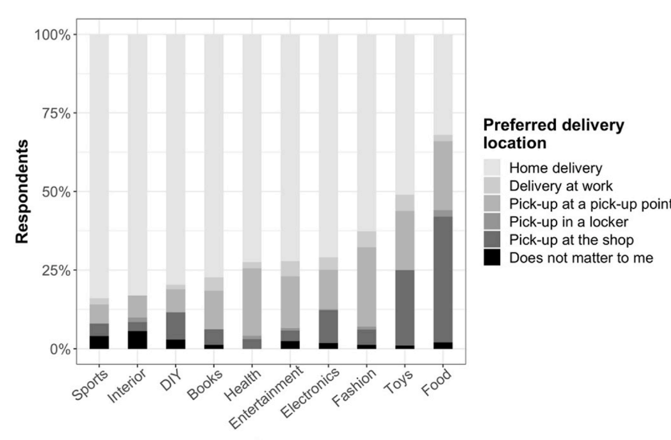


Fig. 5. Delivery location preferences.

Table 3
Multinomial regression results.

	Delivery at work	Pickup point	Locker	Shop	Does not matter
Income 500–1,249	6.76	.76	4.77	.29	4.88
Income 1,250–1,749	6.73	.43	5.05	.05	5.28
Income 1,750–2,499	7.33	.49	5.50	.13	4.51
Income 2,500–3,249	6.50	.30	6.37	.21	4.92
Income 3,250–4,250	7.37	1.02	7.28	−1.40	4.74
Income >4,250	6.71	−.91	−3.01***	−.78	−4.06
Gender Male	−.03	−.44***	1.25	.14	1.38**
Age 30-39	.63	.19	1.92	.32	.17
Age 40-49	.64	.31	1.45	.38	−1.24
Age 50-59	−1.39**	.09	−8.96	−.04	−1.01
Age 60-69	−7.73	−.24	−6.52	.48	−.54
Age 70	−5.55	−7.48	−.16***	−7.48	−6.87
Higher secondary	.04	.41*	1.17	.37	.28
Higher education	.74	−.21	−.64	.72**	−.58
Post-university	1.58*	.02	−1.72	1.68**	−6.79
1 child	.36	−.01	−1.40	−.22	−.44
2 children	−.72	−.15	.67	.20	.24
3 children	−1.33	−.50	−9.78	−1.10	.11
3+ children	1.16	.16	−10.47	−.92	−6.06
Suburban	.40	.22	−.45	.08	−.47
Rural	.81**	.14	−.11	.01	−.22
Books	.06	−.30*	−.14	−.67***	−.19
DIY_garden	−.38	−.58**	−1.82	.02	.11
Electronics	−.62**	−.35**	1.07	−.11	.12
Entertainment	−.44	.31*	.27	.15	−.49
Fashion	.31	.50***	7.14	−.25	−.67
Food	−.76	.55**	2.62**	.88***	−.64
Health_beauty	−1.27***	−.18	.60	−.31	−.22
Interior	−.15	−.49**	1.88*	−.33	1.02**
Sports	−.17	−.20	−.44	−.06	−.73
Toys	.93***	.30	2.09*	1.02***	−.39
Services	−.15	.38*	−2.78*	.15	.20
Constant	−10.00	−2.52***	−19.54	−2.89***	−8.65
DF	165				
Note:	*p < 0.1; **p < 0.05; ***p < 0.01				

Table 4
Forecasted delivery location.

Delivery location	Forecasted	Survey
Home	78.0%	75%
Shop	6.4%	7.6%
Pickup point	11.2%	11.3%
Locker	0.3%	0.3%
Work	2.7%	4.7%
Does not matter	1.4%	1%

log odds of delivery at work decrease with 15.23 compared to the log odds of delivery at home. Hence, *Interior* goods are less likely to be delivered at work. This quantifies the observation described above.

