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Behavioural simulation of urban goods transport and logistics: the integrated choices of end consumers

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Abstract

This paper presents an advancement on the calibration of a model system for estimating goods attracted within urban and metropolitan areas. In particular, the models for simulating freight required by end consumers are reviewed and the main variables affecting purchasing behaviour in relation to quantity bought are investigated through data from an end-consumer survey carried out in Rome. The results show, and experimentally confirm, that quantity bought by end consumers at shops depends on their socio-economic characteristics as well as by land use of zone where shops are located.

*Keywords:*urban goods transport; city logistics; end consumers' choices; shopping purchases; behaviour; RUM.

1. Introduction

Urban goods transport (UGT) analyses has traditionally focused on restocking flows neglecting the other related mobility components such as shopping at shop/store and delivering of e-purchases (Cirianni et al., 2013; Taniguchi, 2015; Browne et al., 2015; Gatta and Marcucci, 2016; Russo and Comi, 2017; Taniguchi and Thompson, 2018; Hu et al., 2019). For example, at-store shopping flows (i.e. end consumers' movements) represent between 45% and 55% of the total goods traffic. Although recent research pointed out such a segment of mobility in the framework of goods movements (Gonzalez-Feliu et al., 2012; Nuzzolo and Comi, 2014; Dablanc et al., 2017; Musolino et al., 2018 and 2019; Marcucci et al., 2018), further effort is needed. Therefore, the paper, as a first objective, recalls a general system of models (Russo and Comi, 2010; Comi et al., 2014) developed within random utility theory (RUT) for simulating

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goods flows in relation to trips undertaken by end consumers for purchasing, given that goods attracted (moved) in urban area is mainly addressed to satisfy end consumer requests (as shown by studies recalled earlier). In general, the whole urban freight modelling system could receive input from high level models (e.g. input/output models, Russo and Musolino, 2012) and the lower level models (as those presented in this paper) is asked to monitor and evaluate *ex post* the urban/metropolitan freight system.

Therefore, starting from the literature review, the second objective of the paper is to model urban freight movements, mapping the end consumers' behaviour, which generates them. For this aim, the macro-behaviour of end consumers (that requires to buy goods) and retailers (that sells goods) is briefly recalled (Russo, 2013):

- end consumer's macro-behaviour:
  - *pull-type* behaviour, the end consumers arrives at the purchasing place (e.g. zone *d*), performs the transaction and purchases the commodity; the end consumer transports the good to the consumption site (e.g. zone *o*); both in going from *o* to *d* and from *d* to *o*, the end consumer may make other stops;
  - *push-type* behaviour, the end consumers may or may not (e-commerce) go to the purchasing place (e.g. zone *d*), perform the transaction and purchase the good; the commodity is transported to the site of consumption (e.g. zone *o*) by actors other than the end consumer (Lim et al., 2018; Sampaio et al., 2019);
- retailer's macro-behaviour may be also summarized in two classes:
  - *pull-type* behaviour, the retailer goes to the acquisition place (e.g. internal zone *w*, or external zone *z*), purchases (acquires) the goods; the retailer transports the goods to the retail outlet *d*; along the path the retailer may undertake other stops;
  - *push-type* behaviour, the retailer may or may not go to the place (e.g. internal zone *w*, or external zone *z*), purchases (acquires) the goods; the goods are transported to the sales outlet *d* by actors other than the retailer.

Such an improved understanding of end-consumer activity and the subsequent restocking performed by retailer would help planners to better define measures to implement for improving city sustainability and liveability taking into consideration which choice dimensions are impacted. The attention paid by planners to city sustainability goal is strongly increasing pushed by the international objective to reduce CO_2 in the city, and to move towards zero emissions by 2030. Therefore, based on the statement that goods movement in urban areas are addressed to satisfy the end consumers' request and the large share is yet performed at shop even if the advancement of city smartness (process of smart city as defined in Russo et al., 2016), specifically in EU, moves quickly towards a high percentage of push-type one, the third objective of paper germinates, i.e. to point out pull-type end-consumer behaviour and to underline shopping trip generation/production and hence the quantity bought by end consumers at shops (purchase dimension). Therefore, within pull-type movements by end consumers, the quantity asked for satisfying end-consumers requests can be obtained. This goods process, named *attraction*, is simulated through disaggregate probabilistic-behavioural models and an advancement in model calibration/estimation is presented.

