Title: Reciprocal congestion:
The impacts of freight vehicles on cars' travel times, and *vice-versa*

FINAL REPORT
December 2015

Principal Investigator
Adrien Beziat

Researchers
Adrien Beziat
Laetitia Dablanc
Martin Koning
Florence Toilier (Laboratory of Planning and Transport Economics)

MetroFreight Center of Excellence
IFSTTAR – 14 Bd Newton 77445 Marne la Vallee France

Title: Reciprocal congestion:
The impacts of freight vehicles on cars' travel times, and *vice-versa*

Abstract

Researchers recognize both the impacts of road congestion on the performance of freight transport operations and the impacts of road congestion caused by freight vehicles on private passengers' travel times. However, it remains very complex to measure congestion at the scale of an urban area, because it requires traffic counts on a large portion of the road network. Moreover, the congestion impacts of private cars on the freight traffic have been rarely addressed in the literature. This paper presents a methodology allowing us to measure road congestion at an urban-level, using (macro) OD matrices and (micro) data for private passengers and freight vehicles in the case of the Paris Region (France). First, we develop one theoretical framework which enables us to express congestion functions of each traffic class (small or large vehicles) as well as the reciprocal influence each traffic class has on the other in terms of travel times. Then we present the empirical material used to test this framework. Building on our econometric results, we propose relationships expressing the travel times of each vehicle class as a function of similar and dissimilar types of vehicles' traffic. Future research will rely on these functions to calculate various marginal congestion costs.

Key-words: freight; road congestion; multi-class traffic; Paris region

INTRODUCTION

Urban areas are characterized by high density of activities and population. Very desirable advantages emerge from this spatial concentration: households and firms may access a large variety of jobs, goods and services; the flow and the spread of ideas are more intense; economic agents may share the funding of indivisible commodities (Duranton and Puga, 2003). But at the same time, high density can lead to several negative externalities (O'Sullivan, 2009) ranging, for instance, from expensive land rents, criminality, pollution, and congestion of the transport networks.

Over the last fifty to sixty years, policies' paradigm regarding automobile use and road infrastructure has evolved tremendously. During the post WW2 period, there was an incredible rise in the number of automobiles, accompanied by massive investments and spending on road infrastructures (Newman and Kenworthy, 1989). It was deemed that the best way to avoid road congestion in urban areas was to improve the existing stock of infrastructures (widening of roads, creation of expressways) and to build new highways or ring roads. This trend led to sprawling cities and the demand for road infrastructures rapidly caught up with the supply, leading to an increase in road congestion and time losses for commuters (the so-called "Downs Paradox", see Duranton and Turner, 2011). Since the 90's, the paradigm has shifted, both at the local and national scales. Most cities are now trying to limit the use of cars and are encouraging the use of public transport such as subway or bus lines (OECD, 1996).

While this strategy deals with passenger trips, it does nothing to prevent road congestion caused by freight trips. Freight transport operators have basic needs in terms of flexibility, reliability and most importantly, door-to-door trips (Nemoto et al., 2006). These needs make modal-shift impossible in most instances. For this reason, commercial transport relies on heavy and light road vehicles, such as van or trucks. As a result, freight trips remain one of the most challenging issues for local authorities willing to promote sustainable transportation. In many urban areas, such as the Paris region, this challenge has led to the progressive development of ideas such as "Low Emission Zones" (Proag and Patrick, 2012), using existing subway and tramway lines to carry goods (APUR, 2014), or the use of urban consolidation centers projects (Dablanc, 2005), although none have really come into fruition yet.

PROJECT OBJECTIVE

Purpose of study

The issue of congestion is particularly important for the Paris region ("*Ile-de-France*"). Every year, more than 62% of kilometers of queues registered on French roads are located in the areas surrounding Paris (URF, 2013). The Paris region is one of the most congested urban areas in Europe: in 2013, motorists spent an average of 55.1 hours per year in traffic jams, only behind London and Stuttgart in Europe (INRIX, 2014). While congestion has been studied extensively from the perspective of passenger vehicles (Koning, 2013; Leurent and Breteau, 2009), very few studies have dealt with freight trips.

This paper proposes an empirical assessment of road congestion in the case of multi-class traffic for the Paris Region. Understanding road congestion caused by freight vehicles is crucial in order to design and enforce adequate and efficient public policies. Moreover, we want to highlight the congestion impacts of private passengers' trips on freight traffic. This reciprocal phenomenon has been rarely addressed in the literature. The two vehicle classes considered here are, on the one hand, small vehicles (cars and vans) and, on the other hand, trucks (large vehicles). This research is part of an ongoing project aimed at calculating marginal congestion costs for freight and passenger vehicles in the Paris Region.

