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MASS-GT: An empirical model for the simulation of freight policies

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ABSTRACT

Despite the importance of urban freight transportation for the accessibility and livability of cities, few systematic, quantitative and empirical methods exist which allow an impact assessment of urban freight transportation solutions or policies. There is a lack of transparent literature on the full specification and estimation of these models, which not only hampers continued research, but also the development of evidence-based urban freight transport policies. We present the urban freight simulator Multi-Agent Simulation System for Goods Transport (MASS-GT) with its full specification and empirical implementation for a study area in The Netherlands. It concerns an agent-based model based on a framework of discrete choice and optimization models, which describes logistic choices of shippers, carriers, producers and consumers. The disaggregate level of detail allows the analysis of a wide variety of logistic developments and policies across all or specific logistic segments. The model is estimated and validated using a variety of data sources: truck trip diaries, supply/use statistics, an e-commerce demand survey, traffic counts and other relevant statistics. The article presents the full specifications of the model and their empirical estimation, including the data sources used. Also, the validity of the model is evaluated using road freight traffic counts. Finally, examples of applications of the model to case studies are provided.

1. Introduction

Understanding urban freight transport demand is increasingly important for mitigating the negative externalities in urban traffic. For example, despite a small share of freight traffic on the road, trucks in Paris have a disproportional impact of 36 % of total damage caused by pollutant emissions from road traffic [1]. The share of urban road freight in urban traffic externalities is expected to increase further due to the increasing defragmentation of urban deliveries, fueled by rapid growth figures for e-commerce orders. This increases the urgency of identifying efficient urban freight planning policies. Simulation models can be used for policy evaluations at the appropriate levels.

To address this challenge, various models have been developed during the past decade [1–6]. None of these, however, have presented a comprehensive approach in terms of (1) inclusion of logistics decisions concerning freight demand including consumption and distribution, mode choice and routing of flows, together with (2) a systematic estimation, calibration and validation of models

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using micro-level (i.e. freight trip and shipment level) area-specific observations. As a result, there have been no examples of models that build a strong evidence base for urban freight policies. Mostly data is not available or fragmented, making it challenging to develop simulation methods that recognize where the relevant logistics response mechanisms have been finetuned using local area data.

SimMobility freight [3] was one of the first comprehensive examples of an empirical urban freight simulator. Still, also for this model, surveys from outside the study area had to be used for the empirical basis. Other recent examples include CRISTAL [4], an advanced agent-based model that links national supply chains to urban freight demand. However, while the model is conceptually advanced, the empirical implementation still lacks estimation on choice data. A key lesson is that the empirical implementation of such models still leaves many open research questions before we arrive at effective and validated simulation tools. In addition to finding sufficient freight data, the second challenge lies in finding a balanced trade-off between simulating logistic behavior and maintaining computational efficiency.

This article describes the specification and estimation of the Multi-Agent Simulation System for Goods transport (MASS-GT), including the implementation for The Netherlands. MASS-GT is an agent-based model consisting of a framework of discrete choice and optimization models to describe the logistic choices of shippers, carriers, producers and consumers in freight transport demand. The model is developed following an evolutionary development path, incrementally adding complexity to the model [7]. Earlier publications described partial models with their calibration, and this is the first paper which discusses the connections between these with the complete model application. An additional contribution of this article is a validation of the model with traffic counts and sensitivity runs. The organization of the paper is as follows. Section 2 gives an overview of literature on urban freight simulators. Section 3 describes the model framework and the specifications of submodels. The empirical implementation is discussed in Section 4, including the data sources used, the resulting empirical models with estimated choice parameters, the validation of the model and its application. General conclusions and recommendations for urban freight demand models are provided in Section 5.

2. Literature review

The agents behind urban freight demand are very diverse, ranging from receivers such as retail stores or big industrial enterprises to the carriers that operate the transportation. Simulation models with the representation of agent behavior are therefore better capable of capturing the relevant logistic choices and responses and can therefore provide more valid assessments of urban freight policies. However, microscopic and systematic approaches for a system-wide assessment of impacts of freight transportation policies are still scarce: freight data is either not available or fragmented and thus simulation tools are often limited in scope.

Freight demand models have been developed for many decades. Over the last years, a new generation of simulation models have emerged that simulate the behavior of individual firms [1,5,6]. Recent models are mainly shipment-based [3,8–11]. In another relevant line of research, specific segments or concepts are simulated with dynamic agent-based models [11,12]. These models study dynamic behavior between and with agents (negotiation, learning) and are conceptually more complex but often have a limited empirical implementation or have a small scope to provide valid predictions for all urban freight demand in a study area. Comprehensive microscopic freight demand simulation models typically consist of an integration of a variety of modeling methods such as simulation, discrete choice- and optimization models [13,14].

A big challenge for the implementation of microscopic freight demand simulation models is the availability of appropriate freight transportation data [10]. Data collection, such as a commodity flow survey or truck trip diaries, is time and cost intensive. But innovations and new ways of data collection are providing efficient ways to get access to large samples of disaggregate freight transportation data. Types of data required for simulation include logistic data on freight demand (establishment survey) or freight transportation (truck trip diaries). Often automated data collections (GPS, roadside camera registration) need to be enriched with other available data sources based on ID's or the location of activities in the data. The microscopic approaches operate with more spatial detail and are designed to fit better with the urban context in the transportation domain. The models are used to explore city logistic developments or evaluate policies at this level. Increased data availability and the increased interest into quantitative policy analysis for city logistics has fueled the development of microscopic simulation models such as ULLTRA-SIM in Tokyo [15], Simmobility Freight in Singapore [3], MASS-GT in The Netherlands [7], CRISTAL for the US [4] and MATSim in Flanders and Cape Town [16,17]. The empirical foundation of these models is based on limited available data that is fragmented, or data is even transferred from other contexts [3]. In [18] a tour based urban freight simulator was presented using GPS truck vehicle data: such data provide good foundation for estimating tour patterns but misses other logistic information such as the shipments carried and delivered. Key learning from all these examples is that the data requirements for empirical foundation of urban freight models is challenging.

Also, the scope of existing models does not always fit well with the urban freight context: in CRISTAL [4] the scope is mainly on strategic logistic decision and interregional transport demand, or in other examples the scope is mainly on operational scheduling decisions and vehicle simulation [15,16]. Other examples of microscopic simulation models for urban freight demand simulate on one part of city logistics, such as [19], with a case of food deliveries in Berlin or [20] that focus on delivery bay planning in Rome.

Lastly, in designing a simulation model for urban freight impact assessment it is important to have a complete scope of urban freight demand, and a balanced trade-off between simulating logistic behavior while maintaining computational efficiency and avoiding over complexity. We address this gap by presenting an empirical implementation of an agent-based freight demand model, built on the MASS-GT simulation approach.

In summary, existing approaches for the analysis of system wide impacts of freight policies suffer from two main shortcomings. Existing approaches are either limited by unavailability of sufficient data or their scope is too narrow for a comprehensive assessment of impacts on the level of transport networks. In our research we aim to contribute to the development of effective approaches for the calibration and validation of freight simulation models.

3. Model framework

3.1. Overview

The MASS-GT is a multi-agent simulation model of urban freight transportation activities. An incremental development path is followed, and earlier prototypes were presented in [7] and [21]. A large number of actors influence the decisions made in freight transportation markets [22,23] and their preferences and behaviors are diverse. Recent microsimulation models for urban freight demand distinguish parcel (or micro freight) demand, in addition to the freight transport activities from conventional commodity demand. Each of these demand segments consists of a series of logistic choices. The following figure illustrates the logistic choices behind each demand segment in the conceptualization of MASS-GT. Conventional commodity demand involves choices for: supplier selection, distribution channel, shipment size and vehicle type, delivery time choice, tour scheduling and vehicle route choice. The delivery of parcel demand involves the simulation of parcel ordering, carrier allocation, and scheduling of delivery tours Fig. 1.

MASS-GT simulates choices in this conceptual model at the level of individual firms to better capture agent-specific costs and constraints in behavioral decision-making. The first categories are producing- and consuming firms. Other relevant agents in freight transport are carriers and logistic service providers. In reality for many logistic decisions it is hard to unambiguously attribute the decision to one agent, as a decision can be made by the shipper, carrier, or even the receiver of the goods (e.g. preferred delivery time). Also because sometimes shippers or receivers also act as carriers. Therefore, in MASS-GT, the logistic service providers and carriers are represented by distribution centers and transshipment terminals. The agents that are distinguished in this conceptual model include:

- Producing firms.
- Consuming agents: the receivers of the goods, these can be firms, households or other points of interest (e.g. construction site).
- Distribution centers: locations where transport flows are temporarily stored and further consolidated or deconsolidated.
- Transshipment terminals: locations where transport flows are transferred from one mode to another, e.g. from ship to road or road to rail.

Although local authorities provide the transportation infrastructure, they are not represented directly in MASS-GT, but their policies are part of the use cases and scenario inputs. The attributes of the agents, or a combination of agents, is used to describe the expected behavior or logistic decision. E.g. the shipment size is likely to be influenced if it is going to or coming from a transshipment terminal. If the receiving agent is in a location with access restrictions this will affect the vehicle type of time-of-day decision. The type of origin and destination of the transport defines the flow type of the transport.