As shown in Table 3, *Income* and *Family size* do not really seem to affect delivery location, while Pernot (2020) identified *Income* as a key variable in the choice for pickup point deliveries in her case study. In contrast to Hood et al. (2020), we found that female shoppers are more likely to order to pickup points, while older people are less likely to have goods delivered at lockers. Higher-educated shoppers appear to be more likely to have their goods delivered to shops, while rural residents are more open to delivery at work compared to urban and suburban shoppers. In their elaborate study of the effect of morphology on delivery location, Hood et al. (2020) also found indications of more frequent home deliveries for shoppers living in urban areas compared to shoppers living in rural areas. However, the overall influence of a person's morphology on delivery location was also limited in the case of Yorkshire. We found that *Books*, *DIY*, *Electronics,* and *Interior* goods are less likely to be delivered to pickup points. As described earlier, *Food* and *Toys* orders significantly increase the probability of a shop delivery, while for *Books* the opposite is true. Finally, if the order is of the *Health* type of goods, it is very unlikely to be delivered at work.

4.2. From census to online orders (forecasting)

We strive in this paper to provide a comprehensive framework that demonstrates how to include the consumer in freight modeling. For this reason we try to keep the forecasting model as simple as possible The outcomes of the explanatory frequency model depicted in Table 2 show that only the socioeconomic variables *Income* and *Education* have any significant prediction power and hence only those are retained in the forecasting frequency model. The additional benefit is that these are available through census data, which further increases the applicability of the model. The probability of a certain e-commerce frequency given an individual's income and education level are shown in Fig. 6. The corresponding coefficients and their significance can be found in table 7 in the appendix. The overall trend is one of higher odds for people with higher education and income levels. Yet the impact of education is most pronounced for the lowest two levels, while income is the biggest differentiator in online shopping frequency for individuals with higher education levels. Even with the limited set of predictors, we obtained an R^2 of 0.54 by comparing the expected probability of the online shopping frequency for the different combinations of the variable levels in Fig. 6 with their observed values in the survey dataset. This result encouraged us going forward.

We came to a number of orders per day in each statistical sector by converting the forecasted online shopping frequency into an absolute value. For this, we used a normal distribution. The mean and standard deviation for the different ordinal levels can be found in Appendix A. These parameters are chosen so that in 95% of the cases, the forecasted absolute number of orders falls within the expected frequency range. For example, 95% of the forecasted absolute online orders for consumers expected to shop 'Every 6–12 months' falls in the range of 1–2 orders per year. This forecasted amount was then distributed among the different

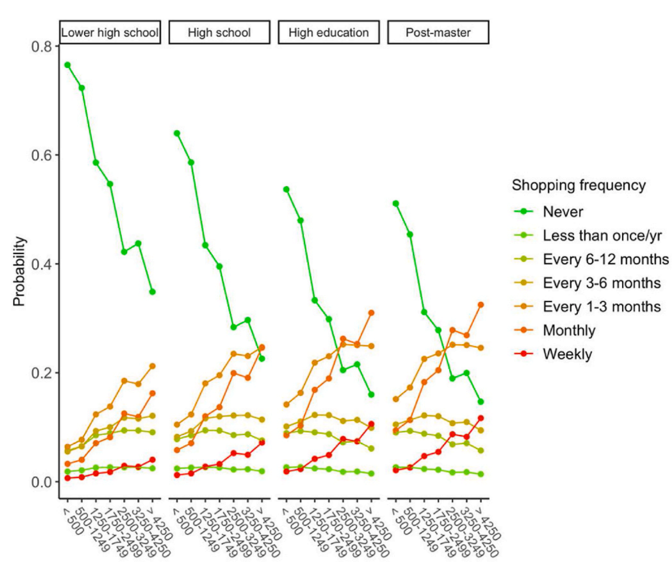


Fig. 6. Probabilities of frequency forecasting model.

location alternatives according to the significant socioeconomic variables from Table 3 (*gender*, *age*, *education*, *morphology*). Compared to the original survey results, the delivery location forecasting model slightly overestimated the number of orders to be delivered at home at the expense of those being delivered to shops and workplaces (Table 4). However, these deviations were minimal despite using the simpler multinomial logit. The good performance of the model was confirmed by the R^2 of 0.84 calculated in a similar way as in the previous step, that is, by comparing the predicted probabilities with the surveyed probabilities for the different combinations of variable levels.

