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How large are the costs of local pollution emitted by freight vehicles? Insights from the COVID-19 lockdown in Paris

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Abstract

Building on the exogenous shock linked with the first COVID-19 lockdown in France (March-May 2020), we propose an original approach relying on econometric modelling to estimate the impacts of road freight transport on the concentration of NO_2 , NO_x and PM_{10} in Paris. We argue that this shock led to a significant change in the composition of road traffic, with an increase in the relative share of freight vehicles with respect to passenger cars, due to the combined exodus of numerous inhabitants, the prohibition of non-mandatory trips and the promotion of home-deliveries. As light-duty vehicles and trucks pollute more than passenger cars, we hypothesize that it led to a rise in the average emissions of pollutants per kilometer traveled in Paris. We confirm this assumption by applying a simple econometric analysis to a rich dataset containing hourly pollutant concentrations and hourly traffic flows recorded in various locations of the French capital city. Relying on the econometric results and on additional back-of-the-envelope computations, we propose tentative estimates of the health impacts of road freight transport. As compared to a counterfactual in which freight traffic in Paris would have declined in the same proportion as cars during the sanitary crisis, hence resulting in a larger decrease in pollutants concentrations, we conclude that around 7 lives have been lost. Crossing this estimate with the official value of statistical life in France, our central scenario approximates at 0.20 euro/km the excess external cost of the local pollution emitted by freight vehicles as compared to cars.

Keywords: Road freight traffic, Air pollution, Covid-19 lockdown, Health, External cost

JEL Classification: R40 , Q53 , I18

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1 Introduction

In the EU-28, the yearly number of premature deaths attributed to local pollutants amounts to approximately 450,000 [13]. Exposure to excessive concentrations of nitrogen dioxide (NO_2), fine particles matter (PM_{10} and $\text{PM}_{2.5}$) or ground-level ozone (O_3) leads to both short- and long-run morbidity, through respiratory troubles, cardiovascular diseases, mental insanity, etc. Among the many sources of air pollution, it is well recognized that road transport in general, and freight transport in particular, constitute major contributors [12], due to the combustion of fossil energies by thermic engines. Moreover, traffic flows of light-duty vehicles and trucks in cities clearly follow an increasing trend, notably due to the rise of e-commerce and home-deliveries: in Europe, the projected growth rate of road freight traffic for the period 2015-2050 thus reaches 1.7% per year [16]. All in all, this explains why the implementation of Low Emission Zones is often seen as a promising solution to mitigate the emissions of local pollutants by commercial transport and to stimulate the transition towards the electrification of the fleets [2, 11] and/or innovative delivery schemes, such as off-hour deliveries [22], cyclo-logistics [28] and crowdshipping [29].

The present paper develops an original approach that relies on econometric modelling to estimate the impacts of road freight transport on the concentration of NO_2 , NO_x and PM_{10} in Paris city, as well as the related short-term sanitary damages. These outcomes play a key role in the socioeconomic assessment of transport policies, as the external cost of local pollution is - with time losses related to road congestion - one the most painful non-market failures caused by urban transportation, far above the nuisances linked with GHG, noise and accident risks [5, 17, 37].

We exploit the exogenous shock of the first COVID-19 lockdown, which we hypothesize may have differently affected car and freight traffics in Paris. More precisely, we argue that the share of freight vehicles (i.e. trucks and vans) as compared to passenger vehicles (cars) in total traffic was increased during the first lockdown imposed in France between March 16th and May 11th 2020 (so that there was a “less than proportional” decrease of freight vehicles in total traffic). Indeed, it has been observed that numerous inhabitants and tourists (between 580,000 and 610,000 individuals on the overall) chose or were forced to leave the city at these dates [23, 30], implying a -25% decrease in the volume of night stays in Paris with respect to early March [24]. This drop logically (and sharply) reduced personal mobility, and this reduction was reinforced by the promotion of teleworking and the prohibition of non-mandatory trips. Additionally, home-deliveries by merchants and by freight professionals strongly increased during the same period [10, 15, 21], due to the huge growth in online purchases by the residents who stayed at home [27], especially for grocery and food items¹. For instance, one survey collected by [1] shows that 40% of economic establishments in Paris have introduced home-delivery services during the COVID-19 lockdown, light-duty vehicles being in that case the main transport mode mobilized. Regarding consumers, 32% of the Parisians surveyed have purchased food items online, home-deliveries being in such a case the most prevalent channel to get the orders (with 62% of respondents choosing it).

All in all, this evolution can be thought to have induced a rise in the marginal impact of road traffic on local pollutants’ emissions and concentrations during the COVID-19 lockdown in Paris, given that freight vehicles pollute more per kilometer than passenger cars, irrespective of the pollutants considered².

We test this intuition by exploiting a rich dataset combining hourly pollutant concentrations and hourly traffic flows recorded in various locations of the French capital city. Importantly, the sensors that collect count data in Paris do not allow to distinguish between the different types of vehicles present on the pavements (i.e. small cars or large trucks), similarly to a large array of traffic sensors in use around the world. This motivates our estimation strategy to estimate the pollution attributable to freight traffic. The various econometric tests proposed in this article confirm our working assumption that the marginal vehicle had a larger impact on local pollution in Paris during the lockdown. Exploiting this increase, we then tentatively mobilize dose-response functions originating from epidemiological studies [3, 4, 6, 31, 32] to estimate the corresponding health impacts, here ultimately expressed as excess external costs of local pollution emitted by freight vehicles as compared to cars passengers (i.e. the difference between the external costs of local pollution emitted by freight vehicles and the external costs of local pollution emitted by cars).

This research relates to, at least, two strands of the literature.

¹See (in French): <https://www.voxlog.fr/actualite/4277/le-groupe-casino-a-l-heure-du-covid-19>.

²See, among other sources, <http://efdb.apps.eea.europa.eu/>.

First, our work is logically linked with articles that evaluate the impact of freight transport on air pollution and estimate external costs of local pollution. Typically, these papers either use the combination of various modelling tools³ (see [3, 9, 26, 33]) or exhaust emissions measurements [25, 40]. Our econometric approach allows to overcome some shortcomings of these works. Indeed, those articles frequently only focus on emissions (hence neglecting the impact of the local environment on pollutants concentration) and they are often not based on the observation of real traffic flows. Also, in order to move from emissions to concentrations, they usually necessitate the simulation of co-factors such as weather and industry emissions. By contrast, we here run estimates directly based on the observation of real pollutant concentrations, real total traffic flows and real weather characteristics in Paris, these variables being hourly reported *in situ* (and not estimated). Moreover, these articles generally cross their emissions' estimates with some "tutelary" values representing the sanitary costs inflicted by local pollutants to inhabitants. Conversely, we here mobilize epidemiological functions that connect changes in pollutant concentrations to changes in sanitary outcomes, hence estimating directly the health costs linked with modifications in road traffic conditions. Even if our empirical work suffers from some limitations too, we believe that the influence of the statistical noise on final outcomes (i.e. the average external cost of local pollution emitted by freight vehicles) is softened.