The model structure of MASS-GT is depicted in Fig. 2: it shows each module and the main data flow between the modules. Three demand segments of urban freight transportation distinguished and two time scales. The first time scale applies to the long-term tactical decision making behind urban freight transportation demand. It simulates a synthetic demand for shipments and parcels or for services. The second time scale is the daily scheduling of the freight activities. The broad demand segments for urban freight are goods transportation, parcels (micro freight), and services. For the freight shipments in goods transportation demand, and for parcel deliveries different scheduling modules are developed, as the procedure for the formation of tours is very different. The transportation of the different goods, parcels and services are grouped into 8 typical logistics segments for city logistics: Non-refrigerated Food Miscellaneous/ General Cargo, Temperature Controlled, Construction Logistics, Facility Logistics, Waste Logistics, Parcel and Express,

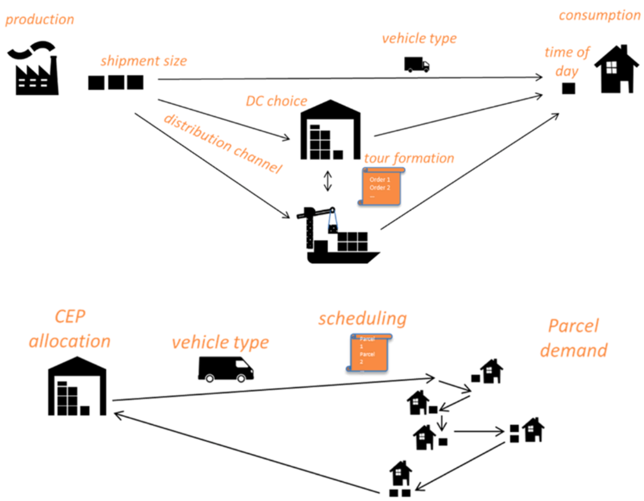

Fig. 1. Conceptual model behind MASS-GT with logistic choices.

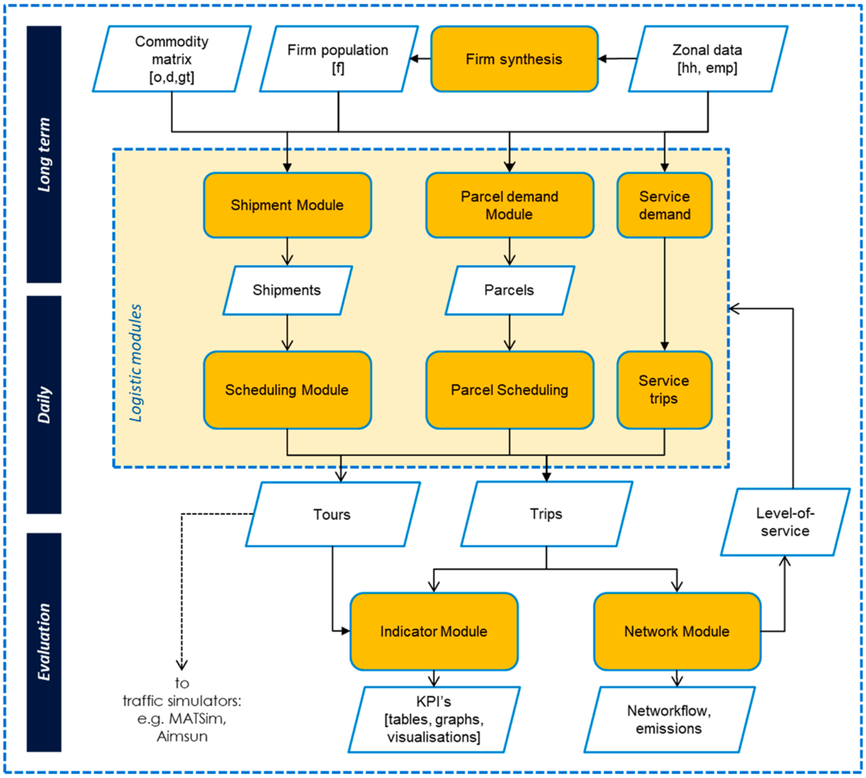

Fig. 2. MASS-GT model structure in the HARMONY TFS release.

and Dangerous Goods logistics.

The shipment module calculates the synthetic shipments that are sent to, from and within the study area. To synthesize this demand, an event-based simulation is used that includes strategic logistic choices such as supplier selection; the distribution structure; simultaneous shipment size and vehicle type choice; and the desired delivery time choice.

The scheduling module simulates the daily decision making behind planning the delivery and collection tours of freight vehicles. It determines consolidation of shipments into one round tour, and the timing of the tour. This means shipment delivery times are the result of two time-of-day decisions: first the desired delivery time window in the shipment synthesis and next the final delivery time that follows from the delivery schedule that is simulated in the scheduling module. The desired delivery time from the shipment module is used to select shipments in the scheduling module to be considered for consolidation in round tours.

Parcel demand and delivery are very distinctive. In most transport demand models this demand segment and vehicle movements are not simulated explicitly. However, it is becoming a more significant component for the assessment of city logistic policies: the demand for parcels is growing more rapidly than any other freight segment, and for the last mile delivery, there is a huge interest in providing new services that are more efficient. The demand for parcels is simulated bottom-up from households (for B2C demand) and companies (for B2B demand). Also, the delivery of parcel demand starts from the depots of the parcel carriers. The module distributes the demand over these depots. The conventional mode of delivery is light commercial vehicle (LCV). The parcel scheduling module allocates the parcels to vehicles and determines the vehicle patterns for the deliveries. These delivery tours are input to the network module to calculate vehicle kilometers and emissions.

MASS-GT also uses two auxiliary modules. The first is a network module. It performs an all-or-nothing route assignment on a congested network. This is used by MASS-GT in two ways: first of all to calculate transportation time and distances, and second of all to calculate performance indicators at network level. The module provides also an accurate estimate of the emissions by each vehicle and allows full flexibility for the measurement of emissions at link level, by logistic segment or even the load of a vehicle. Finally an indicator module summarizes important indicator of fright demand, logistic performance, and network externalities for quick output analysis. The following sections describe the technical specifications for the Freight Shipments and Parcel demand modules, and the Network module.

3.2. Simulation of freight shipments

3.2.1. Shipment module

Freight shipments are simulated in a top-down approach. As argued in [7], this top-down approach allows the model to start from an exogenous national or interregional forecast of commodity flows. This creates consistency between the urban freight demand simulations and macro-economic and interregional transportation forecasts. The module breaks down the aggregate commodity demand into individual shipments by allocating the demand over distribution channels (and logistic nodes), discretizing aggregate flow into individual shipments and assigning them to producers and/or consumers. The shipment module follows a stepwise procedure where different logistics choices are simulated consecutively. The shipment synthesizer flowchart in Fig. 3 represents the steps

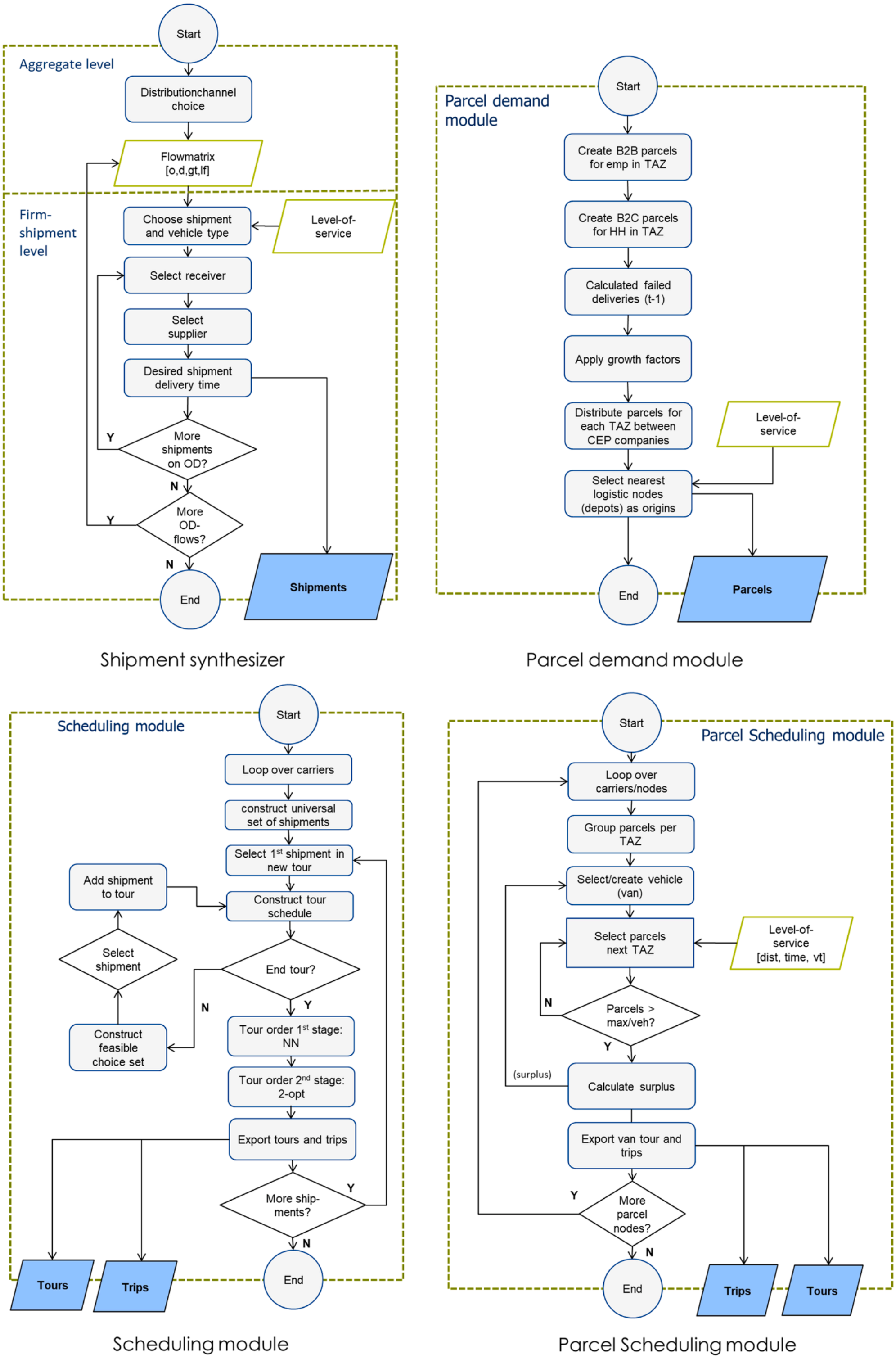

Fig. 3. Flowchart of the demand modules in MASS-GT.

described below.