The paper is organized as follows. Next Section 2 recalls the general modelling framework developed by authors and pull-type end-consumer movements are outlined, while some advancements in model estimation are presented in Section 3. In fact, moving from this general modelling framework, the quantity attracted by urban areas can be linked to trips undertaken by end consumers for shopping. The dimension of each purchase (e.g. quantity of goods purchased) represents the core of the estimation process. Currently, only models for the aggregate freight type class have been proposed (i.e. durable and non-durable goods; Russo and Comi, 2012), then in the following, disaggregate models (in which the explanatory variables refer to single end consumer) for several freight types are presented. Then, new models are developed to express the end consumers' choices as a function of their characteristics (i.e. age, gender and employment status) and of undertaken trip (i.e. travel time and costs, zonal active and passive accessibility). Finally, Section 4 closes with a summary and discussion.

2. The movements of the end consumer

Moving from the general modelling framework proposed by Russo and Comi (2010), and Russo (2013), the quantity attracted by urban areas can be linked to trips undertaken by end consumers for shopping. Then, assuming that the end consumer is in zone *o* (i.e. in the sense that s/he consumes the considered goods in the zone *o*) and s/he can have push or pull-type behaviour, the total quantity attracted by zone d, $Q_{s,tot,d}$, consists of three components and hence can be expressed as:

$$Q_{s,tot,d} = Q_{s,d}^{pull} + Q_{s,d}^{push} + QE_{s,d} \tag{1}$$

where

- $Q_{s,d}^{pull}$ is the total quantity of freight type s required in zone d for satisfying end consumers' needs through a pull-type behaviour living/working inside the study area;
- $Q_{s,d}^{push}$ is the total quantity of freight type s required in zone d for satisfying end consumers' needs through a push-type behaviour living/working inside the study area;
- $QE_{s,d}$ is the goods quantity bought/sold in d given by the demand of end consumers living/working in a zone z external to the study area.

Both the first two terms of *eq. (1)* can be decomposed into the product of some sub-models, each relates to one or more choice dimensions as detailed in the following sections for the pull-type one.

The pull-type behaviour

It is hypothesized that the decision maker (end consumer) lives/works and/or consumes the goods at zone o, while s/he purchases at zone d. Therefore, given that goods flows are estimated to support a given end consumers' need, the total quantity of freight type s attracted from zone d, $Q_{s,d}^{pull}$, can be calculated as (Russo and Comi, 2010):

$$\begin{aligned} Q_{s,d}^{pull} &= \sum_{o} Q_{s,od}^{pull} = \sum_{dim}\sum_{o} TRIP_{s,od}(dim)\cdot dim = \sum_{dim}\sum_{o} TRIP_{s,o}\cdot p\left[d/os\right]\cdot p\left[dim/dos\right]\cdot dim = \\ &= \sum_{dim}\sum_{o} n(o)\cdot \sum_{x} x\cdot p\left[x/os\right]\cdot p\left[d/os\right]\cdot p\left[dim/dos\right]\cdot dim \end{aligned} \tag{2}$$

where

- $Q_{s,od}^{pull}$ is the quantity bought in zone d by end consumers living/working in zone o (sold by retailers of zone d);
- $TRIP_{s,od}(dim)$ is the number of trips for purchases of freight of type s, from o to d, concluding with purchases of dimension dim;
- $TRIP_{s,o}$ is the number of trips for purchases of freight type s with origin in the inner zone o;
- $n(o)$ is the number of end consumers (e.g. families) of zone o;
- $p[x/os]$ is the probability for end consumer E conditional upon having o as zone of residence and purchasing freight of type s, of undertaking x trips in a set time with x equal to $0, 1, \ldots, n$; it is estimated by a *generation/production model*;
- $p[d/os]$ is the probability of trips being undertaken by end consumer E going to destination d conditional upon leaving from o for purchases of type s; it is estimated by a *distribution model*;
- $p[dim/dos]$ is the probability to conclude a trip with a purchase of dimension dim ($0, dim_1, dim_2, \ldots, dim_n$; e.g. 0, less than 1 kg, between 1 kg and 2 kg, more than 2 kg) conditional upon undertaking a trip from zone o to zone d for a purchase of goods type s; it is estimated by a *dimension choice model*.

