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The Impact of COVID-19 on Mobility and Congestion

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Abstract

The COVID-19 pandemic has been posing unprecedented challenges for the transport sector. Urban travel has declined all over the world, but not uniformly for all modes; public transportation has taken the hardest blow. As a result, there has been a widespread reduction in public transport ridership: according to recent estimates, passenger numbers in cities around the world have been at the peak of the pandemic down 70 to 90 percent. This paper examines the short-run economic impact of the pandemic, as well as the generic and sector-specific restrictions that were adopted to control the outbreak of the pandemic, based on a rich database tracking on a daily basis public transport usage and traffic congestion. The analysis confirms the significant impact of sector-specific restrictions and broader lockdown measures in terms of reduction in urban mobility and congestion. The analysis finds that the spread of the disease itself had an economic impact distinct from that of the lockdown measures. There are also different results on the magnitude of impact of cross-sectoral vis-à-vis sectoral restrictions on urban mobility and congestion. Whereas the magnitude of the spread of the disease is higher than the overall stringency of the lockdown, the impact of restrictions of public transit has been much greater than the spread of the disease and acts indirectly as a disincentive to move on the road. More effective safety measures, such as those related to the use of facial covering, are associated with higher use of public transport and an increase in the likelihood of low congestion. There is no evidence of intermodal competition between public transportation and road transport. In particular, the expansion of car registration has not led to a decrease in public transport mobility, but it is significantly associated with an increase in traffic congestion, particularly in mega-cities.

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The Impact of COVID-19 on Mobility and Congestion*

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1. Introduction

The COVID-19 pandemic significantly affected lifestyle and mobility worldwide, ranging from a dramatic decrease in travel to an unprecedented increase in teleworking. These impacts resulted from governmental measures, with some affecting whole sectors in the economy, and some affecting crucial infrastructure sectors, such as transport. After the outbreak of COVID-19, the local governments of many cities have suspended the operations of buses and subways to prevent people from being infected with COVID-19, reducing the gathering of crowds, and required new safety standards, including requirements to wear masks. These measures implied a major reduction in service capacity compared to the pre-COVID-19 era, by affecting ridership due to a dramatic decrease in travel demand levels as well as imposing regulations that have consequences for service capacity. Such restrictions have significantly affected people's mobility behavior, with individual choices to refrain from traveling in order to reduce exposure and risk of contamination.

One of the sectors that has experienced a major impact is transportation, which is the focus of this paper. Urban travel has declined all over the world, but not uniformly for all modes; public transportation has taken the hardest blow, as shown by survey-based data (Molloy *et al.*, 2020; Astroza *et al.*, 2020, Tirachini and Cats, 2020). As a result, there has been a widespread reduction in public transport ridership: according to recent estimates, passenger numbers in cities around the world have been at the peak of the pandemic down 70% to 90% (Google, 2020). Much of the changes in travel demand has been attributed to individuals' adjustments in their daily travel activities such as replacing out-of-home activities with in-home activities. The impact of COVID-19 on public transport varies depending on the stage of the coronavirus spread. The loss of public transport demand can mostly be attributed to reduced travel demand resulting from a combination of public health restrictions, working from home, online schooling, shift to online shopping, transit service cuts, and loss of employment and fear of infection (HoneyRos´es *et al.*, 2020; De Vos, 2020).

The sharp reduction in public transportation demand due to the new physical distance behaviors and the fear of COVID-19 contagion challenges the future sustainability of mobility in cities. This is because in some cases the reduction in services has been accompanied by a reduced service supply and exacerbated by the perception of public transportation as riskier than private or personal means of transport because of the closer contact to other people that is possible, sometimes unavoidable, in public transportation vehicles and stations. Since the beginning of the pandemic, most public transport operators have quickly stepped up and taken concrete action to make transit systems COVID-safe for staff and passengers. But despite the best efforts of professionals across the sector, the COVID-19 crisis has dealt a massive blow to public transport. The economic and social effects of the COVID-19 outbreak in public transportation extend beyond service performance and health risks to sustainable mobility. However, little is known regarding individuals' immediate response in terms of adjusting their travel activities.