PROJECT DESCRIPTION

One main issue when measuring road congestion in the Paris Region is that publicly available traffic data is very scarce, especially for large vehicles such as trucks. It is only available for the main highways, where heavy trucks are distinguished from small vehicles (private cars and vans). The distinction between vehicles' size causes another problem for the measurement of congestion caused by freight vehicles. Thanks to the recent urban freight survey ("*Enquête Transport de Marchandises en Villes*", ETMV), which was administered in 2010 in the Paris Region, we know that about 60% of freight movements (operations of deliveries and take-offs) are done using Light Goods vehicles (e.g. vans or cars). If we want to measure the impact of freight on congestion, we have to take into account small vehicles as well as heavy trucks.

In this paper, we develop a theoretical framework in order to model the travel duration in the case of multi-class traffic. The rest of this research is organized as follows. First, we expose our theoretical framework for measuring congestion functions of each traffic class, and the reciprocal influence each traffic class has on the other in terms of road congestion. Second, we detail the empirical material used

to test this theoretical framework. Finally, we discuss our econometric results. Ulterior research will build on these to calculate various marginal congestion costs.

RESEARCH APPROACH

Conceptual framework

We define road congestion as an event that appears as soon as a given infrastructure – characterized by fixed capacities – cannot satisfy the demand it faces without decreasing the quality of service proposed to users. This means that we only focus on "recurrent road congestion": we ignore accidents or civil-works related congestion (Skabardonis et al., 2003), which may affect the flows of vehicles punctually. We take into account the quality of service in relation to the travel time spent by individual trips on roads. As a consequence, we do not take into account the effect of congestion on departure and/or arrival time (Arnott et al., 1988; Vickrey, 1969) or drivers' productivity and psychological states.

In order to analyze congestion, engineers have proposed various methods (TRB, 2010; Small and Verhoef, 2007). One in particular relates to the relationship between travel-time and the flows of vehicle on a given infrastructure. This relationship has been studied traditionally through a "travel time-flow function" designed by the American Bureau of Public Road:

$$D = D^0 \left(1 + \alpha \left(\frac{F}{K} \right)^{\beta} \right) \quad (1)$$

Where D represents the travel time necessary to perform one kilometer on a given road (or over a given area); D^0 characterizes the "empty road" travel time, i.e. the travel time in the case no single vehicle is using the infrastructure (often derived from the maximal authorized speed); F is the hourly vehicles flow on that infrastructure (per kilometer of road) and K is the theoretical road capacity (expressed in vehicle/hour/kilometer), i.e. a function of road width (number of lanes).

For the purpose of our study, one important limitation of equation (1) is that it does not take into consideration multi-class traffic. F is considered as a flow of homogeneous vehicles, while a reasonable assumption can be made that big vehicles have a different impact on travel times compared to small vehicles.

In order to correct this shortcoming, we differentiate the total flow of vehicle F observed on the road across traffic class i and j vehicles (Setra, 2001; Moridpour and al., 2015). Yun and al. (2010) suggest adapting equation (1), which then becomes:

$$D = D^0 \left[1 + \alpha \left(\frac{F_i}{K} \right)^{\beta} \left(1 + \frac{F_j}{F} \right)^{\delta} \right] \quad (2)$$

where F_i represents the hourly flow of class i vehicles, F_j the one of class j vehicles, and F the total traffic flow. The coefficient β describes the travel time – road usage relationship for class i vehicles, and δ the one for class j vehicles. Note that if $F_j = 0$, then equation (2) collapses to equation (1).

Empirical specifications

Equations (1) and (2) present important limitations. The first one is data requirements. In order to calculate time losses caused by road congestion for an agglomeration, one needs an extensive traffic database. Data from counts and captors sometimes exist, but they are scarce and not always reliable. Most existing studies rely on simulated traffic of vehicles (Yun et al., 2010). When studies use empirical data, it is difficult to generalize the results from a specific infrastructure to the adjacent roads in the area, because of the lack of knowledge on the traffic composition across vehicle classes i and j.

More importantly, equations (1) and (2) focus only on the travel time of vehicles. However, they assume that the impact of traffic flow is homogeneous across vehicle classes. We make the hypothesis that incremental journey times due to the arrival of one additional truck are not homogeneous: The marginal truck is likely to affect differently the traffic speed of small vehicles (cars or vans) as compared to the one of large vehicles. This is a major limitation which may impact transport modeling tools or policies' appraisals, such as optimal road pricing rules (Small and Verhoef, 2007).

In order to overcome those limitations, we now focus on individual trips performed over some large geographical areas (origin-destination pairs rather than specific road segments). Starting from equation (2), we model the travel time D_{ikt} spent by one individual driving a class i vehicle, over a given origin-destination (OD) k, during the time period t, as:

$$D_{ikt} = \alpha_1 D_{ik}^0 + \alpha_2 \frac{F_{ikt}}{K_k} + \alpha_3 \frac{F_{jkt}}{F_{kt}} + \alpha_4 T_i + \alpha_5 X_{ik} + \varepsilon_i \quad (3)$$

The variable D_{ik}^0 represents the minimal travel time necessary to realize the trip over the OD k if roads there were empty. It is found by crossing maximal authorized speeds on this OD with the distance travelled by the class i vehicle. D_{ik}^0 does not depend on the time period.

