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The environmental social cost of urban road freight: Evidence from the Paris region



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ABSTRACT

This paper investigates the environmental impact of urban road freight in the Paris region, focusing on pollutant emissions. We develop a modeling chain including a freight demand model, a multiclass traffic assignment model, and a road emission model. This allows for a detailed representation - spatially and with regard to operations - of urban road freight. We find that while urban road freight represents only 6% of trips and 8% of distances traveled by road in the Paris region, it accounts for 36% of total damages caused by pollutant emissions from road traffic. This is the combined result of light and heavy goods vehicles emitting more than private cars, and of freight traffic being more spatially concentrated (within the city center) than passenger traffic, thereby affecting more population. All in all, the environmental cost of urban road freight is around 2.1 billion \in per year. Some policy implications are discussed.

1. Introduction

Urban freight today faces a paradox. On the one hand, picking-up and delivering the right volume of goods to the right place at the right time has become increasingly crucial to the functioning of cities (OECD, 2003; Dablanc, 2009; Macharis and Melo, 2011). On the other hand, economic and technological constraints (Cullinane and Toy, 2000; Holguin-Veras, 2002; Comi et al., 2012) lead freight operators to resort massively to road transport. Urban road freight (URF) is therefore accused of contributing substantially to environmental nuisances in cities, and more generally to degrading urban livability through its impact on congestion, traffic safety, or the use of public space (OECD, 2003; Cui et al., 2015; CIVITAS, 2015), leading public authorities to enforce policies aimed at making URF more sustainable (*e.g.* road pricing, low emission zones, incentive mechanisms to promote off-hour deliveries or the use of electric vehicles; Holguin-Veras et al., 2006; Mirhedayatian and Yan, 2018; Demir et al., 2014; Cui et al., 2015; Russo and Comi, 2016; Ellison et al., 2013).

While data collection efforts have been engaged over the last decade (Toilier et al., 2016; Allen et al., 2010; Holguin-Veras and Jaller, 2014), a fine knowledge of urban road freight is still lacking to corroborate the claims regarding its alleged environmental impact. As opposed to private car (PC) trips - for which information from households travel surveys (and increasingly from big data

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Abbreviations: BPR, Bureau of Public Roads; HGVs, Heavy Goods Vehicles; IdF, Île-de-France (the administrative region including Paris); LGVs, Light Goods Vehicles; OD, Origin-Destination; PCs, Private Cars; tkm, ton-kilometers; URF, Urban Road Freight; VDF, Volume-Delay Function; vkm, vehicle-kilometers; VOC, Volume-Over-Capacity

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sources) is available -, authorities are rarely aware of distances traveled by LGVs and HGVs (Light/Heavy Goods Vehicles) and urban freight origins and destinations within their jurisdictions (EC, 2013; CIVITAS, 2015). First, the commercial nature of URF implies information privacy in most countries. Second, traffic sensors usually cover but a small share of the road network and cannot distinguish LGVs from PCs. Last, organizational features of URF (*e.g.* direct or round trips) make its observation complex. Assessing precisely the environmental impact of URF consequently remains a major challenge to date, be it for public stakeholders or the academic community.

This paper aims to bridge the gap between common beliefs about the environmental impact of urban road freight and its empirical measurement, focusing on pollutant emissions.¹

We develop a modeling chain that enables us to estimate travel demand for URF and the resulting emissions for up to 30 pollutants. This includes greenhouse gas emissions, firstly carbon dioxide (CO_2) , which by contributing to global warming lead to several adverse economic effects (Tol, 2009), as well as local pollutants such as nitrogen oxide (NO_x) or fine particulate matter (PM_{10}) , which may endanger the health of exposed populations (Kampa and Castanas, 2008; WHO, 2016). Using this modeling chain, we estimate the environmental social cost of URF for a major metropolitan area.² Accounting for 18% of the French population and 30% of the national GDP in 2012, the Paris region is one of the wealthiest areas in Europe, but also one of the most heavily congested (Inrix, 2014). Concerns related to air pollution are nowadays of major interest to elected officials (IdF, 2016) and to the population (EC, 2016). As a consequence, it seems relevant to specify the magnitude of environmental social losses caused by urban road freight.

This paper extends the vast body of literature on the environmental impact of road traffic (see the survey by Shorshani et al. (2015), or specific case studies by Xia and Shao, 2005; Tirumalachetty et al., 2013) by specifying the contribution of URF. This is especially relevant inasmuch as freight transport and passenger transport are typically subject to distinct transport policies considering economic, technological and organizational differences between the two. From a methodological point of view, our modeling chain represents URF with a great level of detail regarding operations as well as the spatial resolution. While freight trip generation is now well addressed, from delivery models to commodity flow based models (Boerkamps and van Bisbergen, 1999; Munuzuri et al., 2009; Nuzzolo et al., 2012), trip distribution has seldom been addressed as, unlike for passenger travel, it cannot be treated using gravity models: one product can travel through several warehouses, in various vehicles and packaging types (Ogden, 1992). An original method such as provided by the Freturb model (Routhier and Toilier, 2007) is therefore needed. The proposed modeling chain allows to estimate freight travel demand for an entire metropolitan area (and not for a single economic site as in Aditjandra et al., 2016), while taking into account the main specificities of URF, such as the distinction between direct and round trips or between own-account and third party operations (unlike Kanarogou and Buliung, 2008). In contrast to previous environmental economics studies carried out at a national scale (e.g. Muller and Mendelsohn, 2007), the fine spatial resolution at the municipality level allows accounting for the greater damages of air pollution in dense areas where more population is exposed, as established by the "Impact Pathway Approach" developed in the frame of the European ExternE research project (Friedrich and Bickel, 2001). This proves especially important in the case of urban road freight, as we find it to be more spatially concentrated than passenger private transport, combined with the fact that density levels strongly vary within the Paris metropolitan area.

The rest of this paper proceeds as follows. Section 2 describes the methodology, and Section 3 the data. Section 4 presents the main results which are discussed in Section 5. Section 6 concludes.

2. Methods

The methodology involves two main steps (Fig. 1)³: estimating first pollutant emissions, then the environmental social cost of road traffic. Four classes of vehicles are distinguished throughout computations - PCs, LGVs, and HGVs (rigid and articulated)⁴ -, allowing us to isolate at each step the contribution of URF.

We start by estimating travel demand related to URF. Based on the characteristics (industry sector, size, premises, etc.) and the spatial distribution of firms within the Paris region, the Freturb-Simetab models (Routhier and Toilier, 2007; Gardrat et al., 2014) estimate generation coefficients (number of weekly deliveries and pick-ups) for all firms, then the resulting travel demand. The corresponding outputs are Origin-Destination (OD) matrices, disaggregated according to the three freight vehicle classes (LGVs and rigid/articulated HGVs). Next, combining the OD matrices for URF and PCs,⁵ with transport costs parameters and the road network characteristics, we compute the multi-class traffic equilibrium (Dafermos, 1972) using the TransCAD software. Reflecting strategic interactions among drivers during route choice, it is essentially similar to a Nash equilibrium (Correa and Stier-Moses, 2011). This gives us for each road link the traffic flow, its composition by vehicle class, and the average vehicle speed. These data are finally fed to the Copcete model (Demeules and Larose, 2012). Taking into account the vehicle type, the traffic speed, the technological composition of the vehicle fleet, and so on, Copcete provides estimates of pollutants emitted by each vehicle class, again at the road

¹ French official guidelines (CGSP, 2013) suggest that in the case of road traffic, losses linked to climate change and air pollution largely prevail over other environmental nuisances (e.g. noise). Accordingly, the latter are not considered in this paper; neither are social losses linked to traffic safety or to the use of public space.

 $^{^{2}}$ In this paper, we use the term "environmental social cost" to refer to the specific part of the social cost (of road traffic) related to pollutant emissions (CO₂, NO_x and PM_{2.5}).

³ The detailed methodology is described in Appendix A.

⁴ The distinction between LGVs and HGVs is based on the UE definition, i.e. whether the gross combination mass is below or over 3.5 t.

⁵ Considering the focus of our paper, the passenger travel demand model used to generate the OD matrices for private cars is not presented; rather, we treat the OD matrix for PCs as an exogenous input. See Section 3.2 for more details.



Note: exogenous input data are identified by stars; modeling tools are underlined; estimated outputs are framed. Source: authors' elaboration.