The orders to be delivered at the workplace were then redistributed according to commuting patterns in Belgium. In total, on average 55% of all orders destined for workplaces were redistributed from the statistical sector of the home address to that of the potential work locations. Since most workplaces are located in urban areas, this translates geographically into a shift from orders destined for rural areas to those destined for urban areas (Fig. 7). This is an interesting effect, as it occurs for an estimated 2–2.5% of the online orders, which for our study amounts to an estimated number of around 4,000 orders on a daily basis.

The model predicted an average of 1.7 orders per 100 people per day in Belgium. It was difficult to validate this number due to the lack of insight into retail data. However, we did have delivery data (parcels) provided by two parcel carriers in Belgium. The carrier data were assumed to be B2C data, although the data providers stressed the difficulty of separating B2B from B2C. Due to the many company decisions of both shipper and carrier in the process from order to stop, it is currently not possible to use the parcels to validate the absolute number of orders. However, we were able to validate the geographical distribution of our model by comparing it with the data provided by the two parcel carriers, assuming a spatially homogeneous proportionality between orders and parcels. We calculated the correlation between the predicted share of orders and the effective share of parcels in each spatial unit. The coefficient of determination (i.e., the R^2) of the forecasting model was 0.49, indicating a strong predictive power, given that it was based entirely on census data and given our inability to understand the intermediate decision-making process. The largest residuals occurred in the centers of the largest cities, especially in Brussels, where the model underestimated the total number of deliveries compared to carriers. Analysis of the carriers' datasets indicated a substantial number of parcels destined for retail addresses there, which strongly influences the error. A more general accuracy was measured by evaluating the number of statistical sectors for which the model correctly forecasted a higher or lower than average share of parcels. Overall, for 85.96% of the statistical sectors, the predicted orders and the observed parcels showed a relationship similar to the average of our study area (i.e., both above average or both below average) (cf. Fig. 8). This indicates that the model functions well for predicting both frequency and location and thus can be used in future planning tools, which is what we aimed for at the start of this study.

4.3. From online orders to household freight trips

Finally, to illustrate the transport effects of B2C e-commerce, we converted the number of orders into parcels and trips. We used the example of the city of Mechelen. Mechelen is a representative medium-sized city in our study area (approximately 85,000 inhabitants), located in the heart of the Flemish Diamond between Antwerp and Brussels. Company data show a total demand of 1,707 parcels per day for the study area. These parcels were distributed among the spatial units according to their order probability, following the previous analysis. The parcels were grouped into stops and finally into trips according to the different consolidation levels, shown in Table 5. These range of the consolidation levels was derived from data of the parcel carriers. From our analysis, we conclude that a 50% increase in the parcel per stop ratio results in a 20% decrease in household freight trips at the zonal level. However, this strongly depends on the fragmentation of the CEP market and the demand density in the study area. The effect of the former is explained in more detail in Cárdenas et al. (2019); the latter is related to the socioeconomic context, which is detailed below.

A spatial disaggregation of our example is given in Fig. 9. Fig. 9a shows the absolute number of freight trips generated in each sector per day, and Fig. 9b shows the total freight trips per 100 inhabitants per day in each sector. The historic city center is indicated by a star. On average, each sector is visited by 3.6 delivey vehicles on a daily basis. The city center and its immediate surroundings are characterized by a higher number of freight trips. The map closely follows that of the population, although income and education cause local variations, and the central area benefits from additional parcels delivered to workplaces. Fig. 9b is in many ways the reverse of Fig. 9a. High values per 100 inhabitants can be observed in the green belt in the west-northwest, while the lowest values occur in or adjacent to the city. The effect of the fragmented CEP market is very clear. Assuming a parcel per stop ratio of 1.4 (the average