Second, this research contributes to the recent literature that deals with the drop in mobility due to the COVID-19 crisis and with the corresponding improvements in environmental amenities and sanitary conditions [7, 8, 18, 20, 35, 38, 39]). In addition to providing robust empirical evidence for Paris, one of the biggest (and most polluted) city in Europe, our exercise is focused on the evolution of freight traffic during the first lockdown and on the associated health impacts, which, to the best of our knowledge, have been overlooked in previous research. For example, the technical report by Santé Publique France [32] evaluated at 360 avoided deaths the reduction in short-term mortality, due to the drop in air pollution (NO₂ and PM₁₀) during the COVID-lockdown of Spring 2020, at the scale of France, without discussing the specific impact of trucks and light-duty traffics. Whereas the improvements in air quality in Paris' region over March-May 2020 was associated with 69 lives saved according to [35], the contribution of freight movements to these improvements was not evaluated. In a sense, our article is closely linked to that by [34] who compile, for the Berlin case study, a dataset highly similar to ours. These authors correlate, via random forests techniques, the evolution in NO₂ and PM₁₀ concentrations during the lockdown in Germany with changes in cars and trucks traffics in Berliner streets,

³The chaining of models is generally the following (see [17, 36]): (a) researchers start with freight demand generation models, whose outputs are OD matrices for trucks and light-duty vehicles that are plugged into (b) road traffic assignment models used to determine route choices of drivers at the equilibrium. The corresponding information on traffic flows and on average speeds is used to estimate (c) emissions of pollutants based on, for example, the COPERT methodology, whose costs for society are valued (d) by considering some tutelary values reflecting their health and material damages to individuals and buildings respectively. The external costs figures are finally found by dividing the total socioeconomic costs by the total number of kilometers driven by freight vehicles. It is worth noting that, less often, these models can also account for (e) the dispersion and the concentration of pollutants in the atmosphere and, even more rarely, for (f) the dynamic exposure of individuals, by looking at their travel patterns over the course of the day. A sophisticated and recent exercise can be found in [3].

showing that commercial transport was in fact a major explanatory factor of air (bad) quality. Unlike us, however, [34] do not use the estimated variations in pollutants concentrations linked with freight traffic to estimate the health impacts and socio-economic cost of freight traffic using dose-response functions. Moreover, we adopt an original approach as compared to the literature linking COVID-19 with mobility habits, in that we contrast the change in pollutant concentrations observed in Paris with the one that would have been recorded if freight traffic had declined in the same proportion as passenger cars, thus looking at potential negative consequences of the lockdown on air quality and health outcomes (i.e. if the increase in pollution due to the increase in the share of trucks in traffic had been larger than the decrease in pollution due to the decrease in total traffic).

The rest of this article proceeds as follows. Section 2 describes the sources of the various databases and presents descriptive statistics. In Section 3, we formalize our intuition - the marginal impact of road traffic on pollutant concentration was increased during the COVID-19 lockdown -, translate it into an econometric model and comment our estimates. Then, building on these estimates, Section 4 presents an evaluation of the health costs linked with the "less than proportional" decrease in freight traffic during the COVID-19 lockdown. Section 5 concludes and calls for further research.

2 Data

2.1 Data sources

For our empirical analysis, we mobilize several datasets, which cover the geographic area of Paris *intra-muros* between January 2018 and September 2020.

First, we rely on hourly air pollution data provided by *Airparif*, with the concentrations of NO_2 , NO_x and PM_{10} in $\mu\text{g}/\text{m}^3$ recorded at 9 distinct measurement stations, 6 of which are "traffic" stations located very near roads and 3 of which are "urban background" stations located further away from roads (see Figure 1 for a depiction of the air pollution stations). Even if our econometric analysis mainly focuses on NO_2 , we also use the data regarding NO_x and PM_{10} concentrations in the same measurement stations.⁴

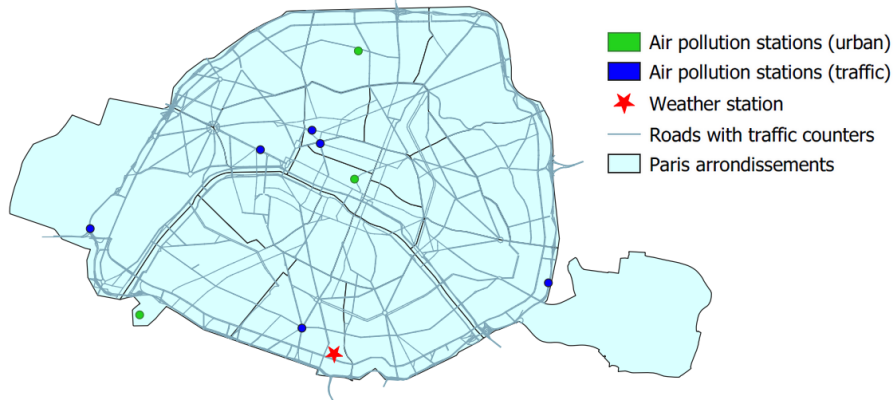
Second, we use hourly aggregate traffic counter data reporting traffic flows and loops occupancy rates from Paris city's open data website (<https://opendata.paris.fr/pages/home/>). This system covers 4,400 road segments and 600 km out of the 1,700 km of roads existing in Paris *intra-muros* (see Figure 1 for a depiction of the instrumented road segments). Importantly, we collected this information for buffers of different sizes around the pollution stations under study: 50m, 100m, 200m and 500m.

⁴Our empirical analysis mainly focuses on NO_2 concentrations because the dose-response function used to estimate the health impacts in Section 4 was calibrated for this pollutant (and not for NO_x). We test the robustness of our results for PM_{10} concentrations, but, whereas road traffic is an important source of NO_x pollution (which transforms into NO_2 in the atmosphere), it is not the prime emission source of PM_{10} .

Third, we use hourly weather information (temperature, wind speed...) from the unique weather station in Paris, which is located in the *Montsouris Park* in the south of Paris (see Figure 1). The planetary boundary layer height⁵ being an other good predictor for the evolution of the concentration of air pollutants, we use hourly data from the dataset ERA 5 provided by the European Centre for Medium-Term Weather Forecasting (ECMWF).

Eventually, we added hourly electricity consumption data measured at the whole Paris Metropolis level, because this data was not available for Paris *intra-muros* only.

Fig. 1 Data collection sites



Additional data is required for the back-of-the-envelope computations in section 4. Regarding the drop in freight vehicles during the Spring 2020 lockdown, we mobilize both quantitative and qualitative data. The former comes from the SIREDO database collected by the Directorate for the Roads in Paris region (DIRIF). It reports, each month, for 100 distinct locations on the road network, both the average flow of total vehicles and the share of trucks within the total. However, for 18 counters only is the data not patchy between 2019 and 2020. We thus focus on these 18 counters. Qualitative data mainly comes from the survey collected by the *Fédération Nationale du Transport Routier* and cited by the 2020 Parisian transport report *Bilan des Déplacements*⁶. Professionals representative of the freight transport sector were asked about the evolution of their activities in the Paris region during the sanitary crisis. We will additionally refer to a carriers' survey conducted by the City Logistics Chair at the Gustave Eiffel University (see also [10])⁷. Eleven carriers of diverse sizes

⁵The planetary boundary layer corresponds to the lowest part of the atmosphere. It is the area within which there is a substantial vertical mixing of the air, which dilutes the concentrations of pollutants. The mixing mostly disappears above this layer [14]. The height of the planetary boundary layer varies across time, depending on many climatic factors that are totally independent from human activities, such as the heating flux between the sun and the earth. This height is commonly used as a proxy for air pollution in the atmospheric literature [19].

⁶See: <https://cdn.paris.fr/paris/2021/12/14/79de82e8b6aaa708d7ebdecbf498a58f.pdf>.

⁷See: <https://www.lvmt.fr/chaieres/logistics-city/>.

and activity sectors had to compare, every week between March 26th and May 10th 2020, their level of delivery activity to the pre-Covid period. Because only 7 carriers answered this survey at least 4 times (out of 6 time periods), we will only consider their answers.

In order to estimate the marginal external costs of local pollutants emitted by freight vehicles, we will use dose-response coefficients for NO₂ and PM₁₀ from the technical report Santé Publique France [32] to quantify the excess mortality due to the excess air pollution related to the “less than proportional” decrease in freight vehicles. Lastly, we will mobilize the official “value of statistical life” [5] in order to translate into monetary terms the corresponding health costs.

2.2 Descriptive statistics for econometrics

The main descriptive statistics are shown in Table 1. As confirmed by Figure 2, the first COVID-19 lockdown (i.e. the period between the two red vertical lines) is associated with an impressive drop in the NO₂, NO_x and, to a lesser extent, PM₁₀ concentrations recorded in Paris city (-46%, -63% and -17% respectively). The less pronounced decrease in PM₁₀ concentration is consistent with other observations [20, 32, 34] and with the residential combustion activities of households who did not leave the Paris region.