Fig. 1. Methodological framework, Note: exogenous input data are identified by stars; modeling tools are underlined; estimated outputs are framed. Source: authors' elaboration.

link level. This enables us to propose a simplified indicator of individuals' exposure to pollutants emissions from road traffic, at the municipality level.

In the second step, we cross the outputs from the first step with spatialized socioeconomic data and external costs (shadow prices) of pollutants provided by French national guidelines (CGSP, 2013; Ducos, 2014) in order to assess the environmental social cost of URF.⁶ Because road users rarely pay specific taxes aimed at covering the various damages from pollutants emissions (Santos, 2017), these are often referred to as the external costs of transport, thus implying a dead-weight loss for the collectivity. The fine spatial resolution of our estimates allows us to account for the greater impact of local pollution in dense areas as a result of more people being exposed. This point proves especially important in the case of URF, as we will see in Section 4.

3. Data

3.1. Overview of the study area

The $\hat{l}le$ -de-France (IdF) region⁷ was composed of 1300 municipalities in 2012, spanning over 12,058 km². The region is mostly monocentric, population density declining quickly with distance to Paris (Fig. 2).⁸

Whereas the city of Paris had 2.2 million inhabitants in 2012 with a population density reaching 23,700 inh./km², these figures fall to 77,000 inhabitants and 28 inh./km² respectively in interurban areas (Table 1). The spatial pattern is more pronounced for economic activities. The city of Paris concentrates 39% and 32% of regional establishments and jobs, respectively, over only 1% of the regional area, thereby highlighting the strength of "agglomeration economies". Establishments located in Paris are smaller (6.3 jobs per firm on average) than those in the inner suburbs (with 7.8 jobs per firm). Firms in the core of the metro area are mostly specialized in services and high-skilled jobs, whereas (labor intensive) industries or wholesale activities need more space and prefer

⁶ More specifically, for CO₂ we use the carbon price recommended by the national guidelines (CGSP, 2013). In the case of air pollution, rather than the marginal external costs in €/vkm provided in the main report, we use the raw marginal external costs in €/t reported in the annex (Ducos, 2014). Indeed, the marginal external costs from the main report (in €/vkm) were derived by multiplying the raw marginal external costs (in €/t) by average emission factors (in t/vkm). Because we estimate emissions using Copcete, using the raw external costs in combination with our own emission estimates is bound to yield more precise results than using the rough marginal external costs from Ducos (2014) were estimated by following best practices set up by the Impact Pathway Approach, while accounting for national specificities regarding the statistical value of life and population density profiles.

⁷ The administrative Paris region, called *Île-de-France*, slightly differs from the statistical metropolitan area of Paris, but is a good proxy for it, and one for which general data is more easily available.

⁸ As represented in Fig. 2, IdF is divided according to the spatial classification found in the Quinet report (CGSP, 2013) and used to compute the social cost of air pollution in Section 4. Considering its importance and its specificity, the city of Paris is added as a distinct sub-category within the very dense urban area.



Fig. 2. The Île-de-France region, Source: authors' elaboration from CGSP (2013) and 2012 Census (Insee).

Table 1

Socioeconomic data (2012). Sources: IGN, Census (Insee), SIRENE (Insee), Freturb.

	IdF	Paris	VDUA	DUA	UA	DIUA	IA
Municipalities	1300	20	110	141	161	660	208
Area (km ²)	12,058	105	556	968	1293	6432	2703
Mean distance to Paris (km)	41.1	0	11.4	22.1	31.7	46.6	62.3
Population (1000)	11,899	2241	4623	2831	1175	950	77
Pop. density (inh./km ²)	1709	23,656	9646	3009	940	160	28
Establishments (1000)	806.4	318.0	245.9	126.7	58.5	52.0	5.3
Jobs (1000)	5949.2	1900.2	2074.6	1106.6	485.5	362.3	20.0
Job density (jobs/km ²)	988	27,824	4326	1050	389	60	8
Estab. size (jobs/estab.)	5.4	6.3	7.8	7.8	7.2	4.9	2.4

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

peripheral locations, with lower rental prices.

3.2. OD matrices

The SIRENE dataset provides information at the municipality level for IdF and for year 2012 regarding the number of establishments, their industrial classification and their size. After imputing the nature of the premises using the Simetab model (see Appendix A), the augmented dataset is fed to Freturb to estimate goods movements in IdF.

Each establishment emits and/or receives an average of 6.3 freight operations per week (Table 2), for a total of 5.08 million operations per week.⁹ Establishments in Paris city generate the fewest operations (4.9/week), due to the smaller size of firms and to their economic specialization (services emitting and receiving few goods). Around 30% of freight movements are direct trips, with a higher share in interurban areas (50%) where consolidation is less feasible. Third party transport companies operate around 40% of goods movements. Own account transport is more represented in interurban areas (70%), as small firms (B2C services, small retail) are more likely to make their deliveries and/or collections themselves (Toilier et al., 2016). These types of activity also tend to make

⁹ An operation, or movement, is either a delivery or a pick-up of a freight shipment.

Characteristics of freight operations (2012). Sources: authors' calculations from Freturb and Simetab.

	IdF	Paris	VDUA	DUA	UA	DIUA	IA
Operations per establishment (/week)	6.3	4.9	6.6	7.5	8.8	7.1	5.1
Direct trips movements Third party operators movements	29.8% 41.2%	26.9% 40.2%	28.4% 41.4%	29.4% 41.7%	30.1% 44.1%	34.2% 39.7%	50.7% 31.1%

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

Table 3

OD matrices for urban road freight and private cars (2012). Sources: authors' calculations from Freturb for URF and from DRIEA for PC.

	Daily trips to:									
		Paris	VDUA	DUA	UA	DIUA	IA	Total		
Daily trips from:	Paris	1,129,372	495,943	107,198	28,178	25,771	1272	1,787,737		
		144,280	74,516	31,665	15,990	<u>11,649</u>	<u>630</u>	278,732		
		(11.7%)	(13.1%)	(22.8%)	(36.2%)	(31.1%)	(33.1%)	(13.5%)		
	VDUA	559,999	3,270,264	747,846	213,058	109,242	5038	4,905,450		
		74,516	139,509	47,617	18,984	8481	412	289,521		
		(11.7%)	(4.1%)	(6.0%)	(8.2%)	(7.2%)	(7.6%)	(5.6%)		
	DUA	93,349	770,811	1,877,459	463,366	262,432	14,975	3,482,394		
		31,665	47,617	48,785	24,457	13,860	620	167,007		
		(25.3%)	(5.8%)	(2.5%)	(5.0%)	(5.0%)	(4.0%)	(4.6%)		
	UA	27,449	208,650	460,160	682,293	267,952	23,106	1,669,611		
		15,990	18,984	24,457	17,397	11,884	860	89,575		
		(36.8%)	(8.3%)	(5.0%)	(2.5%)	(4.2%)	(3.6%)	(5.1%)		
	DIUA	21,253	114,038	286,320	276,152	759,846	45,135	1,502,746		
		11,649	8481	13,860	11,884	15,884	1669	63,429		
		(35.4%)	(6.9%)	(4.6%)	(4.1%)	(2.0%)	(3.6%)	(4.1%)		
	IA	1288	5799	18,329	26,290	47,055	66,091	164,855		
		<u>630</u>	<u>412</u>	<u>620</u>	860	1669	<u>411</u>	4604		
		(32.8%)	(6.6%)	(3.3%)	(3.2%)	(3.4%)	(0.6%)	(2.7%)		
	Total	1,832,712	4,865,507	3,497,314	1,689,340	1,472,301	155,619	13,512,795		
		278,732	289,521	167,007	89,575	63,429	4604	892,872		
		(13.2%)	(5.6%)	(4.6%)	(5.0%)	(4.1%)	(2.9%)	(6.2%)		

Notes: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area. The underlined figures refer to trips made by LGVs and HGVs; the percentages in brackets describe the share of URF on a given OD.

direct trips rather than rounds to collect freight (Gérardin et al., 2000).¹⁰

Using Freturb, we also estimate freight OD matrices (at the municipality level) for three vehicle classes – rigid or articulated HGVs, LGVs – and three times of day: morning peak (7–9 am), evening peak (5–7 pm), and rest of the day.¹¹ The OD matrix for PCs comes from the MODUS regional transport model.¹²

URF accounts for 6.2% of road trips in the Paris region, generating around 893,000 trips per day, against 13.5 million daily trips for PCs (Table 3). About 57% of freight trips are made with LGVs; 25% occur during peak periods. PC trips are more concentrated in time, 33% being made in peak periods. Conversely, URF flows are more spatially concentrated than PC flows: 63% of URF flows are related to Paris and/or very dense urban areas (as origin and/or destination), against only 51% for PC trips. The more scattered spatial structure of PC trips may be partly explained by the density and performance of the public transit network within the city center, combined with an insufficient parking supply in Paris. Accordingly, only 11% of PC trips are related to Paris, even though Paris accounts for 18% of the regional population and 32% of regional employment. Similarly, the share of road trips between Paris and the outer suburbs linked to URF is almost five times the regional average (30% against 6.2%, respectively).