While these new trends in trip making behavior point towards a sustained reduction in public transport demand, they do not necessarily mean a reduction in transit modal share. New evidence seems to suggest that there has been a significant reduction in the modal share of transit in response to COVID-19 (Apple 2021; Orro *et al.*, 2020). This shift can be attributed, at least in part, to negative passenger perceptions of the potential health risks of riding transit (Przybylowski *et al.*, 2021). If these negative perceptions are not properly addressed during the transition stage, the reduction in the modal share of transit may be sustained for an extended period in the aftermath of the pandemic (Przybylowski *et al.*, 2021; Tirachini and Cats, 2020). However, there is no analytical evidence of whether intermodal competition has taken place.

Aversion to crowded public transport is likely to push more journeys onto private road-based transport, with related issues for road congestion. Traffic congestion is a perpetual problem for the sustainability of transportation development. Traffic congestion causes delays, inconvenience, and economic losses to drivers, as well as air pollution. Identification and quantification of traffic congestion are crucial for decision-makers to initiate mitigation strategies to improve the overall transportation system's sustainability. Road traffic is in fact considered as one of the main sources of air pollution in urban environments (Chowdhury *et al.*, 2021, Hamra *et al.*, 2015). In particular, among other pollutants, internal combustion engines emit nitrogen oxides like NO and NOx (mainly from diesel engines), which generate NO2 (Taquechel *et al.*, 2020) and particulate matter (Manisalidis *et al.*, 2020) such as PM10, which also originates through mechanical processes. Both primary and secondary pollutants are transported far from roads, thus worsening the air quality of whole urban areas. In addition, transport externalities soundly affect not only the environment, but also the society and economy of cities. For all these reasons, the United Nations included the creation of sustainable cities and communities as one of the 17 Sustainable Development Goals in agenda 2030, in which sustainable transport is one of the themes of several targets and goals.

Generally, studies have found that reductions in air pollution during the pandemic were most prominent for NO2, which is notably influenced by car traffic. While many other environmental indicators of air pollution (e.g., PM2.5, O3, CO) have been tied to adverse health outcomes (see Manisalidis *et al.*, 2020 for a review), a growing amount of evidence has specifically found adverse health effects from NO2 pollution. Rossi *et al.* (2020) indicated that vehicle flows significantly affect NO, NO2, and NOx concentrations, although no evidence of a relationship between traffic and PM10 was highlighted. According to this perspective, measures to limit traffic flows seem to be effective in improving air quality only in terms of reducing nitrogen oxide. Aletta *et al.* (2020) presented the results of a simulation approach using Floating Car Data (FCD) from vehicles equipped with an On-Board Unit GPS system. During the lockdown period, the traffic in Rome (Italy) was reduced by 64.6%, which had a positive impact on noise emissions reduction. On a broader scale, Chen et al. (2020) revealed that reductions in NO2 and CO were common but heterogeneous across the United States, after adjusting for temporal trends. Another US-based study by Berman & Ebisu (2020) found similar results at the county level; using two-sample aggregated comparisons, they found that urban counties saw especially large reductions in NO2 after March 13, 2020, compared to historical data. At the global level, Venter et al. (2020) connected mobility data with environmental indicators to argue that a strong link exists between global vehicle transportation declines and the reduction in ambient NO2 exposure, though they did not assess how differences in lockdown policy measures differentially affected NO2.

Liu *et al.* (2021) correct for temporal trends and accounted for lockdown timing in the Californian context, finding that sharp decreases in air pollutants occurred shortly after the lockdown policies were implemented. This illustrates the important influence of lockdown timing. Another study focusing on Seattle, WA, Cui (2020) find through sophisticated time series analyses that local traffic decreased considerably, while air quality improved during lockdown. He emphasizes the importance of adjusting these analyses to take into account meteorological conditions. Zhang *et al.* (2021) report that, compared with the base period from 2018 to 2019, the COVID-19 lockdown measures significantly reduced air pollutants in China. Winchester *et al.* (2021) find that when cities' most stringent social distancing policies in the United States were implemented, a significant reduction in average daily congestion and decrease in average daily mobility and average daily NO2 compared to unrestricted days.

In this context, real-time information can play a most valuable role for policy makers in developing countries, particularly to address the questions highlighted in what follows. How has the massive blow in public transportation been affected by the evolution of the pandemic, sector-specific restrictions and the stringency of lockdowns? What were the relative impacts of the disease versus the sectoral restrictions and health policy remedy of lockdown? Has the use of private vehicles increased? What is the evidence that a silver lining story in terms of reduction in congestion can be drawn after the relaxation of lockdown measures?