At the same time, vehicle flows on Parisian roads were dramatically reduced: -66% during the COVID-19 lockdown, when considering the 100m buffer, with a larger drop for weekends than work days (-77% for weekends and -62%)⁸. Using official statistics published by Paris municipality in its *Bilans des Déplacements*, we can estimate that the huge decrease in total flows documented above was associated with a major increase in average traffic speeds in the French capital city, from 20 km/h for the period over March-May 2019 to around 30 km/h during the COVID-19 lockdown⁹.

Eventually, Table 1 also shows that the weather characteristics and the planetary boundary layer height remained unchanged, while electricity consumption in the Parisian metropolitan area decreased by 20%.

2.3 Descriptive statistics for traffic flow composition

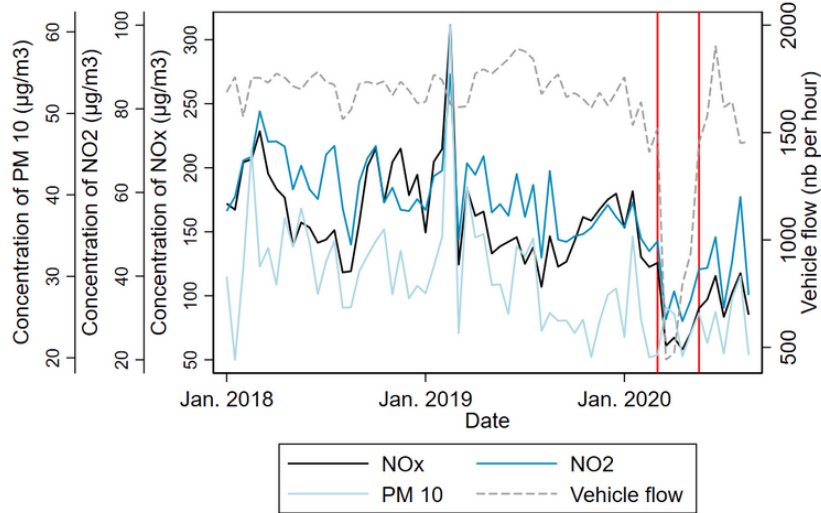
Detailed data on freight vehicles flows in Paris is unfortunately missing, but the Parisian transport survey *Bilan des Déplacements* for 2019¹⁰ indicates that light-duty vehicles and trucks were responsible for about 18% (respectively 15% and 3%) of

⁸The intensity of traffic flows in the 100m around each air pollution measurement station differs a lot depending on the station (it is 10 times higher in the vicinity of the station “Boulevard Périphérique Est” located along Paris’ ring-road as compared to the vicinity of the station “Place Victor Basch” inside Paris).

⁹The average speed for Spring 2019 is based on monthly figures for Paris *intra-muros* and for the Paris ring-road found on <https://www.paris.fr/pages/les-chiffres-des-deplacements-a-paris-en-2019-16899>. For 2020, we use <https://cdn.paris.fr/paris/2021/12/14/79de82e8b6aaa708d7ebdecbf498a58f.pdf>.

¹⁰See: <https://www.paris.fr/pages/les-chiffres-des-deplacements-a-paris-en-2019-16899>.

Fig. 2 Evolution of the concentration of air pollutants and average vehicle flow



total traffic flows during that year. The figures for 2020 are, however, unknown.

During the COVID-19 lockdown, we hypothesize an increase in the share of freight vehicles as compared to cars, because numerous inhabitants and tourists chose or were forced to leave the city [24, 30], but also because home-deliveries by freight professionals were somehow promoted [1, 10]. Evidence from three data sources regarding the evolution of the share of trucks and light-duty vehicles in road traffic during the COVID-19 lockdown substantiates this.

The first data source is the SIREDO database. Table 2 reports the average (computed over the 18 aforementioned counters located in the Paris region but outside Paris) total vehicle flow and share of trucks for each month between January and September 2020, as well as one year before. In the two last lines, the evolution of the total flow of vehicles between 2019 and 2020 as well as the evolution of the flow of trucks are reported. We observe, as expected, the drop in the total flow between March and May 2020. Concurrently, it is clear that the share of trucks increased, especially in April where it reached 14.9%. Consequently, while the total flow of vehicles decreased by 47% between mid-March and mid-May 2020 as compared to one year before, the flow of trucks decreased by only 40%.

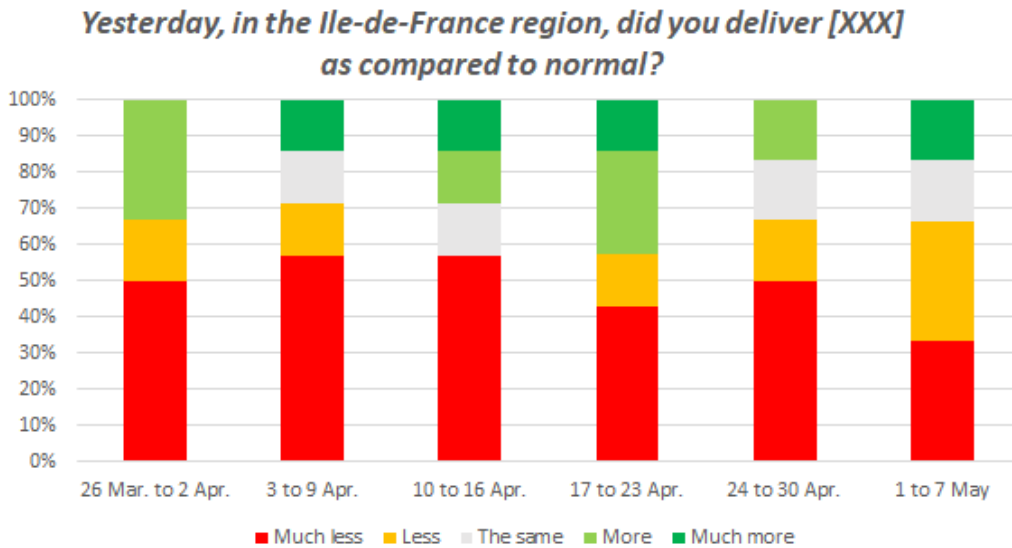
Our second source of evidence regarding the evolution of freight flows corresponds to a survey collected by the *Fédération Nationale du Transport Routier*. It estimated that 52% of trucks usually operating in the Parisian region were immobilized during the lockdown¹¹. This figure is somewhat larger than the one estimated with the SIREDO data. However, one should recognize that freight operators may have

¹¹See <https://cdn.paris.fr/paris/2021/12/14/79de82e8b6aaa708d7ebdecfb498a58f.pdf>.

optimized their delivery rounds in response to the huge improvements in driving conditions within the French capital city, as reflected by increase in traffic speeds [10], thereby further reducing the total number of trucks and vans on the roads¹².

Our third source of evidence regarding the evolution of trucks' and light-duty vehicles' movements in Paris is the qualitative survey of the City Logistics Chair. As shown on Figure 3, the majority of the employees of the 7 firms who answered the survey at least 4 times reports a decline in the volume of goods' deliveries in Paris, as compared to "usual", for every weeks during the lockdown.

Fig. 3 Evolution of deliveries in the Paris region during the COVID-19 lockdown according to the survey of the City Logistics Chair



Put differently, these various sources of evidence make us fairly confident in the fact that freight vehicles flows in Paris have indeed declined between mid-March and mid-May 2020, in a lower extent than passenger cars' flows. Note that a similar observation was made for the Berlin case study [34]. For our benchmark back-of-the-envelope calculations in Section 4, it seems fairly reasonable to consider a -50% reduction in trucks' and light-duty vehicles movements in Parisian streets.

¹²This was observed in New-York in the context of off-hours deliveries experiments [22].

3 Econometric modeling

In this section, we check empirically if the change in the composition of traffic in Paris during the first COVID-19 lockdown indeed led to an increase in pollution due to road traffic.