3.3. Road network

The road network includes the most important roads in IdF (freeways, arterials, collectors), totaling 39,420 links for a length of

¹⁰ Specifically, two thirds of operations are done in direct trips when consignees pick up the goods themselves.

¹¹ Flows of goods between IdF and other regions as well as transit flows are not considered in our study. Although leading to a downward bias in our results, this should not alter our main conclusions seeing that we focus on URF.

¹² Developed by the Direction Régionale et Interdépartementale de l'Equipement d'Ile-de-France, MODUS is focused on passenger transport and calibrated using a regional trip survey and traffic counts.



Fig. 3. Road network, Source: authors' elaboration with TransCAD, from DRIEA.

Table 4
Results of the traffic assignment model.
Source: authors' calculations from TransCAD.

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	IdF	Paris	VDUA	DUA	UA	DIUA	IA
Peak periods							
PC (veh/h)	745	1146	858	664	646	526	404
LGV (veh/h)	33	95	40	23	17	10	3
HGV (veh/h)	28	69	33	22	18	11	3
VOC ratio	0.45	0.62	0.53	0.44	0.37	0.30	0.22
Vehicle speed (km/h)	41.2	20.7	31.8	40.6	49.4	61.4	70.3
Off-peak period							
PC (veh/h)	303	477	350	272	257	209	146
LGV (veh/h)	20	59	25	14	10	6	2
HGV (veh/h)	17	42	20	13	11	6	2
VOC ratio	0.20	0.29	0.24	0.20	0.16	0.13	0.08
Vehicle speed (km/h)	51.3	33.0	44.3	50.8	58.0	67.5	74.5

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

VOC = Volume-Over-Capacity.

20,500 km (Table B.1 in Appendix B). It is strongly radial, yet with three concentric ring roads (Fig. 3). Road density declines with distance to the urban center and free-flow speeds are higher in peripheral areas, with 63 km/h in diffuse areas against 44 km/h in Paris (Table B.1). Road capacities are relatively stable over space, with a mean capacity around 1700 vehicles per hour.

3.4. Traffic assignment model

The parameters used to derive generalized costs - vehicle usage costs, vehicle occupancy, load weights for goods vehicles, and the values of travel time savings - are reported in Table B.2 (Appendix B). Using these parameters and OD matrices for URF and PCs,

	IdF	Paris	VDUA	DUA	UA	DIUA	IA
VKT (M vkm/day)	154.5	16.5	37.0	30.9	23.8	38.8	7.6
PC	142.4	13.9	33.3	28.4	22.3	37.1	7.4
LGV	6.4	1.5	2.0	1.3	0.7	0.8	0.1
HGV	5.7	1.1	1.7	1.2	0.8	0.9	0.1
VKT (%)	100%	10.7%	23.9%	20.0%	15.4%	25.1%	4.9%
Share during peaks (%)	33.0%	31.5%	32.7%	32.7%	33.2%	33.5%	34.2%
Share of URF (%)	7.8%	15.8%	10.0%	8.1%	6.3%	4.4%	2.6%

Table 5 Distances traveled. Sources: authors' calculations from TransCAD.

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

TransCAD computes the multiclass traffic equilibrium, and the corresponding traffic flows and vehicle speeds at the road link level.

The average PC flow on a given road link is 745 veh/h during peaks and 303 veh/h during the off-peak period (Table 4). The flows are respectively 61 veh/h (33 LGVs/h plus 28 HGVs/h) and 37 veh/h (20 LGVs/h plus 17 HGVs/h) in the case of URF. As a consequence, the mean volume-over-capacity ratio is 0.45 during peak periods (0.20 the rest of the day), hence a mean travel speed of 41.2 km/h (51.3 km/h). Paris roads are the most heavily used (1310 veh/h during peak hours), thus presenting the lowest speeds (20.7 km/h). Regarding URF, LGVs are more intensively used than HGVs in the central areas of IdF.

We now look into distances traveled as a key driver of the environmental social cost of URF. We find that every working day, around 155 million vkm are traveled in IdF, 33% of which during rush hour periods (Table 5).¹³ Paris concentrates 11% of road traffic whereas fringes of the metropolitan area account for 30% of traveled distances. Urban road freight represents around 8% of distances traveled. This share strongly varies over space, however. LGVs and HGVs are responsible for 16% of distances traveled in Paris, against only 2.6% in interurban areas. This marked difference stems from higher jobs per capita ratios in the densest parts of the metro area, hence the relatively greater intensity of URF in comparison to PCs.¹⁴

3.5. Pollutants and vehicle fleet

Copcete allows estimating exhaust emissions for up to thirty pollutants. For concision, we focus our analysis on CO₂, PM_{10} and NO_x, as three major emissions from road traffic accounting for 29%, 25% and 55% of regional emissions, respectively (Airparif, 2013). The vehicle fleet composition according to the four vehicle classes and the various European emission standards is extracted from a French yearly survey (*Enquête Parc Auto – IFSTTAR*)¹⁵ and is based on distances traveled rather than on number of vehicles. Diesel vehicles make up the large majority of those, especially for freight vehicles (Table 6). This can be explained by the national tax system that favored, until recently, diesel fuels. Whatever the type considered, Euro-II or older vehicles account for no more than 12.5% of the fleet in 2012, and only 8.7% for HGVs. Regarding freight vehicles, Euro-IV or V technologies are the most represented.

4. Results

4.1. Pollutant emissions

Every day, road traffic emits 31,271 tons of CO_2 , 123 tons of NO_x and 15 tons of PM_{10} in IdF (Table 7). Emissions are highly concentrated, in time and in space. One third is emitted during peak periods (i.e. over one sixth of the day). Similarly, very dense urban areas (including Paris) concentrate for each pollutant around 40% of emissions, for only 5% of the total regional area. Yet, considering that said areas account for 58% of the regional population and 67% of jobs, this figure of 40% is lower than expected. This results from two opposite forces. Car use is lower in the center of the metro area (see Section 3.2), but unit emission rates are greater because of lower traffic speeds (Ntziachristos and Samaras, 2000; Grote et al., 2016).¹⁶ To confirm the latter point, we reckon a spatial indicator of emission intensity by dividing - for a given pollutant - the share of regional emissions received by a given zone

¹⁵ Considering the lack of information specific to IdF, we use the national composition instead. See the discussion in Section 5.2.

¹³ Checking the consistency of our traffic estimates is not an easy task, especially for URF considering the (very) limited data available. For PCs, according to the last 2010 regional household travel survey the volume of daily trips added up to 15.4 M for IdF, with an approximate network distance of 8.7 km. This leads to an estimated total of 134 Mvkm driven by PCs, close to our own estimate (142 Mvkm). Regarding URF, to the best of our knowledge the only information available comes from Beziat et al. (2017) who use a recent - though very small - urban goods survey carried out in 2011 in IdF. Based on their estimates, we infer a daily total of 11.6 Mvkm for URF, once again in line with our own estimate (12.1 Mvkm). Their results lead to slightly different ratios of LGVs vs. HGVs, however, with 43% of LGVs against 53% in our case. This difference might partly be related to the fact that we use an assignment model to compute distances traveled, which is not the case in Beziat et al. (2017).

¹⁴ The traffic assignment model can also be used to convert the total time spent on roads (3.16 million hours per day) into monetary equivalents. By adding these resources to the vehicle usage costs, we find total generalized costs of road transport equal to 90 million euros per day (Table B.3). URF operators support 12.9% of the total bill, due to higher kilometric costs of LGVs and HGVs and to the larger share of vkm driven in dense areas, at lower traffic speeds.

¹⁶ Emission factor curves are often U-shaped, and for the range of speeds considered one is generally on the left side of the U, so that a decrease in traffic speed leads to an increase in emission rates (per vkm). See Appendix A and Fig. A.1.