- step 1: The first step is to assign, on an aggregate level, the total freight transportation demand to distribution channels. This step calculates the share of each logistics segment for each flow type: transporting goods directly, via a distribution channel, or via a multimodal transshipment terminal. For each logistic segment, the shares for each flow types are derived from observed data. The aggregate demand is split into flow types using these observed distributions. At the end of this step, a flow matrix of origin and destination pairs per flow type and per logistics segment is created.
- step 2: In this step, the freight volumes per flow type are broken down into individual shipments by applying a simultaneous shipment size and vehicle type choice model. The vehicle and shipment size choice model is based on the economic order quantity (EOQ) theory, in which the transport costs and cost of inventory are traded-off against each other within the total logistics costs [24–26]: increasing shipment sizes are more efficient for transport costs but also lead to higher inventory costs. Often the combined shipment size and vehicle type choice is modelled using discrete choice models [24,27–29]. The initial derivation of the model is described in detail in [30]. Here we provide the specifications of the model that is implemented. The estimated parameters are presented in the Calibration section.

The utility function is provided in Eq. (1): it consists of the logistic costs for the corresponding vehicle type and shipment size combination and different alternative specific constants. The logistic costs are determined by the costs of the vehicle, or vehicles, which are required to carry the shipment. The costs are calculated for a complete vehicle, also when it is partially loaded. For the transport costs both the time-based and distance based costs are taken into account. The inventory costs are calculated using the shipment size as a proxy for the total volume that needs to be stored. In addition to the costs alternative specific constants are added for the vehicle type and shipment size class. Finally, interaction terms are added to allow for taste preferences for specific segments, e.g. preference for smaller shipments to dense urban areas, or a tractor trailer combination for long haul transport. The utility to use vehicle type v and shipment size s is specified as:

$$U_{v,s} = \beta_K \cdot \left(\left(c_{t,v} \cdot t + c_{d,v} \cdot d \right) \cdot \left\lceil \frac{S_s}{cw_v} \right\rceil \cdot f_s \right) + \beta_I \cdot I_s + \delta_v + \delta_s + \sum_m (\delta_m \cdot X_m) + \varepsilon_{v,s} \tag{1}$$

With: t: transport time (h) d: transport distance (km)
$c_{t,v}$: vehicle cost per time unit for vehicle type v (€/h/vehicle)
$c_{d,v}$: vehicle cost per unit of distance for vehicle type v (€/km/vehicle)
S_s: weight of shipment size class s (tons)
cw_v: carrying weight of vehicle type v
f_s: frequency of the transport, as total flow divided by the shipment size: $\frac{S_o}{S_s}$
I_s: inventory costs for shipment of size class s (tons)
β_K: estimated coefficient for transport costs
β_I: estimated coefficient for inventory costs
δ_v: alternative specific constant for vehicle type
δ_s: alternative specific constant for shipment size class
δ_m: preference for interaction term m
X_m: interaction term m
$\varepsilon_{v,s}$: unobserved part of the utility

- step 3: After discretizing the freight flows to individual shipments, the simulation is done at the level of individual shipments and firms. First, with a probabilistic assignment each shipment is allocated to a receiver, or the most likely consumer of the shipment. This probability depends on the industry sector and size of the firm. Conventional supply and use tables are used to measure the share in demand of a goods type by industry sectors. This is the 'use' probability of a goods type by an industry sector. Next it is assumed that with the size of the firm the probability that a shipment is received increases.

Thus, the receiver probability of a firm f belonging to industry sector s of a shipment with goods type gt, depends on the firm size and the 'use' probability for the industry sector $P^{use}_{s;gt}$:

$$P^{receiv}_{f;gt} = \frac{E_{f;s} \cdot P^{use}_{s;gt}}{\sum_{i \in dest} \left[E_{i;s} \cdot P^{use}_{s;gt} \right]} \tag{2}$$

If the shipment is delivered to a transshipment terminal or a distribution center, the size of each logistic node is used to calculate the receiver probability.

- step 4: Next, a probabilistic assignment is used to determine the supplier of the shipment, or the most likely producer of the firm. This probability depends on the industry sector, the size of the firm and the generalized transport costs for this supplier. Now, supply and use tables are used to measure the share in production of a goods type by industry sectors. This is the 'make' probability of a goods type by an industry sector. The generalized transport costs are calculated based on distance and weighed with a distance decay function. The probability that firm f is the sender of shipment s depends on the firm size and the 'make' probability for the industry sector $P^{make}_{s;gt}$ and the weighted transport costs $f(c)$:

$$P^{sender}_{f;gt} = \frac{E_{f;s} \cdot P^{make}_{s;gt} \cdot f(c)}{\sum_{i \in orig} \left[E_{i;s} \cdot P^{make}_{s;gt} \cdot f(c) \right]} \tag{3}$$

Conditional to the logistic flow type that is determined in step 1, the shipment can also be sent from a transshipment terminal or a distribution center. In this case the sender probability of a logistic node is calculated from the size of each logistic node and the weighed transport costs to the node.

➢ step 5: In this last step the desired time window for delivery is simulated. Delivery time is generally categorized into discrete time groups in the freight transport models. Receivers dictate in which time window they want to receive their goods. Thus, truck tours are influenced by the time constraints set by receivers of the goods. This explains the reason behind our decision to focus on modeling the desired delivery time to the receivers. The analysis is conducted on shipment level and goods are divided into logistics segments. The rationale behind the application of logistics segments is that each segment includes goods with similar logistics profiles. Goods that belong in different logistics segments cannot be transported in the same vehicle.

Time-of-day choice is modelled using a multinomial logit (MNL) model that predicts the probability of each time period, based on the logistic segment, vehicle type and location types of the loading and unloading zone. Five time periods are distinguished (00–08;08–11;11–17;17–19;19–24) as choice alternative. Each alternative has a different duration. As proven in [31] for time-of-day models the logarithm of the length of the time period (*Dur*) can be added as a size variable to the systematic utility with its coefficient normalized to 1.

The models are estimated per logistic segment. For each time period an alternative specific constant was estimated. The evening period was chosen as reference alternative. The utility also takes into account specific flow types: dummy variables are included for shipment from a transshipment terminal (FromTT) or from a producer (FromP), to a transshipment terminal (ToTT) or a consumer (TC). The flow types from producers and to consumers are also interacted with the degree of urbanization to correct for different delivery times in urban or rural areas. The utility furthermore contains taste parameters for the type of vehicle. The systematic utility for the MNL is defined as follows.

$$U^{TOD}_{i,p} = \delta_p + 1 \cdot \ln(Dur_p) + \sum_{ft} \left(\beta^p_{ft} \cdot X^{ft}_i \right) + \sum_{ft} \left(\beta^p_{ft} \cdot X^{ft}_i \cdot X^{Urb}_i \right) + \beta^{vt}_p \cdot X^{vt}_i \tag{4}$$

δ_p: alternative specific constant for tod period
Dur_p: time interval length for period
X^{ft}_i: flow type of shipment
X^{Urb}_i: degree of urbanization at origin or destination end
β^p_{ft}: preference parameter for period p per flow type
X^{vt}_i: vehicle type

The final output of the shipment synthesizer module is a set of shipments with origin (sending firm/logistic node), destination (receiving firm), shipment size, commodity type (NSTR code), the vehicle type and the desired delivery time.

3.2.2. The shipment scheduling module

The objective of the shipment scheduling module is to simulate the logistic decision making behind daily round tours of freight vehicles. This daily decision making involves two main choices: first tour-formation and secondly delivery time optimization. The initial tour formation model was developed in [32], which had been extended in the new MASS-GT model to include the desired delivery time window of shipments in the scheduling procedure. The starting point for the scheduling procedure is the shipments created in the shipment synthesizer module. The pool of shipments that needs to be collected and distributed, the size of shipments and size of the vehicles are used as conditional constraints in the formation of round tours. The procedure is based on the principle that carriers build tours by incrementally selecting shipments from the pool of shipments until the tour is long enough. In selecting the shipments, the spare capacity in the vehicle and the desired delivery time is taken into consideration to build logical consolidation patterns. Finally, the order of shipments is optimized using an effective two-phased optimization procedure: first, the nearest neighbor search is applied to form a logical order of loading locations and then unloading locations. In the second step, the order within this final consolidation set of shipments is optimized using the 2-opt local search algorithm.