The focus of these studies has been only on a selected number of countries, mostly the United States and developed countries with the exception of few emerging countries. Using a global sample of 186 cities in 39 countries, this paper assesses how mobility and congestion were affected by the pandemic and lockdown measures, including public transport restrictions.

This paper proceeds as follows. Section 2 describes the data that we will subsequently use to provide a real-time estimation of mobility and congestion. Section 3 provides estimates of the impact of the pandemic and lockdown evolution on mobility and congestion. Section 4 concludes with a discussion on policy implications.

2. Empirical Approach

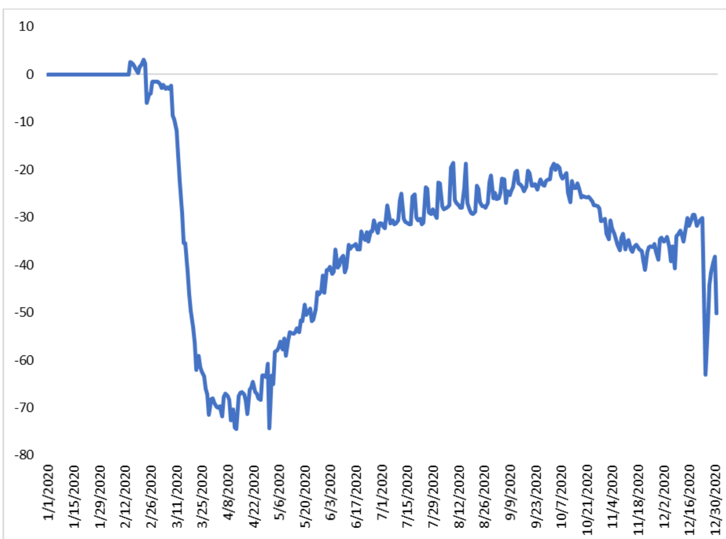
The purpose of this paper is to explore the short-run impacts of the COVID-19 pandemic and its associated policy responses. In this section, we present the data that will be used to capture each of these elements.

2.1 Variable definitions

In our analysis, we capture the changes in mobility using indicators reflecting evolution of public transit and traffic congestion during the pandemic. Data is available for 186 cities in 39 countries including both developed and developing countries belonging to EAP, ECA, LAC, MNA, SAR and SSA.[1]

The trend over time of the average time spent in public transit compared to the selected baseline in 2020 for the overall sample is reported in Figure 1 below. Location data derived from smartphones has become a popular way to illustrate mobility patterns by urban planners and transportation specialists.[2] The Google COVID-19 Community Mobility Reports measure how visits and length of stay at different places change compared to a baseline. The baseline is the median value, for the corresponding day of the week, during the 5-week period from January 3 to February 6, 2020. Hence, a lower value of the index reflects the decreased mobility following the lockdown.

Figure 1: Average value of time spent in public transit for the sample of cities (1st Jan to 31th Dec 2020)



Source: Google Community Mobility Reports

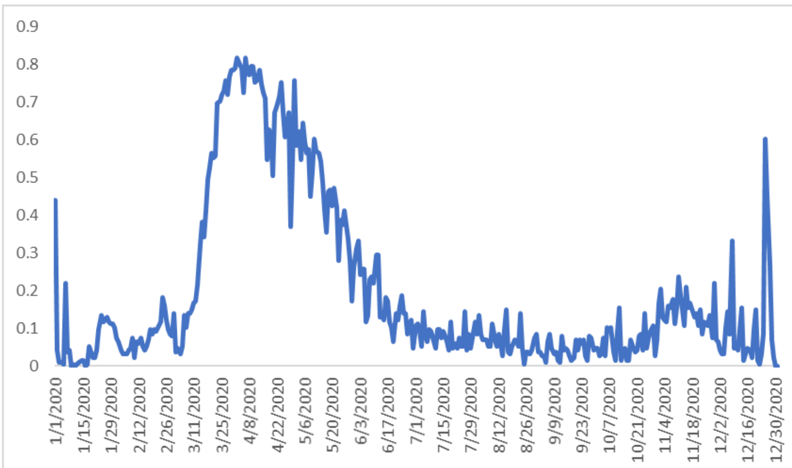
[1] The countries included in the sample are Argentina, Brazil, Bulgaria, Chile, China, Colombia, Czech Republic, the Arab Republic of Egypt, Estonia, France, Germany, Hungary, India, Indonesia, Italy, Japan, Kuwait, Latvia, Lithuania, Malaysia, Mexico, Norway, Peru, the Philippines, Poland, Romania, the Russian Federation, Saudi Arabia, Singapore, South Africa, Spain, the Slovak Republic, Slovenia, Sweden, Thailand, Türkiye, Ukraine, the United Arab Emirates and the United Kingdom.