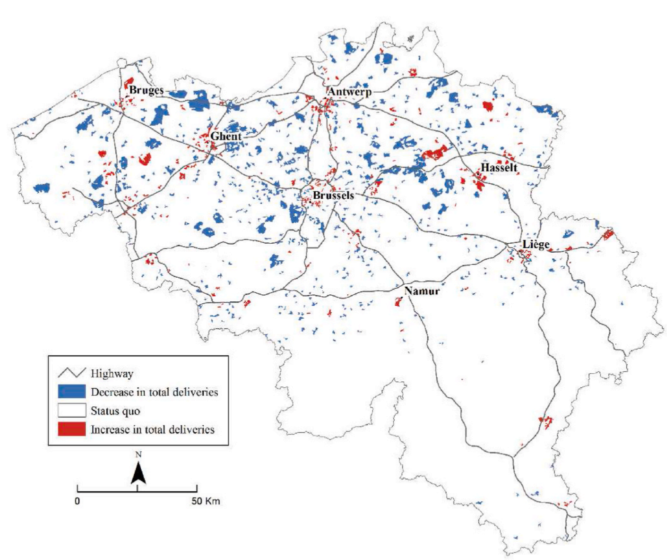


Fig. 7. Geographical pattern of the redistribution of work deliveries.

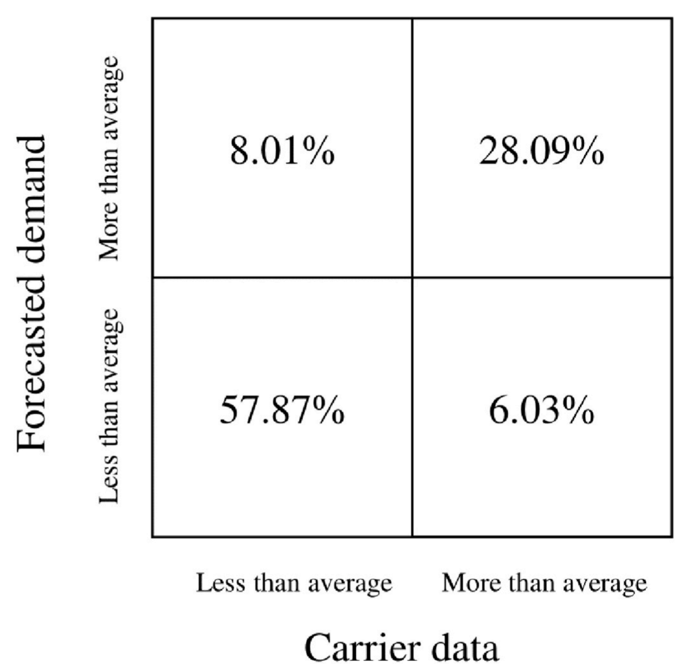


Fig. 8. Accuracy of the spatial distribution of the forecasting model.

Table 5
Household freight trips for different levels of consolidation.

Parcel/stop	1	1.1	1.2	1.3	1.4
Stops	1,707	1,552	1,423	1,313	1,219
Trips	15.8 ± 1.0	14.8 ± 1.0	13.9 ± 1.0	13.4 ± 0.6	13.1 ± 0.3

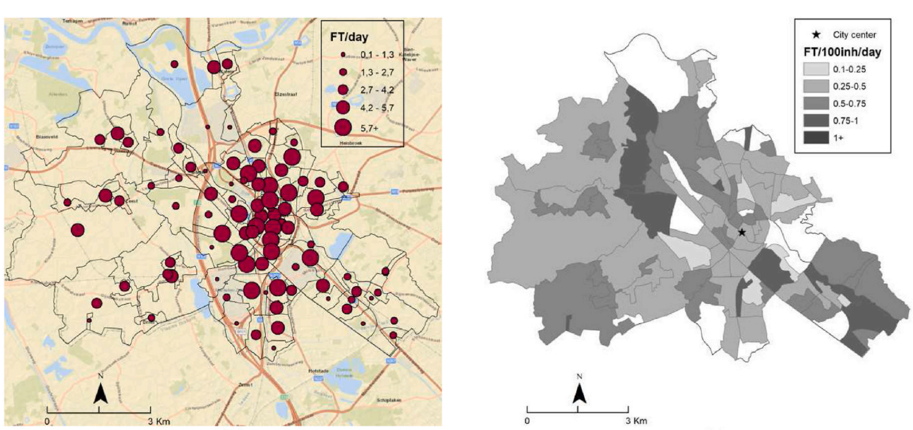
according to the survey), each vehicle stops on average 4.2 times per statistical sector. Instead of having all parcels in a neighborhood delivered in the same trip, the logistics and transport decisions as elaborated in Fig. 2 result in significant local freight traffic, demanding consolidation at the level of the receiver (Holguín-Veras and Sánchez-Díaz, 2016). The translation of orders into parcels is significantly affected by the delivery location. Work and CDP deliveries result in different parcel per stop ratios, which, as clearly shown in Table 5, also affects the number of freight trips that are eventually generated. These findings impact CO2 estimates and are important to consider in studies assessing the holistic impact of e-commerce (e.g., Buldeo Rai et al. (2019) or Jaller and Pahwa (2020)).