Table 6

Vehicle fleet distribution (2012, in % of distances traveled). Sources: Copcete and "Enquête Parc Auto – IFSTTAR".

	PC			LGV		HGV	
	Petrol	Diesel	Others	Petrol	Diesel	Diesel	
Euro-0	1.9%	1.3%	-	0.2%	2.1%	0.2%	
Euro-I	2.6%	3.1%	-	0.1%	3.6%	0.6%	
Euro-II	5.4%	6.3%	-	0.2%	7.0%	7.9%	
Euro-III	4.4%	19.9%	-	0.2%	23.5%	23.6%	
Euro-IV	7.7%	28.1%	-	0.2%	38.7%	33.6%	
Euro-V	3.7%	15.1%	-	0.1%	24.1%	34.1%	
Total	25.7%	73.8%	0.5%	1.0%	99.0%	100%	

Table 7

Pollutant emissions.

Source: authors' calculations from Copcete.

	IdF	Paris	VDUA	DUA	UA	DIUA	IA
CO_2							
Emissions (tons/day)	31,271	4256	7970	6219	4485	7014	1327
PC	25,205	2813	6122	5018	3771	6241	1239
LGV	1688	421	509	324	190	219	25
HGV	4378	1022	1339	877	524	554	63
Emissions (%)	100.0%	13.6%	25.5%	19.9%	14.3%	22.4%	4.2%
Share during peaks (%)	34.2%	35.9%	35.0%	34.0%	33.3%	33.2%	33.8%
Share of URF (%)	19.4%	33.9%	23.2%	19.3%	15.9%	11.0%	6.6%
NO _x							
Emissions (tons/day)	122.5	17.5	30.5	23.7	17.5	27.9	5.4
PC	86.6	8.5	19.4	16.7	13.4	23.7	4.9
LGV	5.9	1.5	1.8	1.1	0.7	0.7	0.1
HGV	30.0	7.5	9.3	5.9	3.4	3.5	0.4
Emissions (%)	100.0%	14.3%	24.9%	19.3%	14.3%	22.8%	4.4%
Share during peaks (%)	32.6%	34.9%	33.4%	32.1%	30.9%	31.5%	33.3%
Share of URF (%)	29.3%	51.4%	36.4%	29.5%	23.4%	15.1%	9.3%
PM ₁₀							
Emissions (tons/day)	14.8	1.9	3.7	3.0	2.2	3.4	0.6
PC	10.4	1.0	2.4	2.1	1.6	2.8	0.5
LGV	0.7	0.2	0.2	0.1	0.1	0.10	0.00
HGV	3.7	0.7	1.1	0.8	0.5	0.5	0.1
Emissions (%)	100.0%	13.0%	25.2%	20.0%	14.8%	22.9%	4.2%
Share during peaks (%)	31.8%	31.6%	32.4%	30.0%	31.8%	32.4%	33.3%
Share of URF (%)	29.6%	46.4%	35.1%	30.3%	26.0%	18.9%	11.3%

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

with the corresponding share of regional road traffic. This indicator – equal to 1 for all zones if emission rates per vehicle-kilometer were constant over space – is greater than 1 in Paris, but then decreases as population density decreases (Table C.1). This confirms that dense urban areas with lower traffic speeds do "over-emit". Nevertheless, the efficiency of public transport and active modes in dense areas strongly curbing road traffic, this "lower traffic share" effect prevails over the "over-emission" effect to produce the above result.

Focusing on URF, commercial vehicles account for 20% of CO_2 and 30% of NO_X and PM_{10} emitted by road traffic in IdF, though representing only 8% of distances traveled. Emission intensity is much greater in the case of freight traffic indeed, especially regarding NO_x and PM_{10} (Table C.1). More specifically, we find that HGVs pollute two to five times more than LGVs depending on the pollutant considered, while accounting for only 47% of distances traveled by freight vehicles. Yet, computations show that reasoning in ton-kilometers instead of vehicle-kilometers leads to the opposite statement: HGVs actually pollute (slightly) less than LGVs per tkm.¹⁷

From a spatial perspective, the share of emissions caused by URF is highly heterogeneous. It varies from around 50% for NO_x and PM_{10} in Paris to only 10% in the fringes of IdF (Table 7). Interestingly, the indicator of emission intensity behaves very differently for

 $^{^{17}}$ Crossing the mean emissions factors (Table C.2) with the load weight of vehicles (Table B.2), we find for NO_X that HGVs emit 2.68 g/tkm vs. 3.13 g/tkm for LGVs. In the case of PM₁₀, we find 0.34 g/tkm for HGVs and 0.37 g/tkm for LGVs. The gap is more pronounced for CO₂: emissions from HGVs reach 392.60 g/tkm, as compared to 893.23 g/tkm for LGVs.



Fig. 4. Exposure to local pollutants from road traffic, Source: authors' elaboration.

goods vehicles (Table C.1). Whereas the indicator strictly decreases from Paris to interurban areas for the whole traffic (mostly composed of PCs), it increases for LGVs and HGVs, save for a few exceptions. The relationship between travel speed and emission factors varies depending on the vehicle type and the pollutant considered indeed, sometimes U-shaped, sometimes monotonously decreasing (Fig. A.1). Accordingly, when the mean travel speed increases from Paris to the interurban areas, the unit emission rate may either increase or decrease depending on the shape considered (Table C.2). In the case of PM_{10} for instance, maximal emission rates are found in Paris city for HGVs, while they are found in interurban areas for LGVs. In the case of LGVs, the peculiar M-shaped behavior of the averaged PM_{10} emission factor highlights that other complex mechanisms are at work. Though not thoroughly investigated in this paper, differences in route choice depending on the vehicle type (being driven by different parameter values) or heterogeneous traffic speeds within zones are likely to explain this puzzling mapping between average emission factors and average traffic speeds.

4.2. Exposure to local pollutants

Road transport is not the sole determinant of air quality. The concentration of local pollutants depends on other sources of emissions - residential or commercial buildings, industries, etc. - located in IdF, but also in surrounding regions. Pollutants disperse in the atmosphere indeed, depending on climatic conditions, urban topography, etc. (Di Sabatino et al., 2007). Moreover, the exposure of individuals varies with distance from the emission point (here roads) and time spent outdoor (Karner et al., 2010). While a detailed impact assessment would subsequently require an even more comprehensive model (*e.g.* Shorshani et al., 2015), we propose a simple indicator of exposure to local pollutants:

$$Exp_{i} = \frac{DPresent_{i} \times (DNOx_{i} + DPM_{i})}{DPresent_{IDF} \times (DNOx_{IDF} + DPM_{IDF})}$$
(1)

where $DPresent_i$ is the density of individuals "present" in municipality *i*, and $DNOx_i$ and DPM_i the density of NO_X and PM₁₀ emissions (in t/km²), respectively. In order to consider the spatial mismatch between residences and work places, $DPresent_i$ is computed as the weighted average between population (during 16 h) and job (during 8 h) densities in city *i*. Finally, Exp_i is normalized by the regional average value.

We find that exposure to local pollutants from road traffic varies considerably over IdF (Fig. 4). The 20% most exposed municipalities are almost all located in the core of the Paris region. Conversely, most of the 20% least polluted municipalities are found within the fringes of IdF. Considering the ranges of the quintiles (with a median of 0.004), the indicator is highly skewed. This suggests that exposure to local pollutants is strongly concentrated in the core of the metro area, where traffic density is very high, speed is very slow (hence a high emission intensity), and where more people are impacted by pollutant emissions. Computing exposure indicators separately for PCs and goods vehicles leads to similar results (Table C.3), except that exposure issues are even

Table 8

Marginal external costs related to pollutants emissions (2012). Source: authors' calculations from Ducos (2014).

	Paris + VDUA	DUA	UA	DIUA	IA
PM _{2.5} (€/ton) NO _x (€/ton) CO ₂ (€/ton)	4,564,011 9070.3 35.8	1,521,337	507,112	169,037	16,963

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

more localized within Paris for URF than for PCs.

4.3. Environmental social cost

Finally, we estimate the environmental social cost of road traffic in general, and of URF in particular. Whereas greenhouse gases contribute to climate change costs (Goulder and Mathai, 2000; Tol, 2009), local pollutants are "costly" inasmuch as exposed individuals are more likely to face health problems, inducing potential earnings losses for households and health expenditures for society. They also imply agricultural losses and building deteriorations (Kampa and Castanas, 2008; Ricardo-AEA, 2014; WHO, 2016). A large literature proposes parameters to monetize these damages (Ricardo-AEA, 2014).