Fig. 3 shows the detailed procedure of the scheduling module. By looping over all carriers, the following heuristic approach is applied:

➢ step 1: Determine the universal choice set of shipments to be collected/distributed during that day.
➢ step 2: Select the first shipment of the tour. The first order is picked randomly.

- ➢ step 3: Construct or update the tour schedule (allocate the shipment to the tour).
- ➢ step 4: Simulate the consolidation decision: to add a shipment or to end building the tour? This decision is simulated with a binary choice model. The probability that the tour is ended is calculated based on the attributes of the tour, e.g. goods type, type of vehicle, and remaining capacity in the vehicle. The binary logit model has alternatives '0 = add shipment' and '1 = end tour'. The utility of the alternative 'end tour' is calculated as follows:

$$U_{cti}^{ET} = C_i^{ET} + \sum_{r=1}^{n_i^{ET}} \left(\beta_{ri}^{ET} * x_{rcti}^{ET}\right) \tag{5}$$

The utility includes a few logical logistic conditions that affect the decision to end the tour. First of all proximity: if there are no shipments that still need to be allocated with a range of α km to the tour that was created then the tour is ended because all non-allocated shipments would require a long additional time. Second, if the vehicle's capacity has been reached the tour is ended. Third, if the tour duration is above nine hours drive time, the tour is ended to respect drive time regulation in The Netherlands.

- ➢ step 5: (conditional: if step 4 = 'add shipment'): determine feasible choice set. This set selects from all shipments assigned to the carrier the shipments from the same logistic segment and of two aligning time periods.
- ➢ step 6: (conditional: if step 4 = 'add shipment'): from the feasible choice set select the most efficient shipment to add to the round tour. As the carrier is striving for optimization, it is assumed shipments are consolidated based on their proximity. In other words, we apply a greedy algorithm selecting the shipment to be added to the tour. Next, the algorithm goes back to Step 3.
- ➢ step 7: (conditional: if step 4 = 'end tour'): end the tour.
- ➢ step 8: Create initial route order of loading and unloading locations using the nearest neighbor search.
- ➢ step 9: Second stage optimization of route order, using 2-opt local search algorithm, an efficient solution to solve a travelling salesman problem with a finite set of destinations [33].

Once all shipment collection and deliveries are scheduled, a matrix of tours and trips is created. Each tour is described by its trips, the vehicle type, the start time and the shipment it consists of. Each trip is described by its origin and destination, goods type, vehicle type and the tour ID.

3.3. Simulation of parcel deliveries

Parcel delivery is creating an increasing number of vehicle movements, mainly with light commercial vehicles and mainly between parcel depots and delivery locations. For the simulation of parcels, a simple but logical procedure is built that consists of two modules: a module to calculate the demand for parcels and a module that simulates the formation of delivery tours. The modules include a number of scenario parameters to simulate developments in the parcel demand market: demand parameters for parcel demand by households (B2C) and businesses (B2B); growth parameters for forecasting demand; delivery success rates; vehicle capacity parameters; locations of depots and market shares of carriers.

3.3.1. Parcel demand module

The parcel demand module estimates the demand for B2C and B2B parcels and assigns the demand to carriers. It uses household and employment populations, and the networks of parcel and express carriers (CEP). Fig. 3 shows the simulation procedure.

The module first calculates the B2B parcel demand by multiplying zonal employment and a parameter for the daily number of parcels per employee. The latter is derived from the statistics of the total B2B parcel market size.

Next step is the calculation of zonal B2C parcel demand with an ordered logit model that was estimated on the MPN, the Mobility Panel Netherlands (introduced in [34]; here we used 2017 data). The model predicts the number of online orders on person and household characteristics: age, household income, urbanization level at their location of residence. Person j is expected to order i parcels per day. This number of parcels i is derived from a vector of attributes for person j, and the estimated threshold bounds μ. The specification of this ordered logit model is as follows:

$$\widetilde{y}_j = \overrightarrow{x}_j \overrightarrow{\beta} + \varepsilon,\ y_j = i \ if \ \mu_i < \widetilde{y}_j \leq \mu_{i+1} \tag{6}$$

Next, the zonal demand is corrected for the non-deliveries of the day before: these need to be repeated and thus in effect increase the number of daily parcels for delivery. This is calculated as the total number of predicted daily parcels multiplied by the delivery success factor.

After this step, a growth factor is applied to correct for the market developments between year of observations and the year of simulation. This procedure preserves the differences in demand between zones while ensuring that the total demand is accurate.

Next, parcel demand (for both segments combined) is allocated to parcel and express companies (CEP). The CEPs' observed market shares in the domestic parcel market, available from open market data publications, is used as input for this.

In the final step, the parcels are assigned to a depot from the corresponding CEP. It is assumed that each CEP has optimized its operations to deliver each parcel from the nearest depot. The output is a set of parcels with an origin (a depot) and a destination (a zone in which households and/or businesses are located).

3.3.2. Parcel scheduling module

The parcel scheduling module consolidates the simulated parcel demand and assigns them to delivery tours. First, for each depot a list of parcels that are to be delivered is created grouped by the specific zone. Delivery tours are simulated using a two-step optimization procedure: first, clusters of delivery zones are formed using a greedy algorithm, forming delivery tours until the assumed maximum capacity of delivery vehicles (180 parcels in the reference case). Next, the order of intermediate stops in the delivery tour is optimized using the 2-opt algorithm, a local search algorithm [33]. Once the delivery tour is formed, the parcels are assigned to a vehicle and the start time of the tour is derived from an assumed time-of-day distribution. The list of remaining parcels is updated, and parcels are again put in the loop to be added to a new tour. Once all parcels are scheduled, a matrix of tours and trips is created.

3.4. Simulation of routes

For the optimization of round tours, and the allocation of supplier selection, MASS-GT needs realistic travel times and distances for the individual transport legs (trips). The Network Module simulates route choices for each freight trip using a congested road network from the transport model and calculates the realistic travel times and distances. In addition to route choice and travel time prediction, the module also performs a shipment-based emission calculation. In this emission calculation the type of vehicle, the types of links it is passing (rural, urban, or highway) and the loading factor are taken into account in the emission calculations. This allows detailed evaluation of emission impacts from changes in vehicle type use, loading efficiency, or route choices.

The module follows two steps:

➢ Step 1. Route choice

Based on Dijkstra's algorithm using a congested traffic network from the static traffic assignment of the V-RMDH model [35].

➢ Step 2. Emission calculation

Emissions are calculated for each vehicle route. The emissions are calculated for CO2, SO2, PM, and NOX using emission factors for the g/km emissions. For this, an average-speed approach is used with emission factors segmented by:

- Road type (urban, highway, country rural)
- Vehicle type
- Load factor

The unit emission factors are derived from the European STREAM method [36] and provided for an empty vehicle and a full vehicle. Interpolation between the emission factor for an empty vehicle and a full vehicle allows selecting the right emission factor for a given loading rate. For each trip, the emissions are calculated on each visited link by multiplying the link distance with the according emission factor.

Table 1
Summary of data sources used.

	Type of data [# or dimensions, granularity]	Use in MASS-GT
Base data:		
Traffic model of the metropolitan area	Zonal socio-economic data [Employment and population, 6625 TAZ]	Employment by economic sector, and number of households by zone.
	Networks [158 thousand links]	Networks
Open Street Map (OSM)	Location parcel depots for CEP couriers [29 depots; address]	Simulation of parcel demand for delivery per parcel depots
Distribution centre database	Locations of multi modal terminals and distribution centres [316 DCs and 90 Transshipment terminals, address]	Generation of freight demand at transshipment terminals and distribution centres
Strategic freight model "Basgoed"	Regional Commodity Matrix [10 goods types; regions]	Demand scenarios for regional commodity demand for the study area
Supply and use tables from Dutch Statistics (CBS)	Supply and use tables by product group and industry sector [10 goods types; 6 sectors]	Calculation of firm-based supplier and receiver probabilities
Data for calibration/validation:		
XML truck trip diaries from Dutch Statistics	Shipments, Vehicle and tour data [2.65 M shipments, address information]	Estimation of shipment size, vehicle type, tour formation, delivery time decisions
MPN household travel survey	Online orderings by individuals [6750 surveys; individuals]	Estimation of parcel demand by households
Monitoring statistics about the parcel market	Parcel market statistics (historic trend) [B2B and C2C; study area]	Parcel market size by B2C and B2B segment, market shares of CEP companies
Traffic model of the metropolitan area	Loop detector count data [2637 count locations]	Validation of simulated outputs
Camera data from Low Emission zone Rotterdam	Camera count data [HGV, low emission zone]	Validation of simulated outputs
Survey in the logistic community of Rotterdam	Behavior and attitude toward zero-emission zone [155 surveys; companies]	Set parameters transition scenarios on use of ZE vehicles or consolidation hubs

The output of the module consists of a network with intensities of freight traffic (individual vehicles) and the emissions on each network link.

4. Implementation

4.1. Data

Availability of urban freight data varies between local contexts, and in many regions the available data is very limited. For this reason, the model is designed to use as much as possible standard public data. For implementation to the case study in South-Holland, The Netherlands, excellent freight data was available that allows a formal calibration of some of the logistic choice models. MASS-GT is implemented for a highly urbanized study area of Zuid-Holland (pop = 3.3 M) which includes the metropolitan area of Rotterdam and The Hague. The model has been designed to use as much as possible data from conventional transportation models as inputs: the transport networks, transportation analysis zones (TAZ), and socio-economic data such as household and employment numbers. The firm population is synthesized from the zonal employment by industry sector. Additional freight data is collected as much as possible from public data sources: such as the location of logistic nodes (distribution centers and transshipment terminals) or parcel market statistics. An aggregate commodity demand matrix for the study area is derived from a strategic freight demand model, in this case the Dutch National Freight Model BasGoed. The make and use probabilities that are used in the shipment module are derived from supply and use tables for the Dutch economy. Supply tables describe the produced amounts of products by industry sectors. Use table describes the consumption (final and intermediate) of product by industry sectors.