Finally, we compared our findings with a similar exercise by Wang and Zhou (2015). We estimated 4.8 orders to be delivered at home per person on a yearly basis (based on 2016 data in Belgium), resulting in 6.2 stops per person per year. The authors did not need to convert orders into parcels because they directly questioned delivery frequency and calculated a number of 5.2 home deliveries per person per year (based on 2009 data in the US). A comparison of the two numbers is difficult. We assumed the absolute minimum of one parcel per order in combination with maximum consolidation per stop (1.4), so in reality the number of deliveries for 4.8 orders per person per year will be slightly higher. The lack of consolidation from order to parcel on the retailer's side might increase the expected number of resulting deliveries. Moreover, the share of online retail in total retail in Belgium in 2016 was approximately double the share of online retail in the US in 2009. Whether this means that we should have found double the number of orders remains to be seen, as shopping patterns may differ between the two study areas. Overall, however, the availability of carrier data at a detailed spatial level is unique, and it allowed us to confidently assess the model's accuracy (cfr. Fig. 8). For this reason, we believe that our conversion from order to parcel is a very good approximation and can serve as a reference for local authorities, researchers, and other stakeholders that need to make this conversion without access to proper data. Finally, the above analysis shows that in Belgium, 22% of the orders ordered by households are not delivered to their home address. This percentage nevertheless constitutes household freight, as they are generated by the new freight actor. When these orders are included, further research will yield a more detailed calculation of the number of household freight trips.

5. Policy implications

The shift from conventional retail to e-commerce requires a paradigm shift in the approach to planning freight transport related to commercial activities. Its absence from the FTG literature to date implies incomplete travel demand estimations, which are commonly used for infrastructure or urban planning exercises. We argue that it is paramount to correctly model the effects of the new shopping behavior on areas that are ill-prepared to deal with freight vehicles. To this end, this paper outlines a framework to improve the quantification of these effects. We identified three key factors that determine the magnitude of freight traffic resulting from online shopping. First, the household has been promoted to a full-fledged freight actor, hence our introduction of the term *household* freight. The defining role of the socioeconomic background in consumer behavior results in strong local variation in household freight activities. It also implies the value of census data for household FTG models. Second, the delivery of online orders strongly depends on the supplier network and distribution system designed by the webshop. Single-item baskets now leave the warehouse instead of the store, shifting logistics responsibilities from the shipper to the carrier. Third, the efficiency of the final freight trips is jeopardized by the fragmentation of the CEP market and, consequently, by the lack of density of the delivery network.

The identification of the three key factors lays out a roadmap for policy measures to consider the effects of household freight transport. First, because individual consumers are active participants in household freight, urban freight management policymakers must consider their intentions and decision-making at the same level as those of logistics service providers. The easiest way to do this, as mentioned above, is to at least take household demand into account. However, since data on household freight demand is still mostly absent, the use of survey data is advised. The models provided in this paper were specifically designed to include such data. In addition to including data, we believe that consumers should be explicitly consulted to ensure that the initiatives taken do not lead to a decline in service levels. By consulting consumers in the same way as other freight actors, policymakers can ensure their initiatives are supported by the actual users and not end up meaningless. We refer to the example of pickup points that can be a sustainable alternative to home deliveries, but which often fail because consumers have little desire to make a car-free pickup trip. Second, retailers are remarkably absent from city logistics literature and policy efforts, despite their important role as shippers of the parcels. This paper demonstrates that retailers bear a significant responsibility in the number of freight flows. This is especially true for large online platforms that seem to offer one basket that in reality comes from several



(a) (b)

Fig. 9. FTG in the Mechelen example. (a) Total freight trips per day in a statistical sector. (b) Total freight trips per 100 inhabitants per day in a statistical sector.

independent retailers operating on that platform, resulting in separate shipments. In addition to the shippers' direct role in the fragmentation of parcels, it are also the shippers who set the price for different delivery alternatives. For these reasons, we encourage policymakers to also consider this actor when optimizing distribution in the city and not only focus on the logistics players.