We here apply the French official parameters available in the appendix of the Quinet report (Ducos, 2014). These external costs have been estimated by following a procedure that is consistent with the "Impact Pathway Approach", while accounting for French specificities. The shadow price of $PM_{2.5}$ is significantly larger than that of NO_x (€9070 per ton), especially in the core of the Paris region where each ton of $PM_{2.5}$ emitted in the atmosphere entails social losses valued at 4.5 M€ (Table 8).¹⁸ Regarding particulate matter, let us note that Copcete estimates PM_{10} emissions, and not directly $PM_{2.5}$. When computing the environmental social cost of road traffic in the Paris region, we will thus consider that 65% of PM_{10} emissions are made of $PM_{2.5}$ (Airparif, 2014). Regarding CO_2 , the Quinet report (CGSP, 2013) recommends a central value of €35.8 per ton in 2012.

By crossing these marginal costs with the tonnages of pollutants emitted within each macro-zone (Table 7), we find that emissions from road traffic entail social losses for IdF evaluated at 23.1 M€/day (Table 9), that is $1.9 \in$ per capita per day. Aggregated over 260 working days, the bill adds up to 6.0 billion €, corresponding to 0.98.4% of the regional GDP (612 billion € in 2012). This figure falls within the upper-bound of estimates found for European countries (de Palma and Zaouali, 2007). Considering that the Paris region is denser, our results seem consistent. Lastly, as the aggregate (private) generalized costs of road transport amount to 90 M€/day (Table B.3), fully internalizing the external costs of local pollutants (through a dedicated tax) would raise the average trip cost for road users in IdF by 25.7%.¹⁹

Our methodology allows us to break down the environmental social cost by area and by vehicle class. Paris and the very dense urban areas of IdF concentrate 77% of the total bill. By contrast, externalities in interurban areas are negligible. Regarding the impact of URF, it is responsible for 36% of the total losses, while representing only 8% of the total distances traveled and 20–30% of emissions. This is the combined effect of freight vehicles emitting more than PCs, but also of freight traffic being more concentrated (in dense areas) than regular traffic, thereby affecting more population. The social cost of URF is especially high in the core of the agglomeration indeed, HGVs and LGVs accounting for 46% of total losses in Paris city. HGVs in particular are responsible for losses equal to 0.29% of the regional GDP (still considering 260 working days per year), against only 0.06% for LGV.

Quite unexpectedly, climate change costs play a minor role in our results: extra losses only amount to 1.1 M/day, in other words 5% of total environmental costs. By contrast, losses linked to the emissions of PM_{2.5} account for 90% of total social costs. Furthermore, URF only represents around 19% of the CO₂ related costs, against 37% of air pollution related ones. Based on the monetary equivalents of environmental damages reported in the French guidelines (CGSP, 2013), currently public policies should focus on addressing local pollution in Paris rather than abating CO₂ emissions, especially so in the case of URF.

5. Discussion

We discuss in this section some limitations of our methodology and/or of our data and to what extent they influence our main findings.

5.1. Influence of the vehicle fleet

Our estimates of pollutant emissions are based on the national composition of the vehicle fleet instead of that of IdF, due to the

¹⁸ Because the densest category proposed by the Quinet report corresponds to a lower bound of 4500 inh./km², central Paris and the very dense urban areas are for all practical purposes assumed to have the same density in our computations, despite the markedly higher density of Paris. By biasing our results downward, this last point implies that our estimates should be rather conservative in this respect.

¹⁹ This is actually an upper bound because introducing this tax would lower road traffic, thus congestion, ultimately leading to a decrease in generalized costs (before tax).

Table 9 Environmental social cost of road traffic in the Paris region (2012). Source: authors' calculations.

	IdF	Paris	VDUA	DUA	UA	DIUA	IA
Total social costs (M€/day)	23.06	6.02	11.64	3.38	1.04	0.88	0.10
PCs	14.80	3.22	7.58	2.37	0.79	0.74	0.09
LGVs	1.34	0.49	0.63	0.15	0.04	0.03	0.00
HGVs	6.91	2.31	3.43	0.85	0.21	0.11	0.01
Total social costs (%)	100.0	26.1	50.5	14.7	4.5	3.8	0.4
Share of URF (%)	35.8	46.4	34.9	29.7	24.2	15.5	8.0
Including CO ₂ related costs							
Social costs (M€/day)	1.12	0.15	0.29	0.22	0.16	0.25	0.05
Share of URF (%)	19.4%	33.9%	23.2%	19.3%	15.9%	11.0%	6.6%

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area. PM_{2.5} emissions are found by applying a 0.65 factor to PM_{10} emissions (Table 7)

lack of data at the regional level. This could bias our results, considering that emission factors are highly sensitive to the vehicle category (in terms of emission standards or weight categories).

A recent study of Carteret et al. (2015), who use video data to estimate the fleet composition by vehicle class (PCs, LGVs, HGVs) and emission standards for the Paris region, finds that the vehicle fleet of IdF is not that different from the national fleet in terms of emission standards, whatever the vehicle class considered. The main exception is for HGVs. Carteret et al. (2015) find old trucks (Euro-0-I-II) to be overrepresented in IdF (16% against 5% at the national level), while recent trucks (Euro-V) are underrepresented (26% against 44%). Similarly, they find 26% of Euro-III HGVs at the regional level, against 21% at the national level. Because the regional fleet of HGVs also strongly differs from the national one regarding the size of vehicles (with typically smaller trucks in IdF²⁰), these various differences compensate for each other to some extent, so that ultimately the authors conclude that using the national fleet instead of the regional one only leads to limited errors for most pollutants, especially for freight vehicles (see Carteret et al., 2015, Table 5). For instance, for LGVs using the national fleet leads to overestimating PM₁₀ and NO_x by +6% and +3% respectively, while being neutral for CO₂. Regarding HGVs, the errors are similarly relatively limited except for CO₂ (+11%). Under-estimation issues are both more systematic and more significant in the case of PCs, with for instance an under-estimation of CO₂ by -25%.

All in all, this suggests that our results are fairly robust for freight vehicles, but likely underestimated for PCs. The issue is more salient for CO₂: by applying the corrections proposed by Carteret et al. (2015), the share of URF falls from 19% to 15%. For local pollutants on the other hand, the share of URF only decreases from 29% to 27% for NO_x, and is virtually unaffected for PM₁₀. Note that the quality of the results of Carteret et al. (2015), based on video data recorded for a limited number of geographical sites, has yet to be ascertained, reason why we use the national composition in our main application.

5.2. Influence of the load factor

Load weights of HGVs being often difficult to measure, we investigate to what extent our results are sensitive to them. The load factor has two main effects on pollutants emissions. Because the truck is heavier as a result, a higher load factor implies greater emission factors per vkm.²¹ For a mean speed of 40 km/h, doubling the load factor of HGVs from 50% to 100% increases the emissions produced by Copcete by 22% for CO_2 , 9% for NO_x , and by only 2% for PM_{10} . As illustrated by this example, emissions per vkm increase less quickly than the load weight - be it only due to the sheer weight of the vehicle - so that a higher load factor conversely implies lower emissions per tkm. Based on additional simulations in Copcete, we may conclude that emissions per vkm are not so sensitive to the load factor – an error of 10% on the load factor entailing an error of 4–5%, 2–3% and 0.2% for CO_2 , NO_x and PM_{10} , respectively – but that emissions per tkm are mechanically sensitive to it from the denominator effect. In other words, errors regarding load factors lead to small errors regarding aggregate emissions and emissions per vkm, but to larger errors regarding emissions per tkm.

In our case study, the average load weights are relatively low: 0.3 t for LGVs and 1.9 t for HGVs.²² In the latter case, crossing this mean tonnage of 1.9 t with the breakdown of the national fleet by weight category yields an average load factor of only 11% approximately.²³ Accordingly, we find that HGVs pollute only marginally less than LGVs when reasoning in emissions per tkm (see

²⁰ The distances traveled by the national fleet of HGVs, as documented in Copcete and considered in this research, is equally distributed between articulated and rigid trucks. By contrast, Carteret et al. (2015) estimate that rigid trucks, typically smaller than articulated trucks, account for 90% of distances traveled by HGVs in the Paris region.