While trip generation and distribution were investigated and some models have been proposed, few researchers have considered dimension choices. In fact, based on the statement that trip generation is mainly affected by socio-economic characteristics and land-use patterns (or the physical characteristics of the area; Cubukcu, 2001; Cao et al., 2010; Comi and Nuzzolo, 2014), some models have been developed. In particular, *statistic-descriptive* models have been proposed to describe the mean number of trips undertaken by the individual end consumer (i.e. average shopping trip index), developing both *aggregate* models, in which the explanatory variables corresponding to the zone of origin (e.g. population, employees related to retail activities, number of shops; Holguin-Veras et al., 2011; Gonzalez-Feliu et al., 2012; Sanchez-Diaz et al., 2013) and *disaggregate* ones, in which the explanatory variables refer to single end consumer (Gonzalez-Feliu*et al.*, 2010; Comi and Conte, 2011; Comi and Nuzzolo, 2014). On the other hand, *probabilistic-behavioural* (or more properly, random utility models; Russo and Comi, 2012) models were also proposed.

There are several methods to model trip distribution, which adapt models developed for passenger to freight and derive from gravitational forms. Amongst others, Ibrahim (2002) and Jang (2005) used joint disaggregated models to describe the generation and distribution of shopping trips. Gonzalez-Feliu et al. (2012) propose gravitational models for simulating car shopping trips, while Gonzalez-Feliu and Peris-Pla (2018) included also pedestrians. Veenstra et al. (2010), through a gravity model, takes the spatial configuration of supermarkets into account. Finally, Nuzzolo and Comi (2014) proposed an aggregate probabilistic distribution model in which the systematic utility to reach zone *d* is expressed as a linear combination of the number of retail employees and the road network distance between zones. On the other hand, few models have been proposed to investigate the dimension choices (Comi et al., 2014), showing that further studies are needed. Therefore, in the following Section 3, extending the first results for such a model for two freight types (durable and no-durable goods; Russo and Comi, 2012), some behavioural disaggregate models of this type are proposed according to different freight types and socio-economic characteristics of end consumers, i.e. age, gender and employment status.

3. Pull-type model estimation

The models were developed using the results of some surveys carried out in a suburb of the city of Rome where more than 200 households have been interviewed. The attention is on shopping journey, considering both home-based trips and non-home based trips (e.g. home-work-shopping-work-home). The survey has allowed investigation of pull-type purchasers' behaviour. In particular, the interviews were structured in two sections: the former related to infer the personal characteristics of those interviewed (e.g. job, age, family composition, income), the latter related to collect data on journey and purchases (e.g. freight types, frequency of purchase trip, origin and destination of trip, transportation mode, dimension of purchases).

The end consumer sample consisted of 62% female and the 38% male. Referring to income, about the 65% declared to have an income less than 40,000 €/year. The 52% are employed. From surveys, it emerged that each family weekly buys and consumes about 52.3 kg of goods and undertakes about 2.4 trips for shopping. These results are similar to those revealed in other Italian cities and towns (Guzzo and Mazzulla, 2006; Russo and Comi, 2010; Crocco *et al.*, 2013; Comi and Nuzzolo, 2014).

This survey also allows a characterization of trips in terms of frequency and purchased freight types. In particular, the analysis of characteristics of purchases (i.e. bundle purchases) and transportation behaviour identified six freight types/categories: foodstuffs, home accessories, stationery, clothing, household and personal hygiene, and other. In the following sections, the dimension choice models for these types of freight are presented.