The urgency of the above recommendations only increased since the COVID-19 pandemic. Shop closures, social-distancing rules and travel bans and faltering supply chains caused a reshuffling of the retail sector (Cappelli and Cini, 2020; OECD, 2020). The consumer is finding his way to the online channel more easily (Anderson et al., 2021; Eger et al., 2021), which increases the pressure on urban logistics systems. Besides the increased levels of household freight, Beckers et al. (2021) noted that small retailers have difficulties to adapt to the new situation, while the logistics sector responds to opportunities by focusing on facilitating the shipment of low volumes of online purchases by local consumers. Contemporary urban freight policy thus not only has the task to strive for a sustainable freight system, it has the opportunity to support the local economy in competing with large retail chains and pure online players, for example by supporting these 'local logistics' initiatives, or providing opportunities for consolidation at the city level.

A prerequisite for local policy to be able to follow the above recommendations is sufficient capacity to manage urban freight. In our study area, we found that this dedicated capacity is scarce. To the extent of our knowledge, few cities have public servants dedicated to urban logistics. Mechelen, the case study in section 4.3, sets the example by having at least one full-time equivalent working on the topic since 2014. This results from consecutive European funding (e.g., Cyclelogistics Ahead, Novelog, Surfhlog, ULaads). Mechelen is therefore one of the leading cities worldwide in terms of urban logistics innovation, despite its small size. For example, the city boasts a *Covenant Urban Logistics*[2] that concretizes the road towards zero-emission urban logistics by 2030. Another encouraging example is the city of Ghent (approximately 360,000 inhabitants), which has set up the platform *GentLevert*[3] to initiate innovative urban freight concepts in collaboration with logistics partners. *GentLevert* is now also developing a sustainable urban logistics plan (SULP) for the city. One dedicated person from the city administration manages the platform and works together with the departments of Economy and Mobility. This is a good example of how to organize local policy on this topic, because in many other cities we see a fragmentation of knowledge and capacity, with one person from a Mobility or Economy department working part-time on city logistics issues.

In addition to improving local urban freight management, we believe that a stronger interventionist approach to urban freight distribution is the way forward to tackle the increased fragmentation of freight flows. By creating a level playing field and being able to regulate who enters the city when and how, local authorities can achieve higher levels of consolidation and steer flows on the axes they choose. This is possible, for example, through the implementation of a Logistics-as-a-Service (LaaS) platform where receivers or shippers upload the parcels destined for an urban area under certain conditions. Such urban freight management however requires a multi-level governance structure to prevent a proliferation of local urban freight measures in a given market, as local administrative borders barely exist for the logistics sector. In the Belgian case for example, this requires balancing the incentives of local authorities (concerned with managing the urban fabric), regional authorities (concerned with transport) and the national authority (concerned with postal services and social exploitation). Such collaboration is currently however non-existent, mostly due to the mentioned absence of capacity on the different levels.

[3] https://gentlevert.be/en/about-gentlevert.