²¹ For LGVs, Copcete considers emission factors independent of the load rate.

²² Load weights reported in Table B.2 come from Beziat et al. (2017). Using one urban goods survey carried out in 2011 in the Paris region, they estimate – among other things – the mean weight of the cargo over the whole vehicle delivery round. This implies that said load weights include empty trips (empty backhaul, intermediary empty trips between deliveries and pick-ups, etc.).

 $^{^{23}}$ While Copcete provides information on the HGV fleet structure according to 14 wt categories, to put it simpler the distribution of traveled distances in 2012 can be approximated as follows: 50% for articulated HGVs (with a mean useable weight of 24 t), 30% for small rigid trucks (6.5 t) and 20% for large rigid trucks (17 t). Accordingly, the average useable weight in our sample is 17 t for HGVs, thus leading to the average load factor of 11%.

Table 10 Sensitivity to external costs. Source: authors' calculations from Ricardo-AEA (2014) and Copcete estimates.

	-			
	Rural areas	Suburban areas	Urban areas	IdF
CO ₂ costs (€/ton)	90.0			
NO _x costs (€/ton)	13,052			
PM _{2.5} costs (€/ton)	33,303	64,555	211,795	
Environmental social cost (M€/day)	0.61	1.00	4.33	5.94
Share in total (%)	10.3	16.8	72.9	100.0
Share of URF (%)	10.9	16.1	30.6	26.1
Share of CO ₂ (%)	59.0	55.7	43.8	47.4
NO _x costs (\mathcal{C} /ton) PM _{2.5} costs (\mathcal{C} /ton) Environmental social cost (M \mathcal{C} /day) Share in total (%) Share of URF (%) Share of CO ₂ (%)	13,052 33,303 0.61 10.3 10.9 59.0	64,555 1.00 16.8 16.1 55.7	211,795 4.33 72.9 30.6 43.8	5.94 100.0 26.1 47.4

Note: "Rural areas" stands for areas with population density below 150 inh./km², "Surburban areas" for areas with population density ranging from 150 inh./km² to 900 inh./km², "Urban areas" for areas with more than 900 inh./km². $PM_{2.5}$ emissions are found by applying a 0.65 factor to PM_{10} emissions (Table 7).

Footnote 17), which would seem still enough to question the environmental relevance of policies aimed at switching from trucks to light commercial vehicles in urban areas. Our previous comments and calculations call for considering this last result with caution, however, as emissions per tkm are quite sensitive to measurement errors. Even if this issue calls for further research, based on the same elements we believe that our main results – namely the aggregate emissions and the corresponding social cost – are fairly robust to errors regarding load factors.

5.3. Influence of the valuation parameters

Our valuation of CO_2 emissions is based on the French official value of &35.8 per ton for year 2012 (CGSP, 2013). While the carbon price issue does remain highly controversial (Tol, 2009), this value may seem relatively low in comparison to recent European values, which range from &48 to &168 per ton for year 2010, with a central value at &90 per ton (Ricardo-AEA, 2014).²⁴ Similarly, the value proposed by Ricardo-AEA (2014) to monetize the external cost of NO_x emissions in France is much larger (&13,052 per ton) than the one considered in Table 8 (&9070 per ton). By contrast, French official guidelines (CGSP, 2013; Ducos, 2014) put a disproportional weight on damages linked to PM_{2.5} emissions as compared to European recommendations. In order to investigate the influence of these cost parameters, we re-estimate the environmental social cost of road traffic in IdF, this time using the external costs reported in Ricardo-AEA (2014).

Following the European official guidelines leads to a markedly lower environmental social cost than by applying French values. Even though Ricardo-AEA (2014) features higher shadow prices for CO_2 and NO_x , the environmental social cost hardly reaches 6 M \in per day (Table 10), as opposed to 23 M \in previously (Table 9). This strong difference is due to the considerably higher shadow price of PM_{2.5} in French national guidelines, which itself results from (at least) two French specificities: the Quinet report (CGSP, 2013) considers a statistical value of life equal to 3 M \in - against 2 M \in in the European Handbook - and it defines valuation parameters for a wider spectrum of urban areas in terms of population density (given the very high densities in some parts of France, especially within the Paris metro area), reasons why we prefer to stick on benchmark results shown in Table 9.

This being said, this sensitivity test confirms most of our previous findings. First, environmental social losses are again strongly concentrated in dense urban areas (73%), where more pollutants are emitted (67%) and more population is affected. Second, the impact of URF remains considerable (26% of the overall social cost) relatively to its weight in the total traffic (only 8% of traveled distances). Third, even if CO_2 emissions now account for a much larger share of total environmental costs (47% on average, against only 5% in our baseline valuation), their relative contribution is lower in dense areas, where air quality issues are preponderant. Lastly, the environmental social cost of URF in the Paris region remains non-negligible. Aggregated over a year, it adds up to around 0.4 billion ϵ , corresponding to approximately 0.07% of the regional GDP.

Overall, from a qualitative point of view, the main difference between the two valuations – using either French values or European ones – relates to the importance of global warming within the total environmental social cost. Considering that the French value in 2012 (35.8C/ton) does seem quite low in comparison to European values, and that the carbon price is expected to soar over the years as CO₂ levels keep rising and the effects of global warming become more harmful for populations, wildlife, and flora, this suggests one should not take our results at face value regarding the contribution of CO₂ emissions to the total environmental social cost and minimize the issue of global warming, which could have grave consequences in the long run.

6. Conclusion

This paper estimates the environmental social cost of urban road freight in the Paris region, focusing on greenhouse gas emissions and air pollution. For that purpose, we develop a modeling chain including a freight (and passenger) travel demand model, a

 $^{^{24}}$ These costs parameters are subject of huge debates among specialists, depending on the social discount rate used for computations or expected future trends in CO₂ emissions notably (Tol, 2009). As such, it is worth noting that CO₂ cost proposed in the previous (2008) European "Handbook on the External Costs of Transport" was equal to ϵ 25 per ton.

multiclass traffic assignment model, and a mobile emissions model, allowing for a fine spatial representation of URF. As a result of several mechanisms at work (heterogeneity in speeds and route choices, non-linearity of emission factors with respect to vehicle speed, etc.), there is no clear mapping between average traffic speeds and average emission factors at the aggregate level: to one same mean traffic speed may correspond various emission factors depending on zonal characteristics. This corroborates the relevance of using a modeling chain instead of a simpler aggregate model. Similarly, the environmental social cost of road traffic substantially varies depending on the vehicle class or the population density, again supporting the use of a full-fledged model (featuring multiclass assignment and a fine spatial resolution).

While representing only 6% of trips and 8% of distances traveled, urban road freight accounts for 36% of the total damages caused by pollutant emissions from road traffic in IdF. This is the combined result of freight vehicles emitting more than PCs, and of freight traffic being more spatially concentrated than passenger traffic, thereby affecting more population. The density and efficiency of the public transport network (combined with a scarce parking supply) help restrict the use of PCs within the central parts of the Paris area. For freight however, alternatives are limited and marginal to date, hence the greater spatial concentration than for passenger traffic. Congestion also plays an important role, inasmuch as lower speeds lead to greater emission factors (André and Hammarstrom, 2000; Grote et al., 2016). Because freight transport is more concentrated within high density areas where traffic speeds are lower due to heavy traffic levels, this also partly explains why URF emits more than PCs.

All in all, the environmental social cost of URF adds up to around 2.1 billion \in per year, or 0.35% of the regional GDP. Our findings also provide some directions for public policies. Based on the current economic evaluation guidelines in France, we find that damages from air pollution are nineteen times higher than damages from CO₂ emissions in the case of URF. Applying European values rather than French one for the cost of CO₂ emissions and of local pollutants leads to a very different picture however, as the weight of CO₂ emissions becomes equivalent to that of air pollution within the total environmental social cost. Be that as it may, the concentration of social losses within the densest parts of the Paris region in both instances strongly advocates transport policies such as low-emission zones or urban tolls that aim to regulate HGVs and LGVs use within the city center, and more generally all policies aiming to address the last-mile issue with green and sustainable logistics. Alternatively, fully internalizing the social cost of pollutant emissions would involve raising the average private cost of HGVs and LGVs by a maximum of 90% and 33%, respectively. Though this seems difficult in the short run for economic reasons, this provides a policy framework. Our findings remain mixed regarding the issue of LGVs versus HGVs. HGVs would emit more per vkm, but only slightly less per tkm. Emissions per tkm are very sensitive to measurement errors, however, which are quite likely in the case of load factors. Considering that HGVs and LGVs are not perfect substitutes to boot, this issue calls for further investigation.