3.1 Intuition and specification

First, we can note that the concentration of pollutant i (e.g. NO_2) in the air can be decomposed into several sources of emission, differentiating between car traffic emissions, freight vehicle emissions and other sources of emissions. Thus, we can specify K_i as:

$$K_i = \beta_{C,i}F_C + \beta_{L,i}F_L + X_i \quad (1)$$

where F_C is car flow, F_L is freight vehicles flow and X_i refers to other polluting sources. Everything else equal, the fact that trucks and light-duty vehicles pollute more on a kilometer basis than cars implies that $\beta_{L,i} > \beta_{C,i}$.

Since loops on Paris roads only report the total traffic flow, we can alternatively express the concentration of pollutant i as:

$$K_i = \beta_{Total,i}F_{Total} + X_i \quad (2)$$

with $F_{Total} = F_C + F_L$ and $\beta_{Total,i}$ being the main parameter of interest.

From these two equations, it follows that:

$$\beta_{Total,i} = \beta_{C,i}\frac{F_C}{F_{Total}} + \beta_{L,i}\frac{F_L}{F_{Total}} \quad (3)$$

As shown in the previous section, an increase of $\frac{F_L}{F_{Total}}$ and a decrease of $\frac{F_C}{F_{Total}}$ appear to have taken place during the first COVID-19 lockdown. If this is true, and given that $\beta_{C,i} < \beta_{L,i}$, it should lead to an increase of $\beta_{Total,i}$ during the lockdown. Put differently, the marginal contribution of road traffic to pollutant concentration in Paris should have increased during the sanitary crisis, *ceteris paribus*, due to a modification in the composition of the overall traffic flow.

We verify this working assumption with a simple econometric methodology using the exogenous shock of the beginning of the COVID-lockdown. More precisely, we estimate both a “naive model” in which the pollution associated with a marginal increase of traffic flow is assumed to remain unchanged during the COVID-19 lockdown, and an “interacted model” in which this assumption is relaxed.

The “naive model” corresponds to the following reduced form:

$$K_{i,s}^t = \beta_{Total,i} \times F_{Total,s,100}^t + M^t + E_y E_s E_t + E_{Cov} E_s + E_{Cov} E_t + \epsilon_{i,s}^t \quad (4)$$

where $K_{i,s}^t$ is the concentration of pollutant i recorded at the measurement station s during hour t , $F_{Total,s,100}^t$ is the total vehicle flow in a buffer of 100m around station s at t and M^t is a vector of controls at time t (weather characteristics in Paris, planetary boundary height and electricity consumption in the metropolitan area). Vectors E_k correspond to fixed effects capturing the specific effects of years (E_y), hours (E_t), stations (E_s) and periods (lockdown or not, E_{Cov} being a fixed effect for the lockdown period) on the concentration of NO_2 .

The interacted model corresponds to:

$$K_{i,s}^t = \beta_{Total,i}^{No-Cov} \times \mathbf{1}_{No-Cov} F_{Total,s,100}^t + \beta_{Total,i}^{Cov} \times \mathbf{1}_{Cov} F_{Total,s,100}^t + M^t + E_y E_s E_t + E_{Cov} E_s + E_{Cov} E_t + \epsilon_{i,s}^t \quad (5)$$

where $\mathbf{1}_{Cov}$ and $\mathbf{1}_{No-Cov}$ are indicator functions of the COVID-19 lockdown period and of the rest of the time period under study.

Our working assumption will be validated if $\beta_{Total,i}^{Cov}$ and $\beta_{Total,i}^{No-Cov}$ are significantly positive and different. Moreover, we expect that $\beta_{Total,i}^{Cov} > \beta_{Total,i}^{No-Cov}$.

In the following, we will present the results of both the “Naive” and the “Interacted” models.

3.2 Estimates

Table 3 presents our benchmark, favorite, estimates. Column (1) shows the most simple specification, without any control nor dummies.¹³ It confirms that the concentration of NO_2 recorded in Paris is significantly and positively impacted by the total traffic flow, both in the naive and in the interacted models. However, the marginal impact of total traffic flow estimated in the naive model can be expected to be biased, because the change in traffic composition during the lockdown is not taken into account. The interacted model solves this issue and a simple Wald test shows that the $\beta_{Total,i}^{Cov}$ and $\beta_{Total,i}^{No-Cov}$ obtained are significantly different at the 1% confidence level (with a Wald test that has a F-statistic of 0.0087). Thus, the marginal impact of total traffic flow on NO_2 concentration is confirmed to be larger during the COVID-19 lockdown. This supports our working assumption that the traffic structure was strongly impacted by the sanitary restrictions, with a larger share of freight (i.e. more polluting) vehicles driving on the roads during the COVID-19 lockdown. Finally, the negative sign of the COVID dummy shows that the lockdown was associated with a strong decrease in NO_2 concentration in Paris, broadly speaking.

According to columns (2), (3) and (4), these overall results hold when introducing successively of different controls, namely all previously lacking fixed effects in Column (2) and electricity and weather variables in Column (3): The traffic flow still impacts

¹³The fixed effect model was favored over a random effect model according to a classical Hausman test.

positively and significantly the NO_2 concentration recorded in Paris, especially during the COVID-19 lockdown. It is worth noting that adding these controls strongly increases the explanatory power of our model, the R^2 of Columns (3) and (4) reaching 52.8%.

Importantly, it appears that observations are not independent between air pollution measurement stations and that our estimates might suffer from intragroup correlation. For this reason, Column (4) clusters observations at the station level and computes robust standard errors. Doing so, the significance level of parameters does decrease, but it is still satisfactory enough for our main conclusions to hold.

Tables 7 and 8 in the Appendix show various robustness tests. In Table 7, the size of the buffers around each air pollution measurement station within which road traffic is computed is modified (from 100m) to 50m, 200m and 500m. In Table 8, the regressions are run on subsamples corresponding to only traffic peak hours or only off-peak hours, or to only weekend days or only weekdays. Broadly speaking, these estimates confirm our main findings.

Then, Table 4, where Column (1) (resp. Column (2)) corresponds to the Column (4) of Table 3 after replacing NO_2 by PM_{10} (resp. NO_x) concentrations, shows that our working assumption that the sanitary crisis led to an increase in the relative share of freight vehicles within total flows in Paris, thereby leading to an increase in the marginal impact of traffic on pollution, is also confirmed when looking at other pollutants.

Eventually, Table 9 in Appendix estimates separately the impact of traffic on air pollution around each air pollution measurement station (i.e. each of the 6 air pollution stations that have instrumented roads comprised in their 100m buffers), for each of the three pollutants (NO_2 in Column (1), PM_{10} in Column (2) and NO_x in Column (3)). It once more corroborates our baseline findings.

4 Back-of-the-envelope calculations

In order to put our results into perspective, we now propose original estimates of the average external costs of local pollutants caused by road freight traffic in Paris.

4.1 Method

Figure 4 illustrates our working strategy. The left part of the figure contrasts the evolution of freight traffic flows in two cases, namely in the hypothetical case in which the flow of heavy vehicles would have been reduced in the same proportion as cars during the COVID-19 lockdown (which corresponds to the arrow $A \rightarrow B$ in the figure, with a freight flow decreasing from $F0$ to $F1U$) and the more realistic case in which the two reductions are allowed to differ (which corresponds to the arrow $A \rightarrow B'$, with a freight flow decreasing from $F0$ to $F1R$). Consistently with the

count data presented in Table 2, freight vehicles “disappeared” from Parisian roads to a lower extent than light vehicles over that period, hence leading to a “less than proportional” decrease in freight flows ($F1R - F1U$).

The right part of the figure depicts the associated changes in NO_2 health costs. As argued before, the air quality would have been less deteriorated if freight vehicles’ flow had experienced a more pronounced decline during the lockdown, similar to the one of cars. The “excessive air pollution burden” caused by the non-proportional change here corresponds to $H1R - H1U$. As a first approximation, the average excess external cost of air pollution caused by freight vehicles as compared to cars hence depends directly on the ratio between $H1R - H1U$ and $F1R - F1U$.