6. Conclusion

In this paper, we took up the challenge to quantify how households' online consumption translates into urban freight traffic. We did this by constructing a comprehensive framework that links socioeconomic variables to freight movements. We found that due to socioeconomic characteristics and logistics and transport decision, a statistical sector (e.g. neighborhood) is on average crossed by 3.6 freight trips per day, with each delivery vehicle averaging 4.2 stops. This results in an estimated 6.2 stops per person on a yearly basis. This calculation assumes a ratio of one parcel per order, making this value the lower limit. Resultantly, ample opportunities for consolidation exist, at the level of the shipper (logistics), the carrier (transport) and the receiver (shopping behavior). Although a medium-sized Belgian city may be considered small compared to cities in many other countries in the world, we believe that our findings can be compared to similar works in other study areas, taking into account the growth in the market.[4] One important remark in this regard concerns the fragmentation of the Belgian CEP market, with six players with an estimated market share between 5 and 20% besides the national post operator, and the absence of Amazon as a dominating online retailer. Hence, the levels of consolidation in other case studies could be higher at the different levels, yielding fewer freight trips on a daily basis. The relevance of our study for other cases also applies to our discussion of the urban-rural differences, both in coefficients and in the shift due to workplace deliveries. Although rurality in Belgium is not comparable to rurality in other countries, previous research has indicated differences in delivery costs up to a factor 10 between urban and rural areas in our study area (Cárdenas et al., 2017a), showing a strong impact of morphology on logistics organization.

The results presented here are a first step in modeling e-commerce FG that affects locations not prepared for intensive freight traffic, such as households, offices, lockers, and other alternative pickup locations. The different models uncovered significant relationships between socioeconomic factors and the probability to shop online on the one hand, and between the delivery location and a range of predictor variables on the other. Moreover, by explicitly basing the forecasting model based on census data, we (i) ensure greater data accessibility at a detailed spatial level compared to industry data and (ii) get to the source of the flows, meaning the consumer. For these reasons, our model framework can be applied in the context of local and regional policymaking. We do not provide a ready-made tool but a blueprint for more accurate modeling of household freight trips, for example in existing traffic models. We hope that policymakers can now get better informed on the occurrence of household freight trips, despite the general lack of consumer data. This is especially true for issues related to the last mile, which typically falls under the jurisdiction of local governments. The knowledge gained should lower the barrier that prevents the inclusion of household freight assessments in, for example, sustainable urban mobility or logistics planning.

Yet there remains room for improvement. First, consumer's delivery choices could be modeled more detailed by including individual preferences in forecasting the delivery location. This is for example possible by upgrading the multinomial logit to a mixed logit. Second, consumer preferences could also be detailed further by including some key variables. Beckers et al. (2021) demonstrated that online shopping frequency and delivery location are influenced by three components: individual (e.g., socioeconomic background), webinfrastructure (e.g., as measured by internet propensity) and the temporal component (e.g., the logistics service provision) This means that other socioeconomic variables such as credit car ownership (Dominici et al., 2021), personal attributes such as attitudes (Shi et al., 2021) or the willingness to pay (Milioti et al., 2021) and geographical variables such as the density of

[4] The Belgian B2C e-commerce turnover in 2016 was estimated around 9bn. (E-commerce Europe, 2016).

the pickup point network (Iannaccone et al., 2021) also affect the generation of household freight trips. Although such an exercise was beyond the scope of this study because we wanted to base our model on census data, the web infrastructure and temporal components can be considered through easily accessible variables, ensuring that their inclusion does not limit the scalability of the framework. In this discussion, however, it should be noted that the consideration of more variables does not linearly improve the quality of the model. We therefore advise against aiming for the largest set of variables but support the identification of key predictors that cover the remaining two components.

Third, validating the model is a difficult task due to the limited availability of data sources. Currently, there remains a gap between orders (which we know how to model) and the number of parcels; bridging this gap allows us to move on to trips. This requires an understanding of the logistics and transport decision-making processes. This not only implies data provision by the carrier, but, as shown in Fig. 2, also by the shipper. For example, in order to validate the forecasting model in section 4.2, we had to rely on carriers to filter data on B2C flows based on the type of shipper. This implies a significant error since companies can also order from consumer-focused online stores. Specifically for this example, the inclusion of shipper data, such as on invoices, would reduce the error. However, such issues can also be bypassed by jointly questioning the *order* and resulting *parcel* frequency in consumer surveys. From a questioning perspective, however, this is more difficult, as it is easier for the respondent to provide an average order frequency compared to the total number of items bought in a certain period. However, it would improve the translation from order to parcels and eventually trips and yield significant insights on the effective potential for sustainability of e-commerce.