The variable $\frac{F_{ikt}}{K_k}$ describes the (similar) class i "flow-to-capacity ratio" faced, on the average, by the traveler on that OD, at that time period. Importantly, the class i flow F_{ikt} depends on both the considered OD and on the time period. By contrast, the road capacity K_k varies only across ODs.

The variable $\frac{F_{jkt}}{F_{kt}}$ represents the share of (dissimilar) class j flow within the total traffic flow faced, on average, by the class i traveler. The class j flow F_{jkt}, as well as the total flow F_{kt}, depend on both the OD k and the time period t.

The vector X_{ik} includes some control variables related to the trip made by the class i vehicle and the OD k. These variables are suspected to influence the travel duration.

Importantly for our purpose, the dummy variable T_i is equal to 1 if the class i vehicle is a truck (0 otherwise).

Lastly, ε_i corresponds to one error term assumed to have zero mean and constant variance. This statistical noise is required for empirical estimates of equation (3) through standard econometric techniques such as "Ordinary Least Squares" (OLS).

According to this framework, the main parameters of interest are α_2 and α_3. They represent the impacts of similar (dissimilar respectively) traffic flows on the travel time spent by the individual i (j). In the case the vehicle i is a small one, α_2 describes the influence of small vehicles on his own travel time and α_3 describes the influence of large vehicles.

Equation (3) models the impacts of similar/dissimilar traffic flows as being homogeneous across vehicle classes. To relax this assumption, we can include "interaction terms":

$$D_{ikt} = \alpha_1 D_{ik}^0 + \alpha_2 \frac{F_{ikt}}{K_k} + \alpha_3 \frac{F_{jkt}}{F_{kt}} + (\alpha_1^* D_{ik}^0 + \alpha_2^* \frac{F_{ikt}}{K_k} + \alpha_3^* \frac{F_{jkt}}{F_{kt}})T_i + \alpha_5 X_{ik} + \varepsilon_i \quad (4)$$

where parameters α_1^*, α_2^* and α_3^* can be considered as "sensitivity premiums".

To fix ideas, suppose that individual i is driving a truck ($T_i = 1$). In that case, the influences of minimal travel time, similar traffic flow and dissimilar traffic share on his own travel time will be equal to $(\alpha_1 + \alpha_1^*)$, $(\alpha_2 + \alpha_2^*)$ and $(\alpha_3 + \alpha_3^*)$ respectively. By contrast, if individual i is driving a small vehicle ($T_i = 0$), respective impacts will be α_1, α_2 and α_3. As a consequence, the statistical significance and the signs of α_1^*, α_2^* and α_3^* inform us about the differentiated responses of trucks' travel times to the surrounding traffic conditions.

Equations (3) and (4) assume that the relationship between travel time and traffic flows is linear. Obviously, alternative specifications (logarithmic, exponential...) should be tested in order to select the one that fits the best with the data. We now present the material allowing us to test empirically this simple framework of multi-class road congestion.
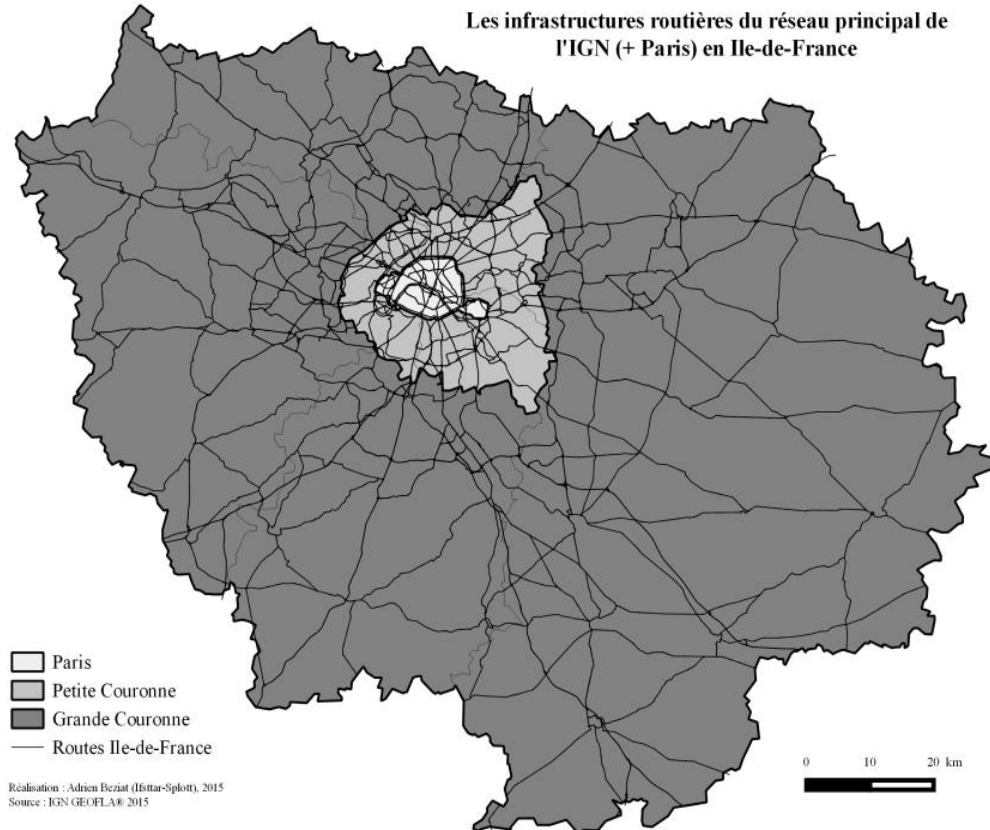