To put this approach into practice, we first estimate the level of pollutant i ’s concentration in Paris due to road traffic during period T according to the econometric model j as:

$$K_i^{T,j} = \beta_i^{T,j} \times F^T \quad (6)$$

where $T = 1$ during the Spring 2020 and $T = 0$ during the same period one year before. The counterfactual, in which heavy and light vehicles’ flows are assumed to have declined uniformly ($j = U$) during the sanitary crisis, is associated with the estimates from the “naive” models detailed in the previous section. Conversely, the real-world setting ($j = R$) with a non-proportional reduction of the two flows is associated with the “interacted” models of the previous section.

By coupling the estimated changes in the pollutant concentrations (i.e. $\Delta K_i^U \equiv K_i^{1,U} - K_i^{0,U}$ or $\Delta K_i^R \equiv K_i^{1,R} - K_i^{0,R}$) with a dose-response methodology, it is possible to estimate the total number of lives saved in the French capital city thanks to the improvement in air quality, according to each econometric setting j :

$$\Delta Y^j = Y_0(e^{\sigma_i \Delta K_i^j} - 1) \quad (7)$$

where Y_0 is the initial level of morbidity and σ_i is a coefficient corresponding to the slope of the function that links the morbidity data with the concentration of the pollutant i ¹⁴. The evolution of morbidity estimated in each econometric setting j must then be multiplied by the duration of the COVID lockdown (D) to obtain the total number of lives spared due to the corresponding changes, and then by the value of statistical life (VSL) to get the corresponding socioeconomic benefits. To make the parallel with Figure 4, the health costs’ burden caused by an excessive air pollution due to the “less than proportional” decrease in heavy vehicles’ flows during the sanitary

¹⁴In general, σ_i can be inferred from tables of Relative Risks (RR), which correspond to the ratio between the level of morbidity in the group after the change in the pollutant’s concentration and the level of morbidity in the group before, for an increase in the pollutant’s concentration of $10 \mu\text{g}/\text{m}^3$:

$$\sigma_i = \frac{\ln RR_i}{10} \quad (8)$$

restrictions is equal to:

$$H1R - H1U = D \times VSL \times (\Delta Y^R - \Delta Y^U) \quad (9)$$

The average excess external cost of local pollutants caused by freight vehicles in Paris (as compared to cars) can be finally approximated by dividing this amount by the difference in freight vehicles' flows between the two settings $F1R - F1U$.

4.2 Application

Different input parameters are required to implement this approach empirically.

First, we focus here on the health costs due to emissions and concentrations in the Parisian atmosphere of both NO_2 and PM_{10} . For these two pollutants, we use the Relative Risks coefficients σ_i from the (official) technical report Santé Publique France [32]¹⁵. Second, the initial level of morbidity in Paris city, Y_0 , can be approximated by 13,485 deaths per year.¹⁶ Third, the Spring 2020 lockdown lasted 55 days, so that D_i equals to 0.15 ($= 55/365$). Lastly, following official guidelines [5], the VSL in France amounted to 3.3 M euros in 2020.

Table 5 shows that applying the same decrease in total traffic flow (-67% over Spring 2019 and 2020 according to our count data) to the different econometric models leads to very different changes in pollutant concentrations during the lockdown. As such, the improvements in air quality found with coefficients estimated from the naive model, ΔK_i^U , are much more pronounced than the ones estimated with the ("true") interacted model ΔK_i^R , especially for NO_2 .

Then considering the dose-response functions, these gaps translate into very different health savings. Whereas the naive model's results imply that about 11 deaths would have been avoided thanks to the decline in road traffic and corresponding improvements in air quality, recognizing that the flow of freight vehicles has been less reduced (i.e. using the interacted model) implies that the indirect sanitary benefits of the lockdown are much more moderate, with only 4 lives spared over the period.

Multiplying the difference of 7 saved lives¹⁷ by the official VSL in France, we conclude that the change in traffic composition during the sanitary crisis (due to the rise of home-deliveries in particular and the use of more polluting vehicles in general) was responsible for excess health costs $H1R - H1U$ of around 23.20 M euros.

¹⁵For NO_2 the coefficient σ_i is equal to 1.0075. For PM_{10} , it is equal to 1.003. See Santé Publique France [32].

¹⁶This number does not include accidental deaths, which amounted to 745 in 2017 for Paris city, see <https://opendata-cepidc.inserm.fr/>.

¹⁷It is worth noting that 95% of this excess health burden comes from a less than expected decrease in NO_2 concentration.

In order to compute, on this basis, the excess external cost of local pollutants attributable to freight vehicles in Paris, as compared to cars, we need figures regarding the less than proportional decline in trucks' and light-duty vehicles' flows. Even if the various databases detailed in Section (2) make us confident about the validity of our working assumption, as additionally confirmed by econometric findings in Section (3), we do not know the precise amount of the decrease in freight traffic. For this reason, Table (6) reports results for several hypothesized changes in freight flows (ranging from -60% to -40%). These estimates rely on the hypothesis of 24 hours of traffic per day, a Parisian road network of 1,770 km and a period of analysis of 55 days.

Considering as "central scenario" a decrease in freight vehicles' flow of -50% during the COVID-19 lockdown (instead of -67% if it had declined in the same proportion as passengers' cars), we end up with an average excess external cost of local pollutants for freight traffic equal to 0.19 euro/vkm. Logically, a larger decrease would imply a larger estimate (0.44 euro/vkm for -60%) and *vice-versa* (0.12 euro/vkm for -40%).

Importantly, the order of magnitude presented in Table (6) is fairly consistent with alternative external costs parameters. Thus, one could deduce from French official guidelines¹⁸ an average external cost of 0.30 euro/vkm for the local pollution caused by freight vehicles in very dense urban areas such as Paris¹⁹. By contrast, private cars are assumed to inflict to Parisian inhabitants external costs of local pollution amounting to 0.09 euro/vkm. Put differently, the gap of 0.21 euro/vkm is really close to our own estimates and we believe our approach to be of potential interest for Costs-Benefits Analyses of policies that would alleviate freight traffic in cities (such as the promotion of cargo-bikes or crowd-shipping deliveries). As opposed to the "Impact Pathway Approach" often used to estimate the marginal external costs of air pollution [17, 37], our parameters do not rely on air chemistry simulations and are directly based on pollutant concentration data. As a consequence, it may be the case that our estimates are less polluted by modelling' errors and noise, hence closer to real damages caused by trucks and light-vehicles traffic.

5 Conclusion

All in all, the methodology presented in this paper seeks to exploit an exogenous shock on the composition of road traffic to estimate the level of air pollution that can be attributed to freight traffic. The chosen exogenous shock corresponds to the first COVID-19 lockdown in France, during which we argue that the share of freight vehicles with respect to (less polluting) passenger cars increased, thereby increasing the marginal impact of road traffic on air pollution. After estimating this increase econometrically, we use a back-of-the-envelope computation to assess to what extent this increase in the marginal impact of road traffic on air pollution mitigated the drop in air pollution due to the COVID-19 lockdown and translate the result into a

¹⁸See <https://www.ecologie.gouv.fr/sites/default/files/V.2.pdf>.

¹⁹This average figure is found by considering that light-duty vehicles (whose external cost of local pollution in very dense urban areas is 0.16 euro/vkm) account for 15% of road traffic in Paris and that trucks (1.00 euro/vkm) represent 3% of flows.

number of additional deaths and the associated economic costs, using a basic dose-response function.