Fourth, instead of modeling the order frequency and delivery location as two separate steps, one might consider integrating both steps into a joint modeling framework. Our reason for not doing so is a lack of insight into the causality between the two. While in many cases the delivery location is chosen after making the decision to shop online, logistics factors such as delivery speed and accessibility of pickup points do influence shopping propensity (Koyuncu and Bhattacharya, 2004; Motte-baumvol et al., 2017). Our hypothesis is that consumers may sometimes have a preferred delivery location and decide to buy online depending on whether the order can be delivered to that location. Whether or not this hypothesis holds affects the complex dynamics between the two steps in the framework, and we believe that further research should clarify these relationships before combining them into a single joint model framework. Fourth, while the frequency prediction does seem to yield satisfactory results, the spatial distribution is more difficult. Several solutions are available to improve our insights. One way is through surveying consumers at delivery alternatives, for instance at shops or pickup points, to better understand their specific location choices.

Finally, we only considered movements by logistics service providers. Dias et al. (2020) argued for the inclusion of passenger trips when talking about household freight, for example to pickup parcels in lockers. However, this includes another dimension of complexity, as concepts such as trip chaining, where consumers combine the pickup trip with other activities, must be included. Given that an estimated 11.6% of the parcels are going to CDPs (Table 4) and require a pickup trip, our model captures maximum 90% of the total household freight trips. Yet, given that the pickup trips occur even more fragmented than home deliveries, this underestimation might be even greater. Yet, the question then remains whether someone picking up a parcel on their way to a sports club is making a freight trip. This complex consumer behavior links freight modeling to activity models and should be considered over the long term to correctly assess the sustainability of different delivery options. At the moment, however, there is little research on these movements, implying many assumptions when attempting to build a comprehensive traffic model. We encourage authors to work on these assumptions, which include, for example, insights into mode choice for pickups, or the relationship between webrooming, showrooming, and channel choice. This, however, requires retailer data, as was the case in Buldeo Rai et al. (2019).

In summary, the heterogeneity of B2C freight flows makes the construction of a freight transport demand model for e-commerce a difficult task. This paper is a first successful step in that direction, but multiple issues remain. Given this initial success, further research should continue gathering B2C freight data to strengthen the predictive power of e-commerce FG models which, in turn, should lead to better holistic assessments of the effects of e-commerce through travel behavior studies.

Credit author statement

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Appendix

Table 6
Parameters used in the normal distribution to convert order frequencies into absolute orders (per year)

Order frequency	Mean	Standard deviation
Never	0.5	0.25
Every 6–12 months	1.5	0.25
Every 3–6 months	3	0.5
Every 1–3 months	8	2
Monthly	12	1
Weekly	80	20

Table 7
Model coefficients of the forecasting frequency model (Fig. 6)

Variable	Coefficient	Std. Error	T-value	P-value
Income 500-1,249	0.4373577	0.4956848	0.8823303	3.78E-01
Income 1,250-1,749	1.0762432	0.4890342	2.2007524	2.78E-02
Income 1,750-2,499	1.2642998	0.4899955	2.5802275	9.87E-03
Income 2,500-3,249	1.7953213	0.4987503	3.5996393	3.19E-04
Income 3,250-4,250	1.791256	0.518211	3.4566151	5.47E-04
Income > 4,250	2.5509893	0.6085684	4.1917874	2.77E-05
Higher secondary	0.6307003	0.1574927	4.0046333	6.21E-05
Higher education	1.0176734	0.1840972	5.527914	3.24E-08
Post-university	0.8456415	0.3969634	2.1302759	3.31E-02
Never|Less than once a year	1.4640538	0.4934926	2.966719	3.01E-03
Less than once a year|Every 6 to 12 months	1.5670581	0.4937201	3.1739805	1.50E-03
Every 6 to 12 months|Every 3 to 6 months	1.9324895	0.4946998	3.9063879	9.37E-05
Every 3 to 6 months|Every 1 to 3 months	2.4271777	0.4961596	4.8919293	9.99E-07
Every 1 to 3 months|Monthly	3.5144518	0.5002784	7.0249926	2.14E-12
Monthly|Weekly	5.3189153	0.5192492	10.2434742	1.27E-24

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