Table 1 provides an overview of the data sources use and how the data is used in the model implementation.

The table makes a distinction between the base data required for building all necessary input files for the model, and data used for calibration and validation of the model. An important empirical source for model calibration is an extensive dataset of truck trip diaries collected by Statistics Netherlands (CBS). This truck trip diaries are collected by a novel automated procedure that extracts the truck trip diaries from the Transport Management System of truck operators. The truck trip diaries provide logistic data at the level of tours, individual trips, and shipments. In total CBS extracted 2.65 million shipment observations from the year 2013–2015 which contains rich information on the loading and unloading locations, the commodity carried, and vehicle types used. The dataset was enriched by georeferencing it to relevant location data [37–39], such as the location of distribution centers and multimodal transshipment terminals. This allowed the calibration of choice models including more attributes that explain the choice behavior of the agents.

For model validation the simulated truck flows are compared to truck count data. We used two different sources of observations for this. First, loop-detector count data that is typically used for the calibration of traffic models. In addition available camera registration data for a screenline (cordon) around the low emission zone in Rotterdam. This registration is highly accurate as the vehicle type is automatically derived from the license plate registration. The registration data is only available by vehicle type classes for research purposes.

4.2. Calibration

The Truck trip diary data (see Table 1) was used to estimate the vehicle and shipment choice model, the delivery time choice model and the incremental tour formation model. The models are estimated using the mLogit package in the R software [40].The parcel demand models are estimated on a travel survey that included additional questions about the use of e-commerce.

The results of the calibration are presented in tables that provide the final estimated parameters for each choice model. These final specifications are based on a systematic process of testing and eliminating variables that were found to be not statistically significant. For more details on the theoretical foundation of the model and the empirical analysis of the estimations we refer to the published articles of the corresponding models. Here we provide a high-level discussion of the final values to explain the behavioral causalities in the parameters.

4.2.1. Vehicle and shipment size choice

Table 2 presents the estimated models for the simultaneous vehicle type and shipment size choice (see Eq. (1) for the utility function). The models are MNL models and are estimated on the truck trip diary data. Due to the distinct preference for vehicle type and shipment sizes, models are estimated per segment. Vehicle and shipment size choice is heterogeneous over commodity groups and freight agents. The results confirmed that firms choose smaller shipments for non-bulk commodities while bulk commodities are preferred to be transported in larger sizes. Estimations also confirmed that haul distance and logistic nodes (distribution centers) are relevant in explaining truck choice: on distances greater than 100 km large trucks and semi-trailers are preferred in bulk transport. For transportations to and from distribution centers we see mixed preferences for large or small trucks: this is likely explained by consolidated transports to and from the distribution centers with large trucks and last mile distribution with smaller vehicles. Adding more distinction between the type of distribution center might increase the significance of these findings. Transport costs also play an important role in vehicle type and shipment size decisions: as transport costs increase, shipments tend to be made in shipment size-truck type combinations where the capacity of trucks is utilized more efficiently.

4.2.3. Preferred delivery time

The final estimated models for the preferred delivery time are presented in Table 3. The model is a MNL model, see Eq. (4), and estimated on the truck trip diary data with complete information on the delivery times of shipments. The evening window,

Table 2
Model Estimation results for the vehicle and shipment size choice model.

	Chemicals		Heavy Bulk		Waste		Climate Controlled		Manufactured goods		Parcel		Transport equipment	
Parameter	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Logistic cost parameters:														
transport cost (tc)	−0.05	−64.44	−0.029	−39.54	−0.042	−38.38	−0.022	−87.57	−0.021	−38.08	−0.046	−64.87	−0.029	−48.37
Inventory cost (ic)	−0.04	−3.97	−0.036	−3.69	0.006	3.7	−0.326	−43.05	−0.33	−22.29	−0.335	−42.19	−0.761	−46.08
Truck type ASC:														
Small Truck	1.17	10.54	0.51	4.8	1.1	7.24	2.1	9.42	3.21	17.31	1.35	14.21	0.98	9.93
Medium Truck	2.77	22.94	1.54	15.61	3.26	25.81	4.56	20.81	1.69	8.68	0.36	3.18	−0.13	−0.96
Large Truck					3.01	23.74								
Small Truck + Trailer							3.17	14.39	−0.16	−0.74				
Large Truck + Trailer			0.89	8.03	−0.72	−4.06	5.84	26.69	4.25	23.03	2.61	27.2	0.99	9.58
Semi- Trailer	4.96	42.6	2.9	30.12	−1.29	−6.56	7.17	32.82	4.77	26	4.28	47.75	4.35	50.71
Interaction Dummies:														
Outbound DC (small trucks)	2.37	20.65	−0.66	−4.19	1.26	2.91	0.49	4.66	1.79	29.61	−0.11	−1.16	1.21	10.42
Inbound DC (tractor trailer & semi trailer)	0.8	4.32	−0.29	−1.16	−14.42	−0.01	0.43	2.88	−2.23	−5.24	−4.72	−6.18	−0.78	−4.36
Long Haul (truck trailer)			3.98	35.45	2.43	9.76	−1.16	−18.67	2.75	31.3	−0.57	−1.99	−0.71	−2.5
Long_Haul (tractor trailer)	0.73	6.73	1.54	16.92	0.47	−1.33	0.02	−0.49	2.03	24.55	0.46	2.77	0.16	−1.21
Dense Area (<3tn)	5.18	49.92	4.77	49.96			3.92	30.55	4.34	67.11	2.23	52.64	1.21	28.51
Sparse Area (>20tn)			1.9	31.38									4.4	62.91
Dense Area_waste (<20tn)					0.27	7.57								
Sparse Area_waste (>20tn)					0.21	5.99								
No. of Obsv	19,609		14,997		12,553		81,257		20,527		17,574		26,578	
No. of Alternatives	21		27		33		28		30		28		28	
Log_Lik(Null)	−59,700		−49,428		−49,892		−56,652		−16,770		−15,779		−16,700	
Final Log-Lik	−6753		−10,189		−13,951		−46,569		−13,191		−14,198		−11,290	
Rho_0	0.89		0.79		0.68		0.83		0.81		0.76		0.87	

19:00–24:00, serves as the base category. The sign and the level of the value of the coefficients indicate if a variable affects positively or negatively the choice of a specific time window. The off-peak and after evening peak seems to be the preferred window for most sectors. However, when the origin is a transshipment terminal, many logistic segments have strong positive parameters for the morning peak and between peak periods. For shipments sent from producers the night period is very unlikely, which is logical as most manufacturing firms are closed outside working hours. Also, the morning peak is less preferred across most segments, which can be expected from the higher congestion levels in the morning peak. Also, the shipments that are sent to consumers are more likely to be transported later on the day, except for the construction sector: in this segment the morning peak and in between peaks period is preferred. For shipments sent from producers in more urban areas we see a pattern for early deliveries, in particular for construction logistics. In other sectors, higher urban density producers are avoided in the afternoon period and evening peak, which is logical as many cities have time specific access restrictions to downtown areas. For deliveries to the consumers, we observe a similar pattern: many sectors, in particular climate controlled and general cargo, prefer the night period before the morning peak. Also, vehicle types have distinctive patterns across the day. Small trucks have the highest preference for the morning peak period for each city logistic segment, except construction and waste collection. Trucks with trailers have a specific preference for the afternoon peak.

4.2.4. Tour formation

Table 4 presents the estimated parameters for the end tour models in the tour formation model. The models are binary logit models, see Eq. (5), and estimated on the truck trip diary data. Models are estimated for the first, and the later shipments in the tour. This is to allow a distinctive preference between the first decision between a direct- or a multi stop tour, and second, to add the 3rd or another additional shipment to an existing tour.

Tour duration has a different impact in the first shipment model and the later shipment model. The negative value for tour duration (***TD***) in the first shipment model says that the changes are smaller to end the tour with only one shipment if the tour is long. This is similar to other empirical studies [41] that also found a preference for direct tours on short transports. For the later shipments it is the opposite: if a multi-stop tour has a longer transport distance, the changes are higher to end the tour and not to add shipments. Most likely this is the result of ensuring not to exceed work shift duration. Most logically, if the weight of the shipments in the vehicle is reaching the capacity ***(W/C)*** the probability of adding a shipment to the tour decreases. Logistic nodes also have a significant impact on tour formation: tours from multimodal transshipment terminals (***anyTS***) have a high probability of being direct, while from distribution centers (***any DC load***) tours have higher probability to add the second or more shipments. This is in line with literature in which it was found that transshipment terminals often serve consolidated shipment flows from producers as part of a longer and often international supply chain [42]. Interestingly, tours in urban areas (***any URB***) also have a higher probability of more shipments. This is in line with typical urban freight distribution where multiple clients are served in one round tour. In these areas, there is a higher density of receivers, and from the truck planning perspective it is also more efficient to go into denser urban areas with fewer vehicles. The type of vehicle also impacts the tour formation: if a truck also pulls a trailer, the probability is higher to end the tour with one shipment. This is logical as the truck cannot be loaded and unloaded without loading and unloading the trailer as well. Finally the goods carried also affect tour formation: multi stop tours are more regular for food and agricultural products. Bulky products, such as fuels, oils metals and construction materials are more likely to be direct.