Several limitations inherent to our approach could be addressed in future works. First, detailed data on the activities of logistics operators during the lockdown would improve the accuracy of the estimate of the share of freight vehicles at that time. Real data counts including both the number of cars and of freight vehicles on a hourly basis would even be better. Then, we can remark that the methodology does not take into account the fact that the COVID-19 lockdown may have had a long-term impact on the composition of road traffic, even after its end (e.g. the share of bikes may have increased permanently and the share of cars decreased permanently...), and it focuses exclusively on the impact of air pollution on the inhabitants of Paris who did not move away (e.g. to a vacation home) during the lockdown. The translation of air pollution into health outcomes could also be perfected, using epidemiological data instead of dose-response functions. And, eventually, it would be interesting to replicate the study in other cities of France and Europe, to see whether freight traffic's impacts on air pollution and health differ across cities and countries.

Statements and declarations

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

6 Appendix

See Tables 7, 8 and 9 for various robustness checks associated with the baseline Table 3.

References

- [1] Atelier Parisien d'Urbanisme. 2020. Commerce et e-commerce à l'heure du déconfinement .
- [2] Browne, M., J. Allen, and S. Anderson. 2005. Low emission zones: the likely effects on the freight transport sector. *International Journal of Logistics Research and Applications* 8(4): 269–281 .
- [3] Brusselaers, N., C. Macharis, and K. Mommens. 2023. The health impact of freight transport-related air pollution on vulnerable population groups. *Environmental Pollution* 329: 121555 .

- [4] Calthrop, E. and D. Maddison. 1996. The dose—response function approach to modelling the health effects of air pollution. *Energy Policy* 24(7): 599–607 .
- [5] CGSP. 2013. L'évaluation socioéconomique des investissements publics .
- [6] Chen, Z., L. Cui, X. Cui, X. Li, K. Yu, K. Yue, Z. Dai, J. Zhou, G. Jia, and J. Zhang. 2019. The association between high ambient air pollution exposure and respiratory health of young children: A cross sectional study in jinan, china. *Science of The Total Environment* 656: 740–749 .
- [7] Cicala, S., S.P. Holland, E.T. Mansur, N.Z. Muller, and A.J. Yates. 2021. Expected health effects of reduced air pollution from covid-19 social distancing. *Atmosphere* 12(8): 951 .
- [8] Collivignarelli, M.C., C. De Rose, A. Abbà, M. Baldi, G. Bertanza, R. Pedrazzani, S. Sorlini, and M.C. Miino. 2021. Analysis of lockdown for covid-19 impact on no2 in london, milan and paris: What lesson can be learnt? *Process Safety and Environmental Protection* 146: 952–960 .
- [9] Coulombel, N., L. Dablanc, M. Gardrat, and M. Koning. 2018. The environmental social cost of urban road freight: Evidence from the paris region. *Transportation Research Part D: Transport and Environment* 63: 514–532 .
- [10] Dablanc, L., A. Heitz, H. Buldeo Rai, and D. Diziain. 2022. Response to covid-19 lockdowns from urban freight stakeholders: An analysis from three surveys in 2020 in france, and policy implications. *Transport Policy* 122: 85–94 .
- [11] Dablanc, L. and A. Montenen. 2015. Impacts of environmental access restrictions on freight delivery activities: Example of low emissions zones in europe. *Transportation Research Record* 2478(1): 12–18 .
- [12] Degraeuwe, B., E. Pisoni, E. Peduzzi, A. de Meij, F. Monforti, K. Bódis, a. mascherpa, C. Astorga-Llorens, P. Thunis, and e. vignati. 2019, 11. *Urban NO2 Atlas*.
- [13] European Environment Agency. 2019. Air quality in europe - 2019 report. No 10/2019 .
- [14] Finlayson-Pitts, B.J. and J.N. Pitts Jr. 1986. Atmospheric chemistry. fundamentals and experimental techniques .
- [15] Florida, R., A. Rodríguez-Pose, and M. Storper. 2021. Cities in a post-covid world. *Urban Studies*: 00420980211018072 .
- [16] Forum International des Transports. 2019. *ITF Transport Outlook 2019*.
- [17] Friedrich, R. 2001. *Environmental external costs of transport*.

- [18] Galeazzi, A., M. Cinelli, G. Bonaccorsi, F. Pierri, A.L. Schmidt, A. Scala, F. Pam-molli, and W. Quattrociochi. 2021. Human mobility in response to covid-19 in france, italy and uk. *Scientific reports* 11(1): 1–10 .
- [19] Godzinski, A. and M.S. Castillo. 2021. Disentangling the effects of air pollutants with many instruments. *Journal of Environmental Economics and Manage-ment* 109: 102489 .
- [20] Guevara, M., H. Petetin, O. Jorba, and H.D.e.a. van der Gon. 2022. European primary emissions of criteria pollutants and greenhouse gases in 2020 modulated by the covid-19 pandemic disruptions. *Earth System Science Data* 14(6): 2521–2552 .
- [21] Guthrie, C., S. Fosso-Wamba, and J.B. Arnaud. 2021. Online consumer resilience during a pandemic: An exploratory study of e-commerce behavior before, during and after a covid-19 lockdown. *Journal of Retailing and Consumer Services* 61: 102570 .
- [22] Holguín-Veras, J., T. Encarnación, C.A. González-Calderón, J. Winebrake, C. Wang, S. Kyle, N. Herazo-Padilla, L. Kalahasthi, W. Adarme, V. Cantillo, et al. 2018. Direct impacts of off-hour deliveries on urban freight emissions. *Transportation Research Part D: Transport and Environment* 61: 84–103 .
- [23] INSEE. 2020a. 14 millions de touristes en moins au premier semestre 2020 en ile-de-france. *INSEE Analyses* (126): 4 .
- [24] INSEE. 2020b. Population présente sur le territoire avant et après le début du confinement. *Communiqué de presse du 8 avril*: 6 .
- [25] Joumard, R., M. André, R. Vidon, and P. Tassel. 2003. Characterizing real unit emissions for light duty goods vehicles. *Atmospheric Environment* 37(37): 5217–5225 .
- [26] Khazini, L., M.J. Kalajahi, and N. Blond. 2021. An analysis of emission reduc-tion strategy for light and heavy-duty vehicles pollutions in high spatial–temporal resolution and emission. *Environmental Science and Pollution Research*: 1–17 .
- [27] Kim, R.Y. 2020. The impact of covid-19 on consumers: Preparing for digital sales. *IEEE Engineering Management Review* 48(3): 212–218 .
- [28] Melo, S. and P. Baptista. 2017. Evaluating the impacts of using cargo cycles on urban logistics: integrating traffic, environmental and operational boundaries. *European Transport Research Review* 9: 30 .
- [29] Pourrahmani, E. and M. Jaller. 2021. Crowdshipping in last mile deliver-ies: Operational challenges and research opportunities. *Socio-Economic Planning Sciences* 78: 101063 .

- [30] Pullano, G., E. Valdano, N. Scarpa, S. Rubrichi, and V. Colizza. 2020. Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the covid-19 epidemic in france under lockdown: a population-based study. *The Lancet Digital Health* 2(12): e638–e649 .
- [31] Samakovlis, E., A. Huhtala, T. Bellander, and M. Svartengren. 2005. Valuing health effects of air pollution—focus on concentration-response functions. *Journal of Urban Economics* 58(2): 230–249 .
- [32] Santé Publique France. 2021. Impact de la pollution de l’air ambiant sur la mortalité en france métropolitaine : réduction en lien avec le confinement du printemps 2020 et nouvelles données sur le poids total pour la période 2016-2019 .
- [33] Savadogo, I. and A. Beziat. 2021. Evaluating the potential environmental impacts of a large scale shift to off-hour deliveries. *Transportation Research Part D: Transport and Environment* 90: 102649 .
- [34] Schatke, M., F. Meier, B. Schroder, and S. Weber. 2022. Impact of the 2020 covid-19 lockdown on no2 and pm10 concentrations in berlin, germany. *Atmospheric Environment* 290: 119372 .
- [35] Schneider, R., P. Masselot, and A.e.a. Vicedo-Cabrera. 2022. Differential impact of government lockdown policies on reducing air pollution levels and related mortality in europe. *Scientific Reports* 12(726) .
- [36] Shorshani, M.F., M. André, C. Bonhomme, and C. Seigneur. 2015. Modelling chain for the effect of road traffic on air and water quality: Techniques, current status and future prospects. *Environmental Modelling & Software* 64: 102–123 .
- [37] Van Essen, H., L. Van Wijngaarden, A. Schroten, D. Sutter, C. Bieler, S. Maffii, M. Brambilla, D. Fiorello, F. Fermi, R. Parolin, et al. 2019. *Handbook on the external costs of transport, version 2019*. Number 18.4 K83. 131.
- [38] Venter, Z.S., K. Aunan, S. Chowdhury, and J. Lelieveld. 2021. Air pollution declines during covid-19 lockdowns mitigate the global health burden. *Environmental research* 192: 110403 .
- [39] Warren, M.S. and S.W. Skillman. 2020. Mobility changes in response to covid-19. *arXiv preprint arXiv:2003.14228* .
- [40] Yang, Z., Y. Liu, L. Wu, S. Martinet, Y. Zhang, M. Andre, and H. Mao. 2020. Real-world gaseous emission characteristics of euro 6b light-duty gasoline-and diesel-fueled vehicles. *Transportation Research Part D: Transport and Environment* 78: 102215 .