In addition of the various issues raised in the previous section, our findings are subject to a certain number of caveats. First, the generality of the results has yet to be assessed through comparison to other case studies. This raises the issue of the transferability of our methodology, based on four main elements: a freight demand model, a passenger travel demand model, an emissions model, and last external cost parameters. National guidelines for economic appraisal would typically include external cost parameters, so that these are usually easily available. Similarly, most large cities around the world – especially in developed countries – have developed their own passenger travel demand model (most often a standard 4-step model) and emissions model in order to meet their study needs. However, fewer have a freight demand model at their disposal (see reviews by Comi et al. (2012) or Comi et al. (2014)). Unlike for passenger travel, freight commercial software are seldom, so that academic models must often be used instead - as we do here. Even more importantly, models need appropriate surveys to be calibrated, which are again less common for freight than for passenger travel. This last point – the availability of a detailed freight demand survey, including trip generation by establishments (in order to quantify trips for each type of activity) and freight rounds surveys (to characterize transport organizations and travelled distances) – is likely the most critical point for the development of a similar modeling chain.

Second, while this paper has shed light on the specific role of URF regarding pollutant emissions in IdF, we have yet to test policy scenarios such as suggested above aimed at reducing those emissions (as done by Kickhofer and Kern (2015); Ellison et al. (2013), Holguin-Veras et al. (2006) or by Aditjandra et al. (2016) for the cases of Munich, London, New York and Newcastle respectively; see also the reviews of policy options by Demir et al. (2014); or by Russo and Comi (2016)). In particular, considering the prevalence of the air pollution issue as regards URF, recent works regarding passenger traffic suggest that road pricing (such as tolls, Fu and Gu, 2017) might be more effective than regulation (such as license plate driving restrictions, Zhang et al., 2017a, 2017b) to reduce air pollution, especially during pollution peaks.²⁵ Finally, our estimates of the environmental social cost of URF are likely conservative, inasmuch as they include neither the effects of air pollution on mental health and subjective well-being (Zhang et al., 2017a, 2017b), nor other nuisances such as noise and lifecycle effects of vehicles and energy.

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²⁵ Regulation policies, insofar as they may be circumvented by road users through adaptation strategies (*e.g.* in the case of license plate driving restrictions through substitution, the purchase of a second car, or the use of alternative modes), may in some cases actually increase air pollution (Zhang et al., 2017a, 2017b). Although users' reactions to road pricing also include strategies with ambiguous effect on air pollution (such as changing route, with possibly longer distances travelled), to the best of our knowledge all studies find that appropriate pricing schemes do decrease either exposure to air pollution or intermediately emissions of local pollutants (see among others Kickhöfer and Kern, 2015; Fu and Gu, 2017; Luechinger and Roth, 2016).

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Appendix A. Modelling framework

A.1. Travel demand for urban road freight

Freturb is a multipurpose model designed for urban freight analysis (Routhier and Toilier, 2007).²⁶ Here it is used to estimate travel demand (i.e. OD matrices) for URF. In Freturb, the number of weekly movements (n_e) generated by an economic establishment²⁷ (e) is explained by its industry sector (a), its number of employees (o), and the nature of its premises (p).²⁸ Accordingly, the total number of movements M_r in zone z writes:

$$M_{z} = \sum_{e \in z} n_{e}(a, p, o).$$
(A.1)

The combination of these variables gives rise to a typology of establishments, comprising 116 different classes noted ε , each representing a unique triplet (*a*, *p*, *o*).

Goods movements may also be broken down according to the transport characteristics: the vehicle class k (LGVs, rigid or articulated HGVs), the management mode m (third party logistics, own account transport shipper or consignee) and the route type r (direct or round trips). This gives:

$$M_{z} = \sum_{\varepsilon,k,m,r} M_{\varepsilon,z} \times f_{k,m,r}(\varepsilon), \tag{A.2}$$

where $f_{k,m,r}(\varepsilon)$ denotes the frequency of characteristics (k, m, r) among establishments of class ε and $M_{\varepsilon,z}$ the number of movements generated by establishments of class ε in zone z.

Next, based on the volumes and types of goods movements in each zone, Freturb estimates the total number of trips t_z in zone z as:

 $t_z = dt_z + se_z + c_z \tag{A.3}$

where dt_z refers to direct trips, se_z to starting and ending trips and c_z to connecting trips of delivery rounds. The distance of each trip type is determined from geographical variables (distance to the center of each zone, density of activities) and the characteristics (k, m, r) of the establishment category ε .

Finally, Freturb applies one typology of trips, characterized by the vehicle class, the trip type, the management mode and the route length. According to this 25 class categorization, the beginning of each τ -type trip which touches the zone z_j matches the movement of τ -type trips generated in z_i . The final OD matrix T_{ij} is the sum of the OD $t_{ij}(k)$ obtained for each vehicle class k:

$$T_{ij} = \sum_{k} \left[t_{ij}(k) \right] \tag{A.4}$$

In order to operate, Freturb requires the distribution of characteristics (a, p, o) within establishments. In our application, the SIRENE database provides information at the municipality level for the Paris region regarding the activity (a) and the size (o) of establishments, but not about their premises (p). The Simetab model allows to tackle this issue by imputing information missing from the SIRENE dataset. To do so, it relies on a typology of urban spaces determined through the analysis of different SIRENE files and other local data in several French metropolitan areas and for various years (Gardrat et al., 2014). Each type of urban space is associated with a given distribution of the characteristics (a, p, o). Using statistical classification methods, Simetab first defines urban categories (highly residential, lower density area, high tertiary activity, commercial, etc.) heterogeneous in their economic structures. Multiple discriminant analyses are then applied to assign each zone present in the dataset to one urban category. By comparing the economic structure of the zones to their typological counterparts, Simetab finally matches each firm observed in the dataset with a category $\varepsilon(a, p, o)$, thus insuring the operability of Freturb.

A.2. Multiclass traffic equilibrium

Traffic conditions in the Paris area are estimated using a static multiclass traffic assignment procedure (Dafermos, 1972),²⁹ available in the TransCAD software.

Originally designed to determine traffic levels on particular roads for a given day period, assignment models can also be used to derive the shortest path between any OD pair, and the corresponding travel time, distance and speed (Coulombel and Leurent, 2013).

²⁶ Interested readers may also refer to Routhier et al. (2001), Bonnafous et al. (2013) and Toilier et al. (2014) for more information about the model specification as well as the quality of calibration regarding freight trip generation and travelled distances.

²⁷ A firm is a legal entity that may consist of several establishments (i.e. premises). We use both terms interchangeably. Note that while the scope of our research includes establishments engaged in an activity, including public administrations, small and large businesses, and so on, it does not include private households. B2C ecommerce flows, therefore, are not considered in our analysis.

²⁸ This was validated using freight surveys collected in France during the 1990s (Patier and Routhier, 2009).

²⁹ The term static emphasizes the fact that one focuses on one given time-of-day period, assumed in steady state, as opposed to dynamic models that seek to reproduce the intra-day dynamics of traffic.

Congestion plays a central role in these models (Ortuzar and Willumsen, 2011). As more users take the same road, it becomes congested and travel time increases. This is represented by a volume-delay function (VDF), the most common - used here - being the Bureau of Public Roads (BPR) function (TRB, 2010):

$$tt = tt_f \times \left(1 + \alpha \times \left(\frac{F}{K}\right)^{\beta}\right),\tag{A.5}$$

where *tt* is the travel time on a given link, tt_f the free-flow travel time (no congestion), *F* the traffic flow, *K* the link road capacity, and α and β are (positive) congestion parameters.

As congestion starts to builds up, some drivers turn to alternative routes, thus causing congestion on the corresponding links. Such strategic interactions between users develop until a traffic equilibrium – called Wardrop equilibrium – is reached (Ortuzar and Willumsen, 2011). At equilibrium, for any given OD pair, the generalized cost of travel of all alternative paths are equalized (the cost of unused paths being greater than this minimum cost), i.e. drivers do not have any incentive to change their routes. The generalized cost associated to a path p synthesizes both time and money as follows:

$$GC_p^k = VOT^k \times tt_p + c^k \times t_p, \tag{A.6}$$

where the variables tt_p and l_p denote the travel time and the length of path *p* respectively, VOT^k the value of travel time savings of class *k* users and c^k the kilometric cost (fuel, insurance, depreciation, etc..). As the route choice involves a trade-off between travel time and distance, the path(s) with the minimum generalized cost would generally be neither the fastest nor the shortest, but rather a compromise between the two.