3.1. The new dimension choice models

It should be noted that when the end consumer arrives in a zone, s/he could or not purchase something. Thus, an intermediate model was included in the general framework in order to estimate the probability to buy or not. The probability to purchase was hence estimated by a binomial logit model in which the systematic utility, $V_{purchase}$, was expressed as linear function of attributes related to socio-economic characteristics of end consumer and the accessibility index of origin zone. Active and passive accessibilities were considered below. While active accessibility measures have been considered, given a zone within the study area, how easily the other zones are reached, the passive accessibility measures how easily the considered zone is reached coming from the other zones belonging to the same study area.

The considered attributes are:

- socio-economic
  - *fam*, number of components of family;
  - *rh*, dummy variable if end consumer is retired or housewife, 0 otherwise;
  - *stud*, dummy variable equal to 1 if end consumer is student, 0 otherwise;
- IAA_o, active accessibility index of origin *o*;

- the *active accessibility* index, IAA_o, has been calculated as:

$$IAA_o = \left[AA_o - \min_z \left(AA_z \right) \right] \Big/ \left[\max_z \left(AA_z \right) - \min_z \left(AA_z \right) \right]$$

where AA_x is the active accessibility of zone x estimated as: $AA_x = \sum_i \left(Ad_i \right)^{0.373} \cdot \exp\left[-3.36 \cdot tt_{xi} \right]$, with Ad_i the number of employees of zone i according to the considered freight type; tt_{ix} the travel time between zone x and i, calculated on the road network according the path of minimum generalized travel cost.

Table 1 reports the parameters estimated for all six identified freight types. The model's capability to reproduce the choices made by sample was measured by the ρ^2 statistic. As revealed by the surveys, the probability of purchasing increases for retired persons and students. This probability also increases with the accessibility of a resident zone, while it decreases according to the number of family components. This results confirms that members of large family on average tend to do not buy because other family members can make the same type of purchase.

Table 1 - Purchase model for all freight types: calibration results (ρ^2 =0.22)

	family components (*fam*)	retired or housewife(*rh*)	Student(*stud*)	active accessibility(IAA_o)	ASA
Alternative	*purchase*	*purchase*	*purchase*	*purchase*	*no purchase*
Value	-0.245 (-1.93)	0.430 (1.44)	1.034 (2.84)	0.667 (1.05)	-0.499 (-1.81)

(-) t-student

Once that the purchase is decided, the following step is to investigate its dimension. The *dimension choice* model allows a quantity dimension (*dim*) to each purchase trip (see *eq. 2*) to be estimated. It gives the probability *p[dim/dos]* that a trip concludes with a purchase of dimension *dim* ($dim_1, dim_2, \ldots, dim_n$) conditional upon undertaking a trip from zone *o* to zone *d* for a purchase of goods type *s*. The calibrated dimension choice model has a multinomial logit structure:

$$p[dim / dos] = exp(V_{\text{dim}}) \Big/ \sum_{\text{dim}'} exp(V_{\text{dim}'})$$

where V_{dim} is the systematic utility to purchase items of dimension *dim* and has been expressed as linear combination of the attributes of end consumer (EC_i) and trip (e.g. travel distance or time, JO_k):

$$V_{\text{dim}} = \sum_i \beta_i \cdot EC_i + + \sum_k \beta_k \cdot JO_k$$

Therefore, the considered attributes are:

- end consumer (EC_i)
  - *age*, age of end-consumer;
  - *inc*, discrete variable equal to 1 for low income family (i.e. less than 40,000 €/year), 2 for medium income family (i.e. less than 80,000 €/year, and 3 for high income family;
  - *gend*, dummy variable equal to 1 if end consumer is woman, 0 otherwise;
  - *wk*, dummy variable equal to 1 if end consumer is worker/employed, 0 otherwise;
  - *rh*, dummy variable equal to 1 if end consumer is retired or housewife, 0 otherwise;
- trip (JO_k)
  - *tt*, travel time between *o* and *d* according to the minimum path;
  - *km*, travel length on the road network between *o* and *d* according to the minimum path;
  - *OD*, dummy variable equal to 1 if origin of trip is equal to destination, 0 otherwise;
  - IAA_o, index of active accessibility of origin *o* (see eq. 3);
  - IAP_d, index of passive accessibility of destination *d*;
  - *empl_sh*, average number of employees per shop in zone *d* according to goods type;
  - *shop*, number of shops in zone *d* according to goods type;
- Alternative Specific Attribute (ASA_x).