Table 1 Descriptive statistics (between January 2018 and September 2020)

	(1)		(2)		(3)	
	No lockdown mean	sd	Covid lockdown mean	sd	All mean	sd
Air pollution						
NO2 concentration	53.05	30.51	28.63	21.98	51.84	30.61
NOx concentration	136.14	124.08	50.13	57.01	131.89	123.06
PM10 concentration	27.64	15.79	22.93	11.26	27.40	15.62
Weather						
Temperature	13.82	7.46	13.61	5.36	13.81	7.39
Air pressure	1016.28	9.49	1018.22	6.88	1016.35	9.40
Wind speed	3.12	1.42	3.04	1.63	3.12	1.43
North Wind	0.26	0.44	0.30	0.46	0.26	0.44
East Wind	0.17	0.38	0.39	0.49	0.18	0.38
South Wind	0.29	0.45	0.18	0.39	0.28	0.45
West Wind	0.28	0.45	0.12	0.33	0.27	0.45
Rainfall height	0.07	0.52	0.08	0.80	0.07	0.53
Relative humidity	69.67	17.94	57.65	19.15	69.18	18.15
Other explanatory factors						
Elec. consumpt. Paris metro.	17355.30	4726.71	13804.73	2295.88	17211.90	4705.41
Boundary layer height	629.57	505.72	601.63	566.94	628.43	508.38
Traffic flow						
Depending on the buffer size						
Traffic flow in 50m-buffer	1598.23	1931.97	567.99	948.50	1560.33	1914.65
Traffic flow in 100m-buffer	1688.47	1899.53	568.30	912.64	1646.32	1883.93
Traffic flow in 200m-buffer	1359.50	1780.51	475.38	847.68	1327.07	1762.92
Traffic flow in 500m-buffer	973.55	806.67	278.40	343.73	946.19	805.00
In a 100-m buffer, depending on the air pollution station						
Blv. Périph. Auteuil	2304.20	1177.79	768.10	586.09	2256.29	1194.12
Place Victor Basch	505.05	212.52	202.76	141.27	490.65	219.33
Blv. Périph. Est	5021.84	1802.86	1959.56	1291.44	4902.02	1881.72
Av. Champs-Élysées	842.23	452.58	161.20	135.10	820.60	461.69
Blv. Haussmann	661.64	344.06	130.62	103.32	638.69	354.09
Place de l'Opéra	541.69	289.26	95.16	78.64	526.49	295.95
In a 100-m buffer, weekends vs. work days						
Weekend	1661.60	1934.14	386.30	598.14	1611.68	1915.63
Work day	1699.16	1885.48	645.05	1006.76	1660.14	1870.97
Occupancy rate						
Occ. rate in 100m-buffer	10.92	10.94	2.66	3.39	10.62	10.87
Observations	171449		7258		178707	

The variable "North wind" (resp. "East Wind", "South Wind", "West Wind") is equal to 1 if the wind direction measured on a 360 degrees scale is in the interval $[0;45]$ or $[315;360]$ (resp. $[45;135]$, $[135;225]$, $[225;315]$), and 0 otherwise. Relative humidity measures the ratio between the observed pressure of water vapour in the air and the maximum pressure of water vapour the air can contain at the observed temperature and pressure. The traffic flow is measured as the number of vehicles crossing the instrumented road segment per hour. The occupancy rate corresponds to the percentage of time the traffic measurement station has been occupied by vehicles during each hour.

Table 2 Average total vehicle flow and share of trucks per day in Paris region (excluding Paris) according to the SIREDO database

Month:		Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.
2019	Total flow	47351	50303	50718	51463	50004	52060	51762	46690	52456
	Share trucks	10,1%	10,0%	9,8%	10,1%	10,1%	9,3%	10,2%	9,1%	9,7%
2020	Total flow	49020	49753	31060	15860	33279	49131	51309	46370	51245
	Share trucks	9,0%	8,9%	11,1%	14,9%	9,9%	9,1%	8,7%	7,8%	9,0%
Δ Total flow		3,5%	-1,1%	-38,8%	-69,2%	-33,4%	-5,6%	-0,9%	-0,7%	-2,3%
Δ Truck flow		-7,3%	-11,8%	-30,8%	-54,3%	-34,9%	-6,9%	-15,4%	-15,0%	-8,7%

Table 3 Impact of the COVID outbreak on the effect of road traffic on NO₂ air pollution

Model	Specifications:	FE station (1)	+ Other FEs (2)	+ Controls (3)	+Clust. st. err. (4)
Naive model	Flow	0.0058*** (0.00008)	0.0085*** (0.00016)	0.0053*** (0.00013)	0.0053** (0.00192)
	Covid	-18.5004*** (0.42653)	-10.3418*** (3.08785)	-18.3736*** (2.56995)	-18.3736*** (3.42164)
R-squared		0.0789	0.2703	0.5276	0.5276
Interacted model	Flow when No Covid	0.0059*** (0.00008)	0.0083*** (0.00016)	0.0051*** (0.00013)	0.0051** (0.00196)
	Flow when Covid	0.0134*** (0.00045)	0.0142*** (0.00069)	0.0124*** (0.00057)	0.0124** (0.00334)
	Covid	-22.9848*** (0.49896)	-9.5467*** (3.08820)	-11.4160*** (3.67031)	-11.4160* (4.93286)
R-squared		0.0816	0.2708	0.5284	0.5284
Observations		102,238	102,238	99,475	99,475
Number of stations		6	6	6	6

The dependent variable is the concentration of NO₂ in the air. In Column (4), the standard errors are clustered at the level of air pollution measurement stations. This clustering is important because the weather data is the same for all observations. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 Impact of the COVID outbreak on the effect of road traffic on PM₁₀ and NO_x air pollution

Model	Pollutant:	PM₁₀ (1)	NO_x (2)
Naive model	Flow	0.0023* (0.00096)	0.0284** (0.00772)
	Covid	-7.5127*** (1.35654)	-56.9699** (15.48900)
	R-squared	0.3711	0.4779
Interacted model	Flow when No Covid	0.0023* (0.00097)	0.0280** (0.00777)
	Flow when Covid	0.0032** (0.00103)	0.0433** (0.01286)
	Covid	4.1285** (1.15325)	-50.1166*** (11.69944)
	R-squared	0.3715	0.4781
	Observations	95,023	99,501
	Number of stations	6	6

The dependent variable are the concentration of PM₁₀ and of NO_x in the air. *** p<0.01, ** p<0.05, * p<0.1.