DATA

The challenge is to gather empirical data that can be used within this framework. In particular, we need data to describe F_{ikt}, F_{jkt} and K_k, respectively the flow of class i vehicles on a given OD during a given time period, the flow of class j vehicles on a given OD during a given time period, and the road capacity on a given OD.

In this paper, we model road congestion at a macroscopic scale, in large geographic areas. As a consequence, we have divided the Ile-de-France region in three concentric zones: Paris (the center of the region), the inner suburbs, and the outer suburbs. The different time periods were defined as the morning peak-hours (6-9 am), the afternoon peak-hours (4-7 pm), and the rest of the day.

The measure of the supply of road infrastructure comes from a database of the National Institute of Geography ("*Institut de Géographie National*"), "*BD TOPO*", which contains all the roads of the Paris Region, in the form of GIS. As our approach of congestion is very macroscopic, we chose to only select the main roadways. The IGN has built a distinction between the main and the secondary networks. It does not depend on the administrative class of the road (national, regional or municipal), but the importance of the road to the traffic. Therefore, the selected roads are those where most of the traffic of Ile-de-France is located. Each road is graded from 1 to 6, 1 being the most important (IGN, 2008). We chose roads of importance equal to 1 or 2 (except for Paris, which does not have roads of importance

level equal to 1, since there are no highways in Paris; therefore, we chose to include the main network of Paris, streets with an importance equal to 3).

Figure 1 - The Paris region and its road infrastructure, divided in three concentric zones

One of the main advantages of the "*BD TOPO*" database is that it contains information on the physical characteristics of the selected roads. It gives information on the length, width and number of lanes of each segment of the road network. This allows us to compute the supply of road infrastructure for each OD pairs K_k by multiplying each kilometer of road lanes by 2,200 vehicles/hour. The latter threshold is generally considered as the theoretical capacity of the main roads in France. In order to calculate the minimal travel time (D_{ik}^0 in previous equations), we also gathered data on speed of the road networks, according to the average authorized speed of the various administrative categories of roads: 120 km/h for highways, 90 km/h for national expressways, 70 km/h for smaller roads and for the rings road around Paris. The streets in Paris were assigned a speed of 30 km/h.

The measure of traffic flows F_{ikt} and F_{jkt} has been estimated using various sources. For passenger transportation, we use a household mobility survey, the EGT ("*Enquête Globale Transport*"). The last EGT took place in 2010 in the Paris Region. It uses a standard methodology, developed in France and used by all local authorities (Certu, 2013). It was administered to a representative sample of 18,000 households, 43,000 persons, for over a week. In total, 143,000 trips were recorded. The EGT survey gives us information on the transport mode used, distance travelled, duration, hour of departure/arrival, origin

and destination of each trip…. Each observation is weighted according to the socio-economic characteristics of the surveyed person and household. This allows us to compute an OD matrix for private passengers' cars in the Paris Region.

The freight flows were obtained using the "*Freturb*" software, developed by the Laboratory of Transport Economics (Lyon University). The results of Freturb are based on surveys administered in French cities in the 90's: over 5,000 establishments and over 1,000 freight tours were surveyed. These surveys give a lot of information on urban freight, and most importantly, the "generation coefficients" of establishments, and the distance travelled during freight tours. The methodology for the freight simulation is presented in details in Routhier and Toilier (2007). It relies on an establishment database, in this case the "*Altarès*" database, which is an extraction of the "*Sirene*" database for the Ile-de-France region.

The Freturb approach is quite different from traditional "4-steps" models. First, it generates goods movements, according to the size and activity type of establishments. Then it distinguishes between tours and single-trips. It generates distance functions, according to several variables (type of establishment, type of vehicle, distance from the city center, transport operator). Finally, it simulates the distribution using a "shortest-path" algorithm. The output is an OD matrix for several time periods, distinguishing between light vehicles (<3.5T in France, e.g. vans essentially), and heavy vehicles (trucks).