4.2.5. Parcel demand

The ordered logit model for parcel demand, see Eq. (6), is estimated on number of online orders per household using the SPSS Statistics 24 package. The observations are from the Mobility Panel Netherlands, the MPN [34], a household travel survey, see Table 5. In one of the yearly batches, additional questions regarding online and in-store shopping were included to analyze the impacts of e-commerce. The household and person characteristics were used to predict the number of parcel orders. Income is the first significant and explanatory variable: with increasing household income the number of online orders increases, with the largest positive parameter value for the highest income category. Age is also a distinctive parameters: the 25 to 39 year old, the reference category, orders more parcels. The level of urbanization was also tested but this parameter was not significant.

4.3. Validation

The final outputs of the model are validated by comparing the simulated truck intensities to observed truck flow data at network assignment level, and by comparing the simulated elasticities to representative values from literature. For the validation of the simulated freight movements, the outcomes of the HGV flows are compared to observed truck counts on the network. The bandwidth in Fig. 4 shows the simulated (red) versus observed intensities (grey).

For a more precise comparison, Fig. 5 shows a scatterplot of the simulated and observed truck intensities. The figure shows a clustering with a reasonable spread around the diagonal. Given that this comparison is based on the direct synthetic results from the demand model without trip matrix estimation to the traffic counts we argue that the simulator is able to give a representative prediction of freight transportation demand for the study area. For truck counts with lower intensities, the model seems to underestimate the volumes from the loop detector counts.

One issue with interpreting count data from loop detector data is a known bias from any long vehicles being registered: the loop detectors register all long vehicles, including transit buses, as trucks and it is not possible to filter these from the observations. Therefore we argue that the larger mismatch at smaller count locations can partly be attributed to a bias from city buses, or other long vehicles that are not freight related. To provide evidence for this, we analyzed available camera detection data that provide a more accurate measurement on the number of trucks entering the current low emission zone in the city center of Rotterdam. Tables 6 and 7

Table 3
Model Estimation results for the delivery time models.

	General cargo		Food		Climate controlled		Facility logistics		Construction logistics		Waste collection	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
00:00–7:59 Before morning peak												
ASC	−1.681	0.112	−0.724	0.093	−1.955	0.053	−2.140	0.093	−1.348	0.456	−0.598	0.319
FromTT	1.321	0.205			3.911	1.002	1.320	0.133	2.456	0.620		
FromP	−1.676	0.085	−1.381	0.073	−1.417	0.081	−1.475	0.110	−1.337	0.307	−0.621	0.376
FromPDense	−0.256	0.131	−0.573	0.095	−0.722	0.053			0.438	0.337	−0.184	0.361
ToTT	0.820	0.112			3.399	0.584	−1.639	0.133	−1.386	0.657		
ToC	−1.657	0.132	−1.050	0.111	−1.446	0.058	−1.448	0.136	−0.173	0.497	−1.440	0.371
ToCDense	1.787	0.173	0.997	0.130	1.085	0.062	0.612	0.124	0.806	0.661	0.475	0.373
SmallTruck	0.429	0.189	1.215	0.591	1.217	0.265						
MediumTruck	1.258	0.057	−2.449	0.108	−1.139	0.048	2.366	0.369			1.093	0.610
TruckTrailer	0.000		−2.232	0.193	−1.438	0.070	0.660	0.187	−1.251	0.797	−0.004	1.091
8:00 – 10:59 Morning peak:												
ASC	−1.320	0.113	−2.534	0.125	−2.747	0.067	−2.523	0.138	−1.101	0.450	−0.912	0.327
FromTT	2.198	0.199	1.568	0.173	4.454	1.005	1.158	0.165	3.901	0.635		
FromP	−1.128	0.089	−1.483	0.109	−0.548	0.097	−1.460	0.140	−1.754	0.311	−0.956	0.381
FromPDense	−0.722	0.137	−0.816	0.133	−0.993	0.069	−1.082	0.137	0.596	0.335	−0.715	0.373
ToTT	0.000				4.454	0.616	−1.368	0.144	−2.915	0.761		
ToC	−0.844	0.134	−0.767	0.132	−0.771	0.078	−1.156	0.150	0.003	0.485	−1.846	0.376
ToCDense	1.380	0.174	1.204	0.151	1.123	0.076	−0.171	0.151	0.197	0.660	0.191	0.384
SmallTruck	3.635	0.174	4.934	0.586	3.343	0.262	3.315	0.120				
MediumTruck	0.000		−1.398	0.143	−1.042	0.070	1.301	0.187			−0.286	0.634
TruckTrailer	−2.118	0.182	−0.395	0.204	−0.400	0.080	0.000		−2.347	0.964	−0.851	1.248
11:00- 16:59 Between peaks:												
ASC	−1.281	0.102	−0.951	0.094	−0.882	0.046	−0.734	0.099	−0.505	0.382	−0.176	0.318
FromTT	1.289	0.207	−1.626	0.280	2.803	1.004	0.863	0.132				
FromP	0.000		0.000		0.012	0.081	−0.320	0.111			0.261	0.380
FromPDense	−0.367	0.121	−1.281	0.097	−1.258	0.046	−0.679	0.083			−1.183	0.368
ToTT	1.344	0.122			2.803	0.590	−0.697	0.122	−1.233	0.646		
TPC	−0.569	0.141	−0.787	0.121	−0.416	0.059	−0.788	0.129	0.391	0.501	−0.708	0.380
ToCDense	1.265	0.179	1.060	0.136	0.685	0.057	−0.539	0.120			0.057	0.383
SmallTruck	1.278	0.188	1.538	0.605	0.170	0.295	0.000					
MediumTruck	0.000		−2.102	0.129	−0.182	0.044	1.271	0.371			0.826	0.618
TruckTrailer	−0.402	0.117	−0.500	0.134	0.016	0.047	0.772	0.186	−0.725	0.756	2.134	1.039
17:00 – 18:59 Afternoon peak												
ASC	−0.941	0.112	−0.650	0.094	−0.635	0.045	−0.105	0.095	−2.278	0.488	−1.479	0.351
FromTT	0.000		−2.457	0.338	0.188	1.059	−0.870	0.146				
FromP	0.485	0.097	0.402	0.084	0.297	0.080	0.704	0.115			−0.358	0.406
FromPDense	−0.481	0.130	−1.323	0.096	−1.067	0.044	−1.111	0.081			−0.831	0.410
ToTT	1.413	0.123			0.188	0.591	−1.419	0.128	0.317	0.731		
ToC	−0.272	0.141	−0.848	0.117	−0.520	0.055	0.247	0.135	−0.873	0.591	−0.245	0.426
ToCDense	0.819	0.180	1.254	0.132	0.908	0.055	−0.548	0.117	0.865	0.745	0.791	0.397
SmallTruck	0.000		−2.317	1.156	−1.236	0.362	−0.915	0.309				
MediumTruck	0.000		−1.952	0.116	−1.871	0.045	0.731	0.389			0.833	0.643
TruckTrailer	0.660	0.091	1.369	0.122	0.835	0.042	1.869	0.176	1.130	0.733	2.640	1.053
19:00 – 23:59 Evening												
ref.	0.000		0.000		0.000		0.000		0.000		0.000	
N	13,164		11,008		38,793		13,279		548		1735	
Log-likelihood	−19,448		−17,861		−69,193		−21,774		−847		−2586	
Log-likelihood final	−13,311		−13,236		−50,864		−17,980		−734		−2263	
adj rho-square	0.370		0.251		0.185		0.157		0.138		0.180	

Table 4
Model estimation results for the End Tour models in the tour formation model.

Variable	First shipment		Later shipment	
	Β	tstat	β	tstat
Constant	1.684	57.89	−2.526	40.42
$\sqrt{(TD)}$	−1.698	45.73	0.386	27.13
(W/C)2	5.471	53.62	3.286	57.91
prox			0.009	16.47
lnstops			−0.911	21.53
anyTS	1.588	42.89	0.526	11.23
anyDC load	−0.578	22.54	−0.191	5.27
any URB	−0.461	12.1	−0.145	4.51
DC unload	−0.475	18.24	0.526	11.23
vehicle type (truck)	−1.295	33.31	−1.968	32.52
(truck + trailer)	1.85	38.12	−0.954	10.85
goods type (agricultural)	−0.736	15.54	2.226	37.99
goods type (food and fodder)	−0.659	20.67	0.871	25.2
goods type (fuels, oils, metals)	1.495	4.44	–	–
goods type (construction materials)	1.452	24.98	0.556	6.86
goods type (manure, fertilizers)	0.713	2.82	−1.105	3.38
goods type (chemical products)	0.583	13	1.517	23.91
N	47,315		44,618	
R2	0.442		0.292	

Table 5
Estimated parameters for the parcel demand model.