Our road assignment model distinguishes four user classes k: PCs, LGVs, rigid and articulated HGVs. While assumed to travel all at the same speed on a given link, each vehicle class is characterized by different values of travel time and kilometric costs. Accordingly, route choices may differ from one class to another for a given OD. Furthermore, all types do not weigh the same within the VDF function. The flows F_k of each vehicle class k are converted into a passenger car equivalent (PCE) metric before being summed (and then used in the volume-delay function):

$$F = \sum_{k} PCE_k \times F_k \tag{A.7}$$

The PCE_k factor describes the amount of road space occupied by one vehicle of class k relatively to one private car, in order to reflect that one truck generates more congestion than one car (Webster and Elefteriadou, 1999; TRB, 2010).

A.3. Pollutant emissions

Copcete (Demeules and Larose, 2012) is based on the European COPERT IV methodology (Ntziachristos et al., 2009; Shorshani et al., 2015). It compiles emission factors for various driving cycles (representative in terms of speeds, load rates, slopes of the roads) and vehicle types (in terms of classes, weights or technologies).

We consider in this research only "exhaust emissions" from road traffic and neglect those related to the evaporation of pollutants. As illustrated on Fig. A.1 for NO_X emitted by diesel vehicles, the unitary emissions depend on the vehicle class and on the engine technology. For a given legal standard and a traffic speed of 15 km/h, HGVs emit three times more NO_X than LGVs, themselves polluting twice more than PCs. The effect of technological changes is substantial, as shown here only in the case of LGVs. Considering one LGV driving at 20 km/h, Euro 4 vehicles emit around three times less NOx per kilometer than Pre-Euro vehicles. Lastly, unitary emissions are not a linear function of vehicle speed. In the case of PCs and LGVs, the U-shaped curves reach their minimal values at travel speeds of 60–70 km/h approximately.³⁰

In addition of these factors, unitary emissions of HGVs are also modeled in Copcete as a positive function of the road slope (assumed to be zero here) and of the load rates of vehicles (assumed to be 50%). Copcete also takes into account for PCs and LGVs over-emissions due to "cold-start phases", i.e. when engines are not warm yet. Although the correction factor theoretically depends on climatic conditions and on the share of distances driven at "non-stabilized regime", Copcete estimates over-emissions based on an average trip distance (6 km here).

Copcete can straightforwardly use the road assignment model outputs, at the road link level. Formally, the total emissions TE_s^j of pollutant *j* on link *s* are given by:

$$TE_s^j = l_s \times \sum_k \sum_x \mathcal{O}_x^k \times F_s^k \times e_x^{jk}(S^k)$$
(A.8)

where l_s describes the length of link s, \bigotimes_x^k the share of vehicles using the technology x within the total flow F_s^k of the vehicle class k, and $e_x^{jk}(S^k)$ the emission factor of pollutant j for the class k vehicles using the technology x, i.e. a function of the traffic speed (S^k). Regarding the parameters \bigotimes_x^k . Copcete considers the precise composition of the French national vehicle fleet for a given year, in terms of emission standards, energy types and weights.

³⁰ Copcete estimates PCs and LGVs emissions for speeds ranging from 10 km/h to 130 km/h. For HGVs, the range is 12–86 km/h. As a consequence, the traffic speeds given by the traffic assignment model have to be adjusted to feed Copcete. Changes are negligible, except for HGVs in interurban areas where the mean speed drops from 73.8 km/h to 69.7 km/h. It is worth noting, however, that interurban areas account for only 2% of total road links.



Fig. A1. NO_X emissions of diesel vehicles, Sources: authors' elaboration from Copcete.

Appendix B. Additional data for the road assignment model

Tables B.1-B.3

Table B1

Characteristics of the road network.

Source: authors' calculations from DRIEA and TransCAD.

	IdF	Paris	VDUA	DUA	UA	DIUA	IA
Road links	39,420	4688	10,959	10,184	6370	6406	813
Total road length (km)	20,480	1033	3220	3479	2990	7554	2204
Road density (km/km ²)	1.7	9.8	5.8	3.6	2.3	1.2	0.8
Free-flow speed (km/h)	58.2	43.7	54.8	61.4	64.1	63.3	62.6
Road capacity (veh/h)	1709	2121	1702	1564	1660	1701	1705

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

Table B2

Cost and technical parameters. Source: Beziat et al. (2017).

	PC	LGV	HGV
Monetary costs (€/km)	0.271	0.365	0.842
Vehicle occupancy (ind./veh)	1.3	1.0	1.0
Value of time of individuals (€/h)	10.7	9.8	9.8
Load weight (tons/veh)	0.0	0.294	1.941
Value of time of goods (€/ton/h)	0.0	0.6	0.6
PCE factors	1.0	1.5	2.0-2.5

Note: we consider a PCE (Private Car Equivalency) factor of 2 for rigid HGV and 2.5 for articulated HGV.

Table B3

Total travel costs. Sources: authors' calculations from TransCAD.

	IdF	Paris	VDUA	DUA	UA	DIUA	IA
Travel costs (M €/day)	90.0	13.4	24.4	18.2	12.3	18.3	3.4
PC	78.4	10.5	20.8	16.0	11.0	16.9	3.2
LGV	4.0	1.1	1.3	0.7	0.4	0.4	0.1
HGV	7.6	1.7	2.3	1.5	0.9	1.0	0.1
Travel costs (%)	100%	14.9%	27.1%	20.2%	13.7%	20.3%	3.8%
Share during peaks (%)	37.7%	41.0%	38.9%	37.4%	35.8%	35.0%	35.3%
Share of URF (%)	12.9%	20.9%	14.8%	12.1%	10.6%	7.7%	5.9%

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

Appendix C. Additional data for the environmental analysis

Tables C.1-C.3

Table C1

Indicator of emission intensity.

		Paris	VDUA	DUA	UA	DIUA	IA
CO ₂	All traffic	1.27	1.07	1.00	0.93	0.89	0.86
	URF	2.15	2.32	2.38	2.52	2.50	2.54
NO _x	All traffic	1.34	1.04	0.97	0.93	0.91	0.90
	URF	3.25	3.64	3.64	3.71	3.43	3.58
PM ₁₀	All traffic	1.21	1.05	1.00	0.96	0.91	0.86
	URF	2.94	3.51	3.74	4.13	4.30	4.35

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

Table C2

Averaged emission factors.

Source: authors' calculations from Copcete.

	IdF	Paris	VDUA	DUA	UA	DIUA	IA
CO_2 by PC (g/km)	177.00	202.60	183.37	176.46	169.30	168.38	168.49
CO_2 by LGV (g/km)	262.61	284.66	254.61	257.15	253.87	259.53	256.28
CO2 by HGV (g/km)	762.04	924.20	785.16	729.26	673.82	648.95	622.65
NO _x by PC (g/km)	0.61	0.61	0.58	0.59	0.60	0.64	0.66
NO _x by LGV (g/km)	0.92	1.01	0.91	0.90	0.88	0.88	0.87
NO _x by HGV (g/km)	5.21	6.82	5.45	4.89	4.33	4.08	3.80
PM ₁₀ by PC (g/km)	0.07	0.07	0.07	0.07	0.07	0.07	0.08
PM10 by LGV (g/km)	0.11	0.10	0.10	0.11	0.10	0.12	0.12
PM_{10} by HGV (g/km)	0.65	0.67	0.65	0.64	0.64	0.63	0.63

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

Table C3

Indicators of exposure to local pollutants. Source: authors' calculations.

	Paris	VDUA	DUA	UA	DIUA	IA
From all road traffic	35.15	4.55	0.52	0.11	8×10^{-3}	3×10^{-4}
From URF From PCs	41.21 29.43	3.81 5.25	0.32	0.05	3 * 10 ° 0.01	7×10^{-4} 5 \times 10^{-4}

Note: "VDUA" stands for very dense urban area, "DUA" for dense urban area, "UA" for urban area, "DIUA" for diffuse urban area and "IA" for interurban area.

Appendix D. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.trd.2018.06.002.

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