The *passive accessibility* index, IAP_d, has been calculated as:

$$IAP_d = \left[AP_d - \min_z \left(AP_z \right) \right] \Big/ \left[\max_z \left(AP_z \right) - \min_z \left(AP_z \right) \right]$$

Where, AP_x is the passive accessibility of zone x estimated as: $AP_x = \sum_i \left(Ad_i \right)^{1.25} \cdot \exp\left[-0.75 \cdot tt_{ix} \right]$, with tt_{ix} the travel time between zone i and x, calculated on the road network according the path of minimum generalised travel cost.

According to survey results, three-dimensional alternatives were considered according to the type of goods (Table 2). Tables 3 and 4 report the results of dimension choice model estimation.

Table 2 – Dimension choice model: weekly dimensional alternatives

	freight types					
alt.	*foodstuffs*	*home accessories*	*stationery*	*clothing*	*household and personal hygiene*	*other*
dim_1	< 1.5 kg	<0.5 kg	<0.5 kg	<0.1 kg	<0.5 kg	<0.1 kg
dim_2	1.5 – 40 kg	0.5 – 5 kg	0.5 – 2.5 kg	0.1 – 0.5 kg	0.5 – 5 kg	0.1 – 1 kg
dim_3	> 40 kg	> 5 kg	> 2.5 kg	> 0.5 kg	> 5 kg	> 1 kg

From the estimation reported in Table 3 for foodstuffs, it emerges that the probability of making a large purchase increases with the travel time spent to reach the destination d (i.e. travel time and distance). The same occurs if the purchases are made in the same zone of residence. The probability of making large purchases also raises with number of family components and family income, while, with opposite sign, if the end consumer is student. The results confirm that foodstuffs purchases are mainly carried out by elders (i.e. mainly to buy daily consumption products), while afar zone could be preferred if large shops are there (e.g. opportunity to find special discounts).

Table 3 – Dimension choice model for foodstuffs, home accessories and stationery

	Foodstuffs (ρ^2 = 0.23)			home accessories (ρ^2 = 0.24)			Stationery (ρ^2 = 0.32)		
attribute	*alternatives*			*alternatives*			*alternatives*		
	dim_1	dim_2	dim_3	dim_1	dim_2	dim_3	dim_1	dim_2	dim_3
km *(travel length)*	-0.715 (-1.39)			-0.080 (-1.66)			-0.042 (-2-10)		
age (*age*)		0.025(1.87)	0.046(2.39)		0.040(2.58)	0.040(2.58)		0.138(2.03)	0.050(1.96)
family components (*fam*)		0.363(2.06)	0.446(2.39)		0.279(1.25)	0.428(2.30)		0.475(1.23)	
income (*inc*)		0.286 (1.75)	0.286 (1.75)		-1.123(-2.42)	-1.123 (-2.42)			0.737 (2.12)
woman (*gend*)							0.743 (1.91)	1.40 (1.95)	
student (*stud*)		-1.131 (-1.43)	-0.746 (-1.61)						
worker (*wk*)								0.545(2.32)	1.191(1.42)
origin=dest. (*OD*)		1.400(3.30)	1.352(1.75)					0.456(2.08)	0.989(2.15)
active accessibility (IAA_o)								-1.465 (-2.08)	-2.753 (-2.26)
passive accessibility (IAP_d)						-0.182 (ln) (-2.36)			
alternative specific attribute (ASA_x)	6.277 (4.10)	2.547 (1.70)		4.100 (2.81)	2.318 (1.99)		5.294 (2.67)	2.774 (1.41)	

(-) t-student

As regards home accessories (Table 3), the end consumer's behaviour is quite similar to foodstuffs. For these products, note the effect of passive accessibility: travelling to no-accessible zone leads to larger purchases being made. The behaviour of purchasing stationery products is quite similar to the above products, but in this case the weight of active accessibility should be pointed out: coming from a high accessible zone, the dimensions of purchase decreases. It confirms that living in these types of zone the end consumer prefers to undertake more trips to buy something (e.g. they are pushed to travel to find special discounts).