	Variable	Estimate	Std. Error	Sig.
Treshold:				
μ_1	0 parcels	−1.487	0.065	0.000
μ_2	1 parcels	−0.872	0.063	0.000
μ_3	2 parcels	−0.330	0.062	0.000
μ_4	3 parcels	0.136	0.062	0.028
μ_5	4 parcels	0.516	0.063	0.000
μ_6	5 to 9 parcels	2.189	0.078	0.000
μ_7	10 to 14 parcels	3.298	0.110	0.000
μ_8	15 to 19 parcels	4.362	0.171	0.000
	20+ parcels	–	–	–
Attributes:	HH Income < 29,5 kEUR	−0.230	0.066	0.000
	HH Income 29,5–43,5 kEUR	−0.240	0.065	0.000
	HH Income 43,5 - 73 kEUR	–	–	–
	HH Income > 73 kEUR	0.355	0.070	0.000
	12–24 years old	−0.586	0.088	0.000
	25–39 years old	–	–	–
	40–49 years old	−0.285	0.077	0.000
	50–59 years old	−0.957	0.075	0.000
	60–69 years old	−1.347	0.076	0.000
	70–79 years old	−1.736	0.089	0.000
	80 years and older	−2.417	0.189	0.000
	Male	−0.105	0.049	0.032
	Female	–	–	–
	Observations:	6745		
	LLH Intercept Only	2550.2		
	Final LLH	1675.8		
	Cox and Snell	0.142		
	Nagelkerke	0.146		
	McFadden	0.043		

compares the registered camera intensities to the loop detector counts on the same cordon. This comparison provides strong evidence for a high overestimation in loop detector counts. This is typical for urban networks with higher intensity of transit operations. We conclude that an exact quantitative validation with loop detector counts is not possible, but we regard the pattern in outcomes as plausible. An interesting direction for further research is to include truck counts in the calibration of the model. Based on the truck counts and synthetic results from the model, calibration weights can be estimated for each freight tour. These calibrated weights can then be used to re-calibrate parameters in the logistic choice models. A first example of such an approach is presented in [43].

The price and other crucial sensitivities of a strategic freight demand model can be validated. In a series of runs the distance costs are increased by 0.10 €/km and 0.25 €/km. The logistic responses to increasing transport costs may include shorter transport distances

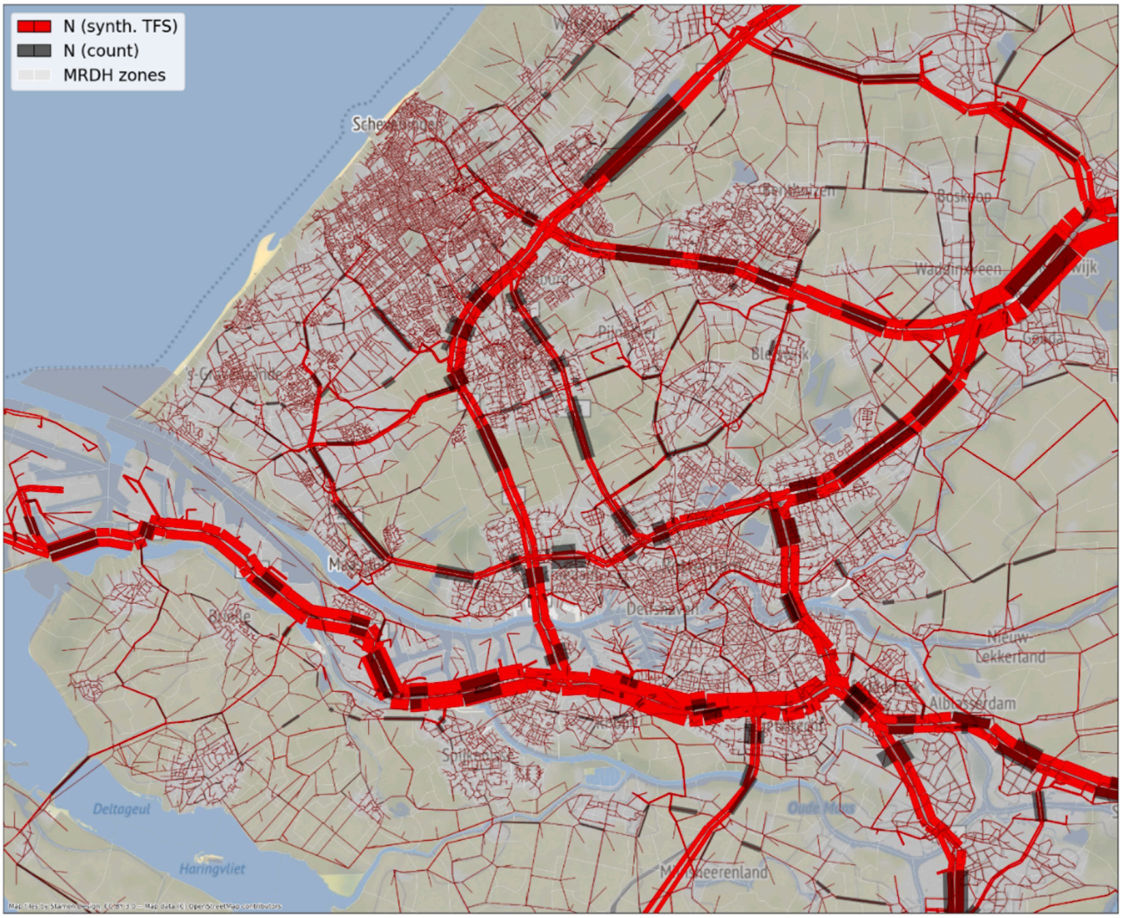

Fig. 4. Match between simulated truck intensities and loop detector count data across the study area.

(to choose products from closer by), and to improve logistic efficiency by choosing larger vehicles or having more consolidation in delivery tours. Since the model considers road freight only, there is no shift to other modes possible. But for urban freight this is a less relevant response.

The cost sensitivity of the model seems plausible. The charge of 0.10 €/km corresponds to an increase of 30 % in total distance-based costs. The distance-based costs make for 20 % of the total transport cost, so on average the total costs increase by 6 % in the 0.10 €/km run. The vehicle kilometers decreased by −0.6 %, so effectively this elasticity of vehicle kilometers to transport costs is −0.10. When compared to cost elasticities for road transport from international literature [44–46] this value seems to fall in the lower end of the plausible range.

The micro freight module was validated testing the response in vehicle kilometers to different parcel market scenarios. The increase in vehicle kilometers is not linear to the increases in parcel demand of 25 and 100 %: as the delivery density increases the delivery routes become more efficient and vehicles can drive shorter round tours to deliver the same number of parcels. It creates higher efficiency. Expressed as an elasticity the sensitivity runs show that the elasticity of vehicle kilometers to parcel demand is around 0.7. In the asset sharing scenario carriers cooperate fully to maximize delivery efficiency. In that case it is assumed parcel demand is fulfilled by the carrier that has the depot closest by. The vehicle kilometers and emissions are reduced drastically: by >50 %. This shows how effective collaboration in the logistics sector could be in mitigating delivery kilometers.

4.4. Application to urban freight policies

MASS-GT aims to support environmental impact analysis of urban freight policies. To illustrate the applicability for urban freight solutions, the model has been applied in a number of city logistic use cases that were developed in collaboration with local authorities. In [21] the introduction of zero-emission zones in Rotterdam was studied. In this use case the emphasis was on the impact of urban freight traffic on local emissions. In the project LEAD, the city of The Hague and local start-ups (bicycle carrier and a pick-up point provider) collaborated in a living lab of crowdshipping solutions [47] describe the impacts of crowdshipping for parcel deliveries studying different configurations of parcel lockers and crowdshipping platform. In this use case the focus was on the shift of last mile delivery solutions for urban deliveries. The applications illustrate how an urban freight simulator can be used to estimate the impacts