Table 1 – Average hourly kilometric traffic flows by OD for cars, vans and trucks

	Cars	Vans	Small Vehicles	Trucks	Total
Paris - Paris	538.5	19.1	557.6	12.1	569.7
Paris - Inner Sub.	544.6	23.5	568.1	17.5	585.6
Paris - Outer Sub.	424.9	10.9	435.8	8.3	444.1
Inner Sub. - Inner Sub.	827.2	28.1	855.3	21.9	877.2
Inner Sub. - Outer Sub.	432.2	8.9	441.1	7	448.1
Outer Sub. - Outer Sub.	381.9	6.6	388.4	5.5	393.9

Sources: EGT and Freturb

Table 1 crosses information obtained from both EGT and Freturb. We can make several observations. First, a large majority of the urban traffic in the Paris region is generated by passenger vehicles. Depending on the OD, average goods vehicles flow represent only between 3% and 7% of the total traffic. Another aspect to consider (especially for a multi-class traffic analysis), is that heavy goods vehicles do not represent the majority of goods vehicles traffic. Trucks represent between 38% and 45% of goods traffic, and between 1% and 3% of the total traffic. These are not surprising results: from the urban freight survey of the Ile-de-France region collected in 2010 (ETMV), we know that about 60% of all the operations of deliveries and take-offs are made using light goods vehicles.

The spatial distribution of the hourly kilometric traffic illustrates that the traffic is highly concentrated in the center of the agglomeration, for the Paris–Paris OD but also for the Paris–Inner Surburbs. Interestingly, the highest number of vehicles per kilometer of lane per hour is in the Inner Suburbs, especially for passenger vehicles, which makes sense considering relatively low percentage of motorized households in central Paris (45% against 70% for the inner suburbs and 85% for the outer suburbs). The low number of hourly traffic per kilometer in the Outer Suburbs can be explained by the very low density of these areas of the region, despite the very intense use of personal vehicles by the population of these parts of the Ile-de-France region.

Next to these aggregated OD matrices, empirical estimates presented in the next section are based on data on individual trips for passenger and freight, between the OD pairs considered and over the three time periods. We have used the two databases at our disposal. The first one is the household mobility survey (EGT) where each observation is now considered as a single trip. It contains the origin and destination, the time of day the observed trip was realized, its distance as well as its duration. The distance was one Euclidian distance, which was converted into a "network distance" following a standard methodology developed by the CERTU for French urban areas (CERTU, 2005).

For freight trips, we used data from the 2010 urban freight survey (ETMV) which was administered by the Laboratory of Transport Economics in the Ile-de-France region (Patier and Routhier, 2009). This survey is composed of two distinct sub-surveys: one about the economic establishments, and the other one about the delivery-drivers which serve the surveyed establishments. We used the delivery driver survey. In total, 345 freight tours were surveyed with an embarked investigator on board the vehicle. The investigator described precisely each trip of the vehicle between the different establishments. For the need of our paper, these 345 tours were decomposed into 2,000 trips with the following variables: origin and destination, hour of the day, duration and length of the trip.

One major problem with this data is the big discrepancy between the number of observations for passenger trips and the number of observations for goods trips. We had a precise description for about 47,000 passenger trips, but only a little more than 2,000 for goods trips. Therefore, we chose to weight each trip according to the importance it had on the flow of a type of vehicles, on a given OD and at a given time of day. Therefore, the weight W_{vkt} of the trip is equal to:

$$W_{vkt} = \frac{f_{vkt}}{Nb_{vkt}} \quad (5)$$

where f_{vkt} is the flow of vehicle v (passenger cars, light goods vehicles or heavy goods vehicles) on OD k during the time period t (morning peak hours, afternoon peak hours or rest of the day), divided by the number of observations Nb_{vkt} for each vehicle/OD/time period combinations. When estimating the impact of the traffic flow on the travel times in the next section, each trip is weighted according to its importance within the total flow. Therefore, all the values in Table 2 are weighted. In addition to the main variables specified in equations (3)-(4), we consider as "controls" of the travel times the area of the studied ODs as well as the fact that the origin and/or destination of the observed trips are (or not) Paris.

8

Table 2 – Summary statistics

	Average	St. Dev.	Min.	Max.	Obs.
D_{ikt} *(min.)*	40.46	29.80	1	198	49,822
Distance (km)	18.78	18.62	0.078	162	49,822
Maximal speed (km/h)	79.28	3.41	65.07	81.52	49,822
D_{ik}^{0} *(min)*	14.06	13.78	0.06	120.23	49,822
F_{ikt} *(veh/km/h)*	644.76	456.50	3.26	1,823.398	49,822
F_{jkt} *(veh/km/h)*	25.85	112.25	3.26	1,823.398	49,822
K_{k} *(veh/km/h)*	9,061.45	2,862.94	4,605.81	12,150.11	49,822
$\dfrac{F_{ikt}}{K_{k}}$	0.08	0.07	0.0004	0.34	49,822
$\dfrac{F_{jkt}}{F_{kt}}$	0.003	0.02	0.0004	0.34	49,822
Trucks (%)	2	1.5	0	1	49,822
Goods (%)	5	2.2	0	1	49,822
Area (1000 km²)	8.60	4.98	0.10	11.90	49,822
Paris (%)	44.0	50.0	0	1	49,822

Sources: BD TOPO, EGT and ETMV

ANALYSIS AND RESULTS

This section focuses on the econometric results of equations (3) and (4), estimated through OLS. For each variable, Table 3 gives an estimate of the coefficient, its t-stat and statistical significance (measured by the p-value: *** means p-value < 0.001; ** means p-value < 0.01; * means p-value < 0.05). Table 3 also gives the performance of each model according to the adjusted R^2. Models were tested with the linear-linear and log-log (where both dependent and independent variables are expressed in logarithms) specifications. According to the R^2 statistics, the latter explains a larger share (96%) of the dependent variable's observed variability. As a consequence, more emphasis should be given to its results. Several conclusions emerge.