Table 4 shows the results of the other three goods types. Referring to clothing, the dimension of purchases decreases with age, while it increases for higher incomes, woman and employees. Workers tend to buy more, while travelling from high active accessible zones the probability to make small purchases rises. Travelling through low passive accessible zones, large purchases are made. The results confirm that if a no-easy accessible zone is reached (due to shop attractivity, e.g. brand) larger purchases are made, and that younger customers (e.g. students) travel for smaller purchases (probably because they have more free time and prefer to look for special discounts). With regard to household and personal hygiene products, a similar behaviour emerges with respect to travel distance. Women and retired persons perform larger purchases in the nearby shops (i.e. OD equal to 1). Finally, for buying other types of goods, the probability for smaller purchases increases with students and low-income families and shops with high number of employees. The results confirm that some bundle purchases are usually at large and far off retail outlets.

Table 4 – Dimension choice model for clothing, household and personal hygiene and stationary

	clothing ($\rho^2 = 0.24$)			personal hygiene ($\rho^2 = 0.22$)			other ($\rho^2 = 0.20$)		
attribute	*alternatives*			*alternatives*			*alternatives*		
	dim_1	*dim_2*	*dim_3*	*dim_1*	*dim_2*	*dim_3*	*dim_1*	*dim_2*	*dim_3*
tt*(travel time)*							-0.487(-1.55)		
km *(travel length)*				-0.170(-1.94)	-0.059(-1.99)				
age (*age*)		-0.024(-1.71)	-0.058(-2.63)						
family components(*fam*)			0.455(1.96)						
income (*inc*)		0.938(2.23)	1.034(2.40)					0.395(1.14)	0.700(1.71)
woman (*gend*)		1.160(2.38)	2.738(3.38)		1.056(2.32)	2.971(2.39)			
student (*stud*)			-1.987 (-1.80)					-0.926 (-1.90)	-0.926 (-1.90)
worker (*wk*)	-1.196(-2.91)	-0.962(-1.60)							
retired/housewife (*rh*)					0.687(1.44)	0.687(1.44)			
origin=dest. (*OD*)	-0.887(-1.39)	-0.940(-1.57)			0.493(1.86)	0.493(1.86)			
Activeaccessibility (IAA_o)	2.940(2.30)								
passive accessibility (IAP_d)			-6.523(-1.96)						
number of employees per shops (*empl_sh*)								-0.333(-2.22)	-0.154(-1.91)
number of shops (*shop*)					0.135(1.80)	0.135(1.80)			
alternative specific attribute (ASA_x)	1.382 (1.88)	1.433 (1.15)		5.190 (3.55)	3.526 (2.72)		1.786 (2.26)	1.716(2.19)	

(-) t-student

4. Conclusions

The paper reported, within the general framework for modelling urban freight demand, some estimation advancements for simulating end-consumer purchasing movement. Some behavioural models for purchase dimension were thus presented. The models were specified and calibrated on the basis of real test cases (suburb of Rome), considering different freight types. These purchase choice dimensions are investigated by the dimension choice models that aim to converting trips into quantities. These models hence provide integration between shopping (passenger) and restocking mobility. Within city logistics scenario definition, this tool allows the effects due to urban freight transport measures on end-consumer behaviour to be captured. For example, the increase of travel costs (e.g. times or lengths) could lead to having larger purchases with a subsequent increase of restocking quantity and of trucks. The quantity of goods purchased by end consumer was shown to depend on the type of freight and is mainly influenced by the socio-economic attributes of end consumers (e.g. income, age, gender) or characteristics of sold freight (e.g. trademark) as well as of accessibility of purchasing zone. Therefore, the attraction macro-model (using such a probabilistic-behavioural model as presented in the paper) allows us to investigate how urban policies modifying the transportation attributes for passenger or the sale network can modify the end-consumer demand and thus the attracted goods quantity changes. These results address the further development of this study: implementation of whole modelling system to a real test case in order to assess the impacts produced by demographic changes as well as by city logistics measures that modify urban network performance.

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