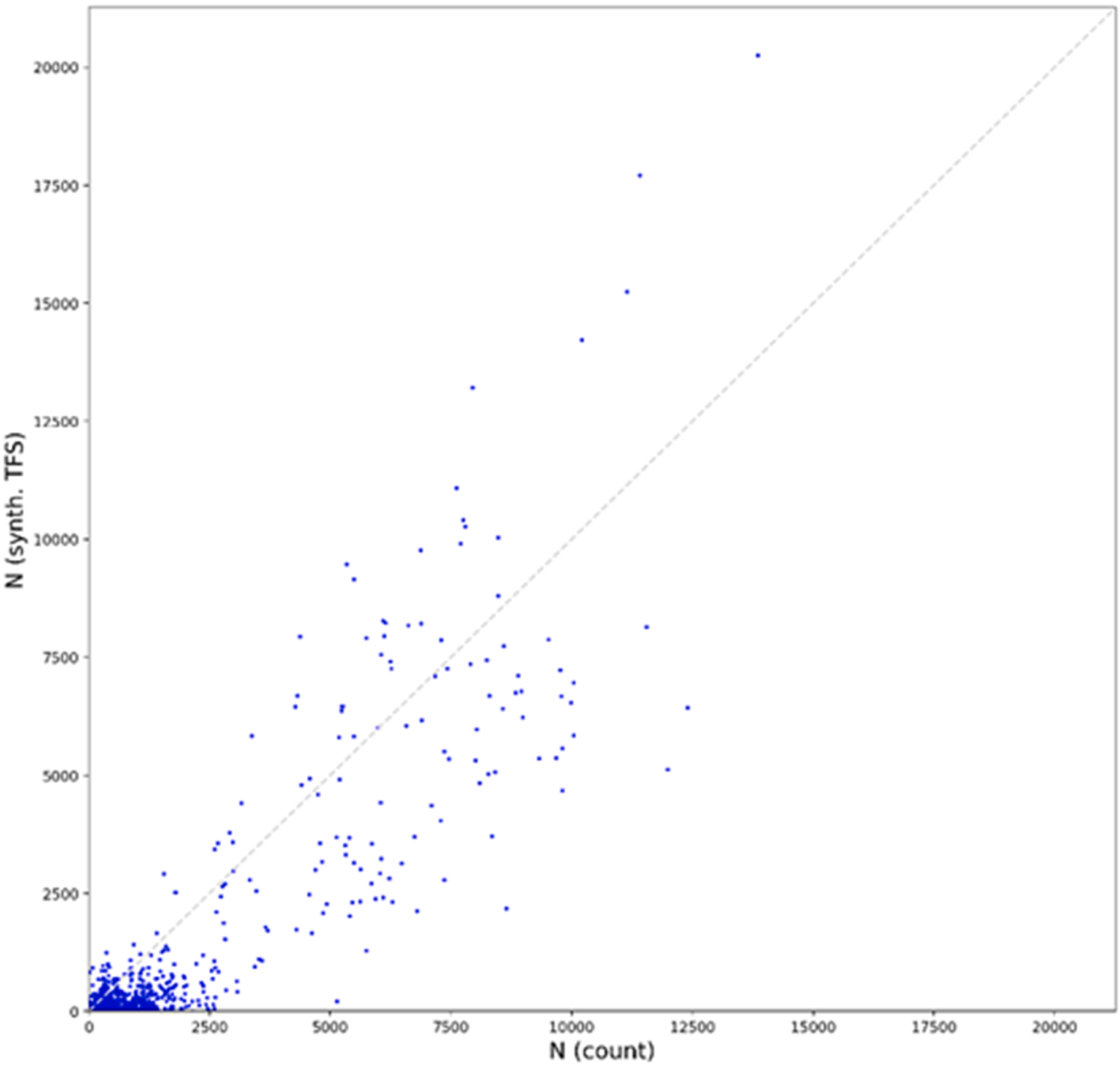

Fig. 5. Scatterplot simulated truck intensities and loop detector count data.

Table 6
Truck intensities at the low emission zone cordon.

Truck intensities to the low emission zone:		
Simulated:	10,177	vehicles/day
Camera data:	10,803	vehicles/day
Loop detector counts:	18,292	vehicles/day

of urban freight policies or technology on urban freight demand, vehicle patterns and network indicators. More specifically, simulation scenarios can be used to explore the impacts of large- scale deployment of new technologies, or new urban freight policies before implementing them. Doing so, it can assist city planners in identifying efficient policies, and last-mile delivery companies to further improve their operations with new technological solutions. Indicators can be used to identify more sustainable urban freight policies.

The simulator predicts urban freight demand, and the freight vehicle operations from which a variety of indicators can be derived. The finest level of detail is the shipment level, but demand can be analyzed by logistic segment, by firm or zone, or shipment sizes. Vehicle indicators include number of arriving and departing trips per zone, the round tour pattern of the vehicle, and characteristics of the tour such as weight and product type carried or number of stops per tour. Finally at network level, the routes of vehicles determine freight intensities on network links, segmented by vehicle type or commodity group, and the resulting emissions of the vehicles. Table 8 provides summary statistics on shipment demand across different types of agents in the model: by the type of producing or consuming firm or by logistic node. Manufacturing agents are important both as producers or consumers of goods: most shipments are

Table 7
Sensitivity runs for model validation.

Cost scenarios			
Indicator	Reference	+0.10€/km	+0.25€/km
Vehicle kilometers (trucks)	9445,097	−0.6 %	−1.8 %
Average shipment distance (km)	121	−0.1 %	−0.6 %

Parcel market scenarios				
Indicator	Reference	Demand +25 %	Demand +100 %	Asset sharing
Number of parcels	312,793	25 %	100 %	0 %
Vehicle kilometers (vans)	86,720	18 %	71 %	−54 %
C02-emissions (kg)	16,754	19 %	75 %	−53 %

coming to or are sent from firms in the manufacturing sector. Transshipment terminals and distribution centers are also important generators of freight shipments. Finally, the region has a high proportion of shipments that are either sent from or going to the outside of the study area. This is a logical result as the study area hosts a large seaport serving Northwest Europe. The vehicle type distributions also show a strong preference for the use of semi-trailers in goods transport, followed by small trucks.

The type of output indicators to be used for an impact assessment depends on the type of application. In [48] four very distinctive urban freight use cases for the city of Rotterdam were analyzed. Depending on the use case, different impacts were analyzed, like emissions, vehicle kilometers, or network intensities. These results revealed logical findings and sometimes non-trivial secondary impacts through the shifts in urban freight demand.

Mode shift to new forms of delivery services, such as consolidation centers, cargo-bikes or crowd-shipping are difficult to predict with utility-based choice models. Firstly because behavioral data on the use of such vehicle is missing, or only from hypothetical choice experiments, and secondly there are many uncertainties on the definitions of this new modes or services that are under development. Use cases with new delivery modes were tested by designing 'expert-based' scenarios, that explicitly explore the impacts of different implementation dimensions of new modes [21,47,49].

To advance the field of research, the code of the model is available as opensource (https://github.com/mass-gt). Implementations in other study areas have been made for a crowd-shipping case study in Rome (Italy) and a parcel locker network design in Thessaloniki (Greece). This illustrates the transferability of the methodology to other urban contexts using local data to construct and calibrate the models.

5. Conclusions and discussion

This article presents the technical and empirical specifications of an agent-based model for urban freight transport. The technical design of microscopic urban freight models typically consists of a variety of modeling methods such as simulation, discrete choice- and optimization models [13]. One challenge is to design a transparent and consistent framework.

This article gives complete technical specifications and discusses the empirical foundation of the model. This way it provides a full overview of the design of the model, and the technical and empirical specifications. The theoretical foundation and empirical estimation of some of the crucial logistic choice models are published in other manuscripts. Also, the effectiveness and possibilities of the presented model has been proven in several case studies.

Overall mileage and emissions are calculated at vehicle and shipment level allowing a detailed analysis of policy impacts. The disaggregate level of detail allows the implementation of a variety of logistic developments and policies (e.g. zero-emission zones, road use charges, hub strategies), or on specific segments (long haul or city logistics, different commodity types). Case studies show that impacts vary across different logistic segments, underlining the need to have sufficient spatial and behavioral detail in urban freight models to make a more reliable impact assessment.

The simulator is calibrated on big freight data and simulates behavioral logistic responses. To improve consistency and level of information for model calibration, data fusion was used to have better data available for model calibration [39]. In developing urban freight models, data is challenging but with a clever combination of use of available sources it is feasible to have an implementation of urban freight simulator at low granularity. Validation of freight simulation results to truck traffic count information can be sensitive to the type of measurement. Our analysis with camera and loop detector data shows that loop detector count data are likely to overestimate truck trips in urban areas with a high share of other long vehicles such as transit buses.

The network module in MASS-GT also allows more in-depth analysis of the patterns of freight tours. The route builder calculates and stores the routes of individual tours. This allows detailed cross-sectional analysis of the transport vehicles using specific corridors in the infrastructure network: what type of vehicles and what types of goods are carried by these vehicles, or where were they originating from? This also allows advanced calibration of synthetic tours: the 'intercept' tours, tours that pass by a truck count location, can be used to estimate calibration factors. These calibration factors can be used to re-estimate the parameters in the logistic demand models. Such a two-step calibration approach has been explored in [43]. A final relevant topic still under lighted in academic literature is effective solutions to reduce simulation variance. In MASS-GT stable simulations with marginal changes in inputs rigid seeding procedures are used to make.

Table 8
Descriptive output statistics across different freight agents: shipments, shipment size and vehicle type distribution.

Agents	Senders		Receivers		Vehicle type (receiving shipments)													
	Shipments [#]	Average weight [tons]	Shipments [#]	Average weight [tons]	Truck (small)		Truck (medium)		Truck (large)		Truck+trailer (small)		Truck+trailer (large)		Semi-trailer		Special vehicle	
Transshipment Terminals	11,805	4.43	10,385	4.46	1469	14 %	607	6 %	66	1 %	80	1 %	2145	21 %	5925	57 %	93	1 %
Distribution Centers	6579	4.03	6111	3.93	2774	45 %	537	9 %	78	1 %	37	1 %	532	9 %	2077	34 %	76	1 %
Agriculture	7038	2.85	164	2.91	5	3 %	10	6 %	1	1 %	8	5 %	25	15 %	115	70 %	0	0 %
Manufacturing	28,647	3.92	31,351	3.64	3653	12 %	1790	6 %	115	0 %	1176	4 %	5884	19 %	18,605	59 %	128	0 %
Retail	87	3.18	1419	3.12	148	10 %	66	5 %	1	0 %	45	3 %	264	19 %	892	63 %	3	0 %
Commercial services	407	3.05	3079	3.67	468	15 %	119	4 %	13	0 %	117	4 %	661	21 %	1684	55 %	17	1 %
Public services	71	2.59	399	3.60	53	13 %	15	4 %	1	0 %	14	4 %	80	20 %	235	59 %	1	0 %
Other	4461	3.05	6559	3.75	894	14 %	316	5 %	29	0 %	213	3 %	1333	20 %	3738	57 %	36	1 %
External	54,110	2.91	53,703	2.93	13,492	25 %	2760	5 %	131	0 %	4344	8 %	8555	16 %	24,200	45 %	221	0 %
Total	113,205	3.39	113,170	3.39	23,392	21 %	6231	5 %	437	0 %	6034	5 %	19,497	17 %	57,511	51 %	580	1 %

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Data availability

The authors do not have permission to share data.

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