First, the travel time is positively influenced by the minimal travel time, whatever the model considered. Put differently, the longer the distance and/or the lower the authorized maximal speed on the OD k, the longer the travel time. Second, the time spent by class i vehicles is positively correlated with the "flow-to-capacity ratio" of similar vehicles. This is consistent with the existence of road congestion. Importantly, we observe that the influence of dissimilar traffic class flow j is often more important: The parameter associated with the share of dissimilar vehicles within total traffic flow is generally larger than the one associated with the flow to capacity ratio of class i vehicles.

Table 3 - OLS estimates

	Lin-Lin	Lin-Lin	Log-Log	Log-Log
Variables	D_{ikt}	D_{ikt}	$\log(D_{ikt})$	$\log(D_{ikt})$
D_{ik}^0	1.38***	1.38***	0.63***	0.63***
	(0.00)	(0.00)	(0.00)	(0.00)
$\dfrac{F_{ikt}}{K_k}$	18.40***	18.67***	0.19***	0.21***
	(1.35)	(1.35)	(0.01)	(0.01)
$\dfrac{F_{jkt}}{F_{kt}}$	9.66***	9.54***	67.75***	70.08***
	(0.29)	(0.29)	(0.53)	(0.54)
T_i	-0.74	-	-43.50***	-
	(0.86)		(0.18)	
$D_{ik}^0 T_i$	-	0.45	-	-0.09***
		(0.05)		(0.02)
$\dfrac{F_{ikt}}{K_k} T_i$	-	1758.23***	-	0.22***
		(351.97)		(0.03)
$\dfrac{F_{jkt}}{F_{kt}} T_i$	-	-2.20***	-	-63.54***
		(0.72)		(0.58)
$Goods_i$	-12.96***	-12.94***	-0.38***	-0.38***
	(0.53)	(0.53)	(0.18)	(0.18)
$Area_k$	0.45***	0.46***	-0.38***	-0.38***
	(0.22)	(0.22)	(0.18)	(0.018)
$Paris_k$	14.08***	14.13***	0.34***	0.34***
	(0.21)	(0.0.22)	(0.01)	(0.01)
Observations	49,822	49,822	49,822	49,822
R^2	84.9	84.9	96.2	96.2

In order to investigate this effect more in depth, we can look at models with interaction terms in equation (4). Given the R^2 statistics, we focus on the preferred log-log model (the last column in table 3). As made clear, trucks are more sensitive than small vehicles to the minimal travel time, to the traffic flow of vehicles belonging to the same class and to the share of dissimilar vehicles class within total traffic. Put differently, trucks are more disturbed by the flow of trucks than cars are impacted by the flow of cars. Moreover, the trucks' travel time responds differently to the change in small vehicles flow as compared to the changes of cars' or vans' travel times in the case where the share of trucks increases. These are important results in that congestion impacts of similar/dissimilar traffic flows will vary according to the type of vehicles (see below).

Lastly, coefficients of most control variables are statistically different from zero. Thus trips linked to goods' movements are shorter than trips made by private passengers. Moreover, trips having Paris as origin and/or destination are likely longer. In addition, the bigger the area of the observed OD, the longer the travel time.

The parameters can be used to calibrate travel time-flow relationships. We distinguish small (S) and large (L) vehicles to get equations (5) and (6):

$$logD^S{}_{kt} = 1.07 + 0.63 \times logD_k^{S0} + 0.21 \times log\frac{F^S{}_{kt}}{K_k} + 70.08 \times log\,(1 + \frac{F^L{}_{kt}}{F_{tk}}) \quad (5)$$

And:

$$logD^L{}_{kt} = 0.56 + 0.54 \times logD_k^{L0} + 0.43 \times log\frac{F^L{}_{kt}}{K_k} + 6.54 \times \log{(1 + \frac{F^S{}_{kt}}{F_{kt}})} \quad (6)$$

Using the exponential transformation, the travel time-flow relationships for small (S) and large (L) vehicles can be re-written as:

$$D^S{}_{kt} = e^{1.07}(D_k^{S0})^{0.63}(\frac{F^S{}_{kt}}{K_k})^{0.21}(1 + \frac{F^L{}_{kt}}{F_{kt}})^{70.08} \quad (7)$$

$$D^L{}_{kt} = e^{0.56}(D_k^{L0})^{0.54}(\frac{F^L{}_{kt}}{K_k})^{0.43}(1 + \frac{F^S{}_{kt}}{F_{kt}})^{6.54} \quad (8)$$

Figures 2 and 3 depict travel times of small and large vehicles as a function of different levels of different traffic classes. As made clear, travel times are an increasing function of the "flow-to-capacity ratio", in line with conventional BPR relationships. However, the (positive) slope of these functions is clearly larger for large vehicles (trucks) as compared to small vehicles (cars or vans).