[2] See, for instance, Calabrese *et al.* (2013) and Hawelka *et al.* (2014) for an example of cellphone data used to track individual mobility patterns at the urban and global levels, respectively.

The dramatic picture emerging from Figure 1 include declines up to 80% and more importantly and differently from other infrastructure sectors that have been bouncing back to pre-pandemic levels by the end of 2020, public transport still suffers from a 50% decline at the end of 2020.

Whereas the decrease in ridership of public transport per se does not necessarily imply a change in intermodal competition towards private cars, the implications in terms of congestion remain unclear. That is why we also investigate trends in congestion, using high frequency data from Tom Tom. Figure 2 reports the percentage of cities with low congestion for the sample of cities. The picture portrayed is different from Figure 1. Whereas indeed during the peak of the pandemic 80 percent of the cities were characterized by low congestion, the percentage drops almost to an insignificant percentage as lockdowns were relaxed and some of the peaks for the second wave of the pandemic were much lower and only of a much shorter duration.

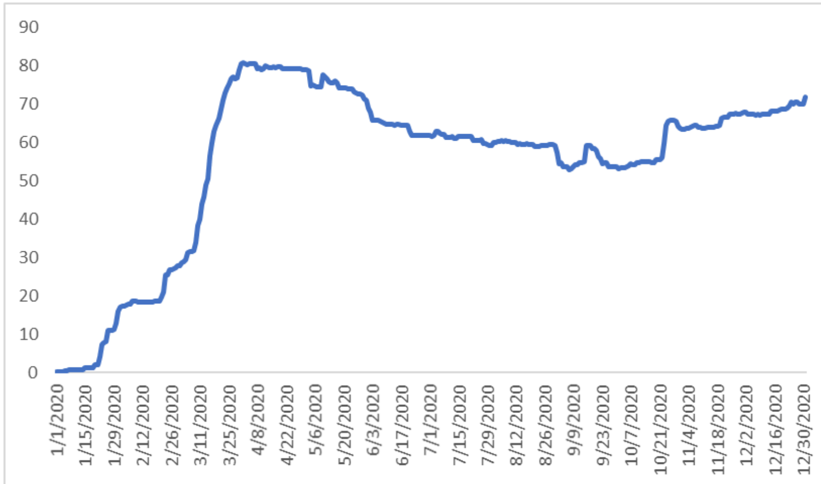
Figure 2: Percentage of cities with low congestion for the sample of cities (1st Jan to 31th Dec 2020)



Source: Elaboration from Tom Tom

The stringency of the national lockdown is measured using both cross sectoral and sectoral indicators. The first index represents the overall stringency of the lockdown, and it consists of the average value of the government response stringency index during the period when a full lockdown was in place, from the Oxford Government Response Tracker. The evolution of this index over time is depicted in Figure 3, ranging from 0 (less stringent) to 100 (most stringent) and is based on the policy decisions taken by governments across several areas: workplace restrictions, mobility restrictions, school closures, and restrictions on gatherings and public events (Hale *et al.*, 2020).