Table 5 Differences in pollutants concentrations and health benefits, across models

	Spring 2019	Spring 2020	Change
Average total flow per km of roads (veh/h)	1,733	568	-67.2%
NO₂ from roads - naive model ($\mu\text{g}/\text{m}^3$)	9.2	3.0	-6.2
PM₁₀ from roads - naive model ($\mu\text{g}/\text{m}^3$)	4.0	1.3	-2.7
Number of lives saved - naive model		11.0	
Health benefits - naive model (M euros)		36.17	
NO₂ from roads - interacted model ($\mu\text{g}/\text{m}^3$)	8.8	7.0	-1.8
PM₁₀ from roads - interacted model ($\mu\text{g}/\text{m}^3$)	3.8	1.8	-2.0
Number of lives saved - interacted model		3.9	
Health benefits - interacted model (M euros)		12.97	
Excess health costs (M euros)		23.20	

Table 6 Average excess external cost of local pollutants caused by freight vehicles in Paris

Traffic decrease	Uniform	Differentiated		
	-67.2%	-60.0%	-50.0%	-40.0%
Total freight flow (M vkm)	238.87	291.53	364.41	437.29
F1U - F1R (M vkm)	n.a.	52.65	125.53	198.42
Excess external cost of local pollutants (euro/vkm)	n.a.	0.441	0.185	0.117

Fig. 4 Strategy to estimate local pollutants' costs caused by a less than proportional decrease in freight vehicles' flow

$F0-F1R$ = Observed decrease in freight vehicles' flow
 $F0-F1U$ = Decrease in freight vehicles' flow that would have been observed if freight vehicles' and cars' flows decreased uniformly

$H0-H1R$ = Observed decrease in N2 health costs
 $H0-H1U$ = Decrease in N2 health costs that would have been observed if freight vehicles' and cars' flows decreased uniformly

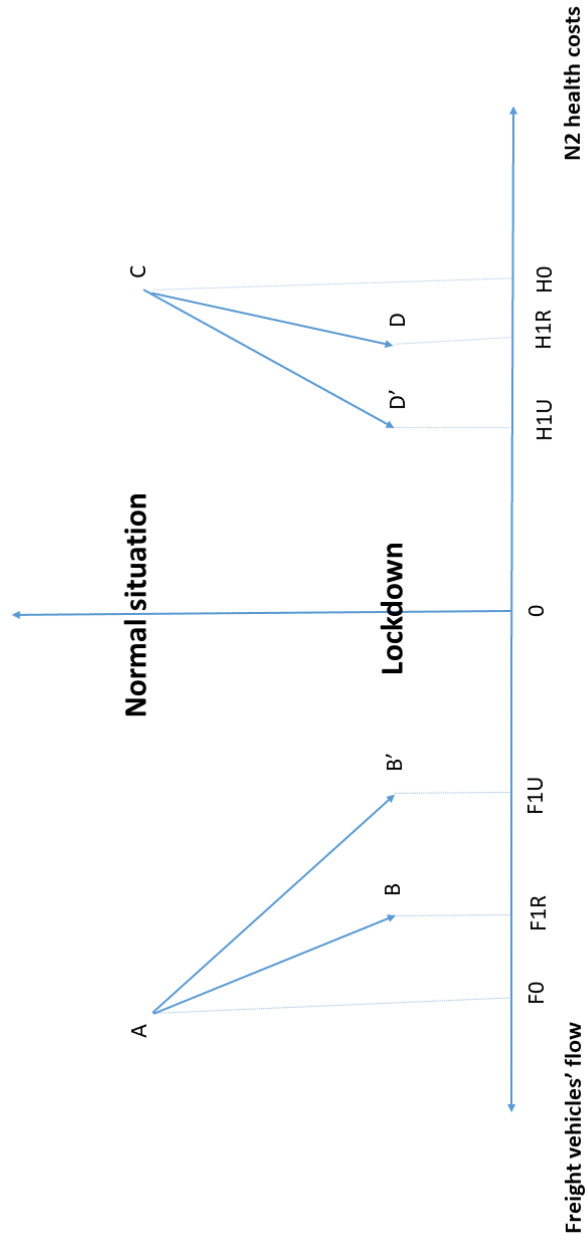


Table 7 Robustness 1: Varying the buffer size around each air pollution measurement station

Buffer size:	50m	200m	500m
	(1)	(2)	(3)
Flow when No Covid	0.0052 (0.00289)	0.0056* (0.00231)	0.0057* (0.00250)
Flow when Covid	0.0116** (0.00327)	0.0126** (0.00360)	0.0208*** (0.00481)
Covid	-8.1462 (4.51313)	-4.2659 (5.17596)	-10.7167** (3.73711)
R-squared	0.5219	0.5240	0.5183
Observations	83,439	126,322	136,760
Number of stations	5	7	8

The dependent variable is the concentration of NO₂ in the air. In Column (1) (resp. (2), (3)), the baseline specification corresponding to Column (4) of Table 3 is applied for other sizes of buffers around air pollution measurement stations: 50 m (resp. 200 m, 500 m). *** p<0.01, ** p<0.05, * p<0.1.

Table 8 Robustness 2: Evaluation on sub-samples

Subsample:	Peak hour	Off-peak hour	Weekend	Weekday
	(1)	(2)	(3)	(4)
Flow when No Covid	0.0040** (0.00154)	0.0054* (0.00216)	0.0055** (0.00163)	0.0039* (0.00181)
Flow when Covid	0.0085*** (0.00181)	0.0148** (0.00417)	0.0133*** (0.00295)	0.0103** (0.00297)
Covid	-26.1164** (7.32116)	-11.6960** (4.11050)	-23.1092 (12.70231)	5.4537 (6.22963)
R-squared	0.4968	0.5254	0.5313	0.5463
Observations	23,966	75,509	29,182	70,293
Number of stations	6	6	6	6

The dependent variable is the concentration of NO₂ in the air. In Column (1) (resp. Column(2)), the baseline specification corresponding to Column (4) of Table 3 is estimated only for peak hours (resp. off-peak hours). In Column (3) (resp. Column (4)), the baseline specification is estimated only for weekends (resp. week days). *** p<0.01, ** p<0.05, * p<0.1.

Table 9 Robustness 3: Evaluation on each air pollution measurement station separately

Station	Pollutant:	NO₂ (1)	PM₁₀ (2)	NO_x (3)
Station 1	Flow when No Covid	0.0057*** (0.00036)	0.0031*** (0.00015)	0.0356*** (0.00176)
	Flow when Covid	0.0218*** (0.00055)	0.0044*** (0.00052)	0.0771*** (0.00274)
Station 2	Flow when No Covid	0.0310*** (0.00259)	0.0098*** (0.00180)	0.1553*** (0.01799)
	Flow when Covid	0.0504*** (0.00361)	0.0102** (0.00346)	0.1316*** (0.01030)
Station 3	Flow when No Covid	0.0026*** (0.00021)	0.0009*** (0.00011)	0.0187*** (0.00028)
	Flow when Covid	0.0088*** (0.00039)	0.0017*** (0.00023)	0.0290*** (0.00164)
Station 4	Flow when No Covid	0.0111*** (0.00044)	0.0058*** (0.00049)	0.0295*** (0.00442)
	Flow when Covid	0.0395*** (0.00354)	0.0013 (0.00265)	0.0868*** (0.01117)
Station 5	Flow when No Covid	0.0197*** (0.00097)	0.0097*** (0.00069)	0.0573*** (0.00711)
	Flow when Covid	0.0565*** (0.00495)	0.0173*** (0.00377)	0.1238*** (0.01728)
Station 6	Flow when No Covid	0.0379*** (0.00156)	0.0156*** (0.00096)	0.1655*** (0.01046)
	Flow when Covid	0.0811*** (0.00595)	0.0225*** (0.00481)	0.2393*** (0.02688)
	Covid	-2.0390 (5.59602)	8.2654*** (1.12361)	-3.0869 (10.81441)
R-squared		0.5385	0.3775	0.4873
Observations		99,475	95,023	99,501
Number of stations		6	6	6

The dependent variable is the concentration of NO₂ in the air in Column (1), of PM₁₀ in Column (2) and of NO_x in Column (3). *** p<0.01, ** p<0.05, * p<0.1.