Figure 2 – The travel time of small vehicles, according to the flow of small vehicles and the share of large vehicles (LV) on total traffic
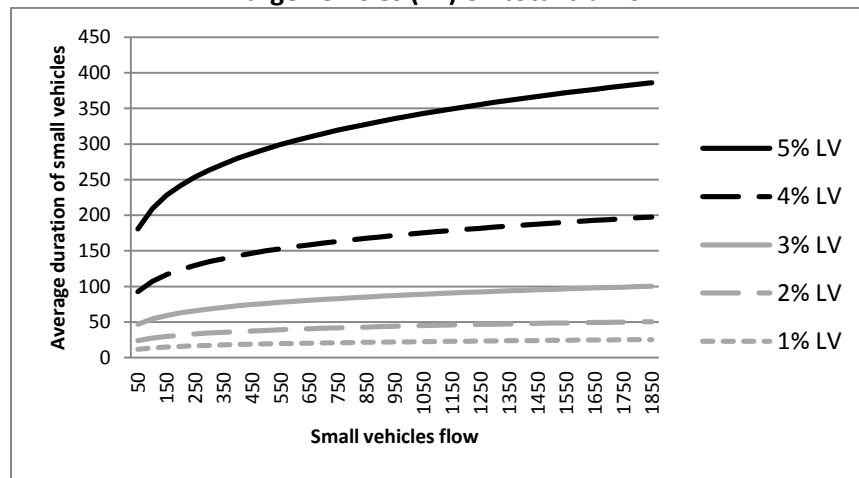
Moreover, we observe that the share of dissimilar vehicles within the total traffic flow has a stronger impact on travel times for cars and vans than for trucks. For a given level of small vehicles traffic (650 veh/h/km for instance), the mean travel time is equal to 50 minutes approximately if trucks represent 2% of total traffic. Travel duration will rise to 80 minutes if the share of trucks increases to 3% of total traffic. By contrast, the maximum growth of trucks' travel times, whatever the level of large vehicles traffic and/or the share of small vehicles within total traffic, never exceeds 10 minutes. As a result, additional time losses for private passengers or vans caused by an incremental truck are likely more expensive than those incurred to trucks in the case small vehicles' traffic would increase.

Figure 3 – The travel time of large vehicles, according to the flow of large vehicles and the share of small vehicles (SV) on total traffic
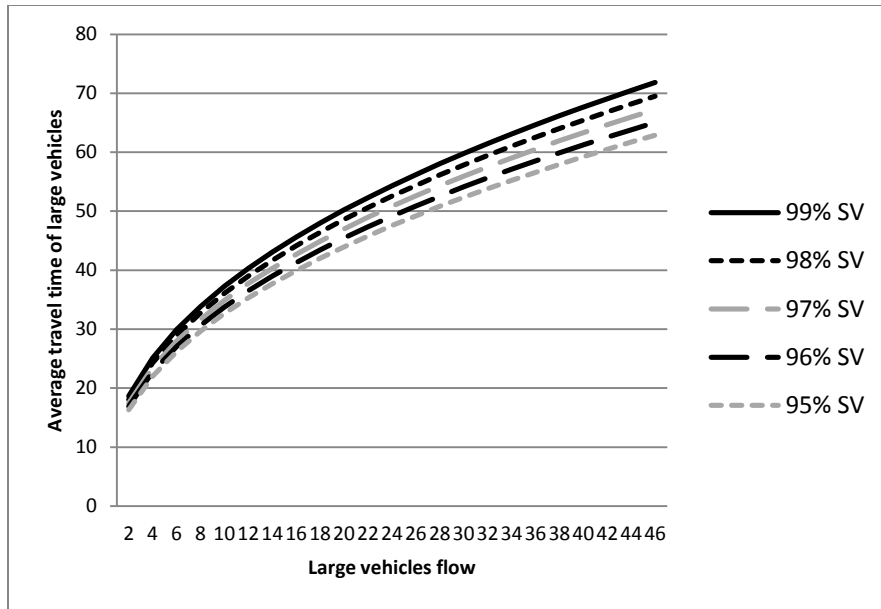
CONCLUSIONS

The aim of this research project was to calculate the impact of freight flows on traffic congestion in the Ile-de-France region. Having an accurate estimation of congestion levels for urban areas is extremely difficult, because traditional travel time-flow relationship functions require extensive traffic databases. Also, distinguishing small freight vehicles and passenger vehicles is almost impossible using traditional counting methods. In this research, we took advantage of two big surveys administered at the same time (2010) in the Paris Region: the household mobility survey (EGT) for passengers and the urban freight survey (ETMV).

The econometric analysis uses these databases. The results show that the theoretical model performs well: the travel time of an individual trip is positively impacted by the 'flow-to-capacity ratio" on a given origin-destination combination. We can also conclude that large vehicles have a bigger impact on travel times of small vehicles, and that they are more impacted by the "flow-to-capacity ratio" of similar vehicles, compared to small vehicles. Figures 2 and 3 show that one additional percent of large vehicles within the total traffic has a much bigger impact than one additional percent of small vehicles.

These results allow us to calibrate travel time-flows relationships. In future research, these will allow us to calculate marginal social and external costs functions, as well as point estimates, differentiated for passenger vehicles, small freight vehicles and large freight vehicles. This research has potentially valuable policy implications: we will be able to propose marginal congestion costs useful in the framework of costs-benefits analyses. Optimal pricing rules could be also questioned in the light of the reciprocal congestion impacts of each vehicle class.

References

APUR. « Le projet TramFret – Mise en place d'un transport de marchandises par le tramway », Note de l'APUR, n°69, avril 2014.

Arnott, R. A. De Palma, A. and Lindsey R. "Schedule delay and departure time decisions with heterogeneous commuters". Transportation Research Record 1197, 1988.

Certu. Calcul a posteriori des distances dans les enquêtes ménages-déplacements, rapport du Certu, 44p, 2005.

Certu, 2013, Les enquêtes déplacements « standard CERTU », note de présentation, 15p.

Dablanc, L. "French strategic approach to urban consolidation", Bestufs II first Workshop, 13-14 January 2005, London.

Duranton, G. and Puga, D. "Micro-foundations of urban agglomeration economies". NBER Working paper series, working paper 9931, 2003.

Duranton, G. and Turner, M. A. "The fundamental law of road congestion: evidence from US Cities". American Economic Review 101, October 2011: 2616-2652.

IGN, 2008, BD TOPO® Version 2, comparatif entre les versions 1.2 et 2, document de description des données, 25p.

INRIX. The future economic and environmental costs of gridlock in 2030 – an assessment of the direct and indirect economic and environmental costs of idling in road traffic congestion to households in the UK, France, Germany and the USA. Report for INRIX, July 2014.

Koning, M. "La variété des coûts de congestion routière: le cas du boulevard Périphérique parisien », Revue d'Economie Régionale et Urbaine, n°4: pp. 737-463.

Leurent, F. and Breteau, V. "On the Marginal Cost of Road Congestion: An Evaluation Method with Application to the Paris Region". Proceedings of the European Transport Conference, Leeuwenhorst, Netherlands, Oct. 2009.

Moridpour, S. Mazloumi, E. and Mesbah, M. "Impact of heavy vehicles on surrounding traffic characteristics". Journal of Advanced Transportation, 2015.

Nemoto, T. Browne, M. Visser, J. Castrp, J. "Intermodal transport and city logistics policies". Proceedings of the 4th International Conference on City Logistics in Langkawi, Malaysia, 2005.

Newman, P.G, J.R. Kenworthy. Cities and automobile dependence: An international sourcebook, Gower Publishing, 388 p., 1989.

OECD. Toward sustainable transportation. OECD Proceedings, Vancouver, Canada, 24-27 March 1996.

O'Sullivan, A. Urban Economics, 7th ed., McGraw-Hill Irwin, 2009.

Patier, D., Routhier, J.-L. "How to improve the capture of urban goods movements data", in Transport survey methods – Keeping up with a changing world. Emerald, Bingley, 251-287, 2009.

Routhier, J.-L., Toilier, F. "Freturb v3, a policy oriented software of modeling urban goods movements", Proceedings of the 11th WCTR, June 2007, Berkeley, USA, 22 p, 2007.

Satya-Lekh, P. and Patrick, L. "Curbing air pollution in Paris: a comparative analysis of the 'Low Emission Zones'". POLIS annual conference: Reducing the impact of transport on air quality, November 2012, Perugia, Italy.

SETRA. Fonctions temps-débit sur les autoroutes interurbaines: rénovation des relations entre temps de parcours et débit pour la simulation de traffic. Rapport technique, Nov. 2001.

Skabardonis, A. Varaiya, P. P. and Petty K. F. "Measuring recurrent and non-recurrent traffic congestion". Transportation Research Record: Journal of the Transportation Research Board 1856, 2003.

Small, K. A. and Verhoef E. T. The Economics of Urban Transportation. Ed. Routledge, 2007.

TRB. Highway Capacity Manual. Transportation Research Board, National Research Council, 2010.

Union Routière Française. Faits et Chiffres 2013 – Statistiques des Transports, URF, Octobre 2013.

Vickrey, W. S. "Congestion theory and Transport investment". The American Economic Review 59-2, May 1969.

Yun, S. White, W. W. Lamb, D. R. and Wu, Y. "Accounting for the impact of Heavy truck traffic in volume-delay functions in transportation planning models". Transportation Research Record: Journal of the Transportation Research Board 1931, 2005.