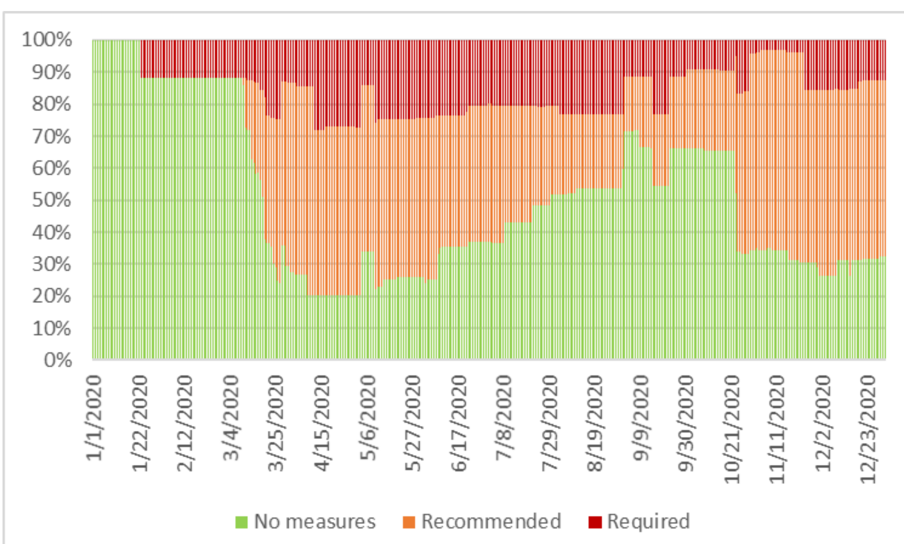
Figure 3: Average value of the stringency index (0-100) for the sample of cities



Source: Hale *et al.* (2020)

The sectoral index captures two important interventions that have been implemented in the transport sector; namely, the closure of public transit and the requirement to use facial covering. The first indicator ranges from 0 indicating no measures, to 1 where the authorities recommend closing (or significantly reduce volume/route/means of transport available) and 2 requires closing (or prohibiting most citizens from using it) of public transit. From Figure 4 it is evident how some restrictions are still maintained even after the significant relaxation of policies during the summer. The majority of the cities implemented mostly restrictions, whereas some of them decided to stop public transit for extensive periods during the pandemic.

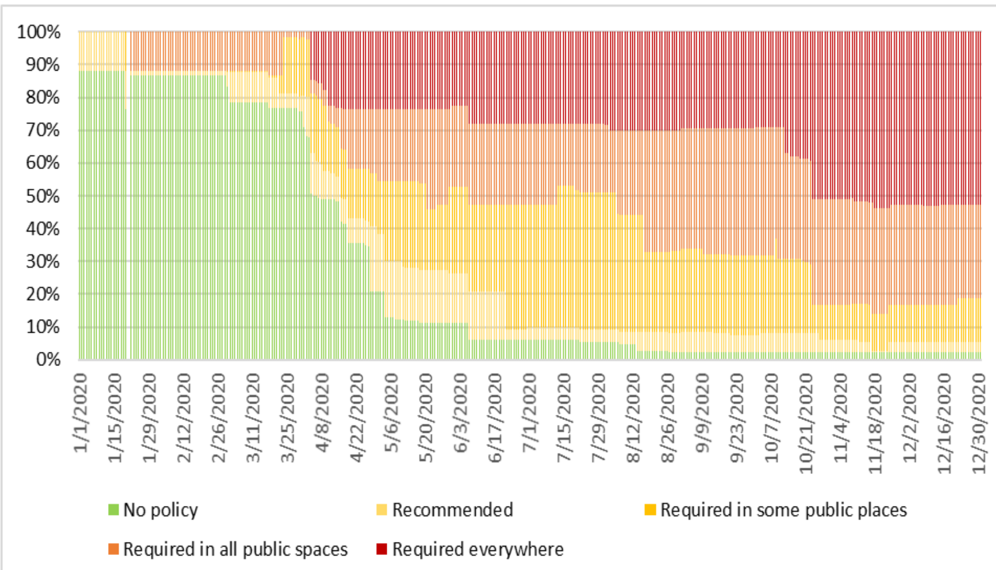
Figure 4: Distribution of cities implementing closure of public transit



Source: Elaboration from Hale *et al.* (2020)

The second indicator ranges from 0 indicating no policy in place to 1 when facial covering is recommended to when it is required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible to 3 when required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible and finally to 4 when required outside the home at all times regardless of location or presence of other people. Differently from the previous policy, in this case the requirement of facial covering has been growing over time and only an insignificant number of cities reverted back to a policy with no policies or policy only recommending facial covering. Requirements of wearing masks in public space, including public transport, reached almost 70 percent towards the end of April. The most stringent requirement reached respectively about half of the cities from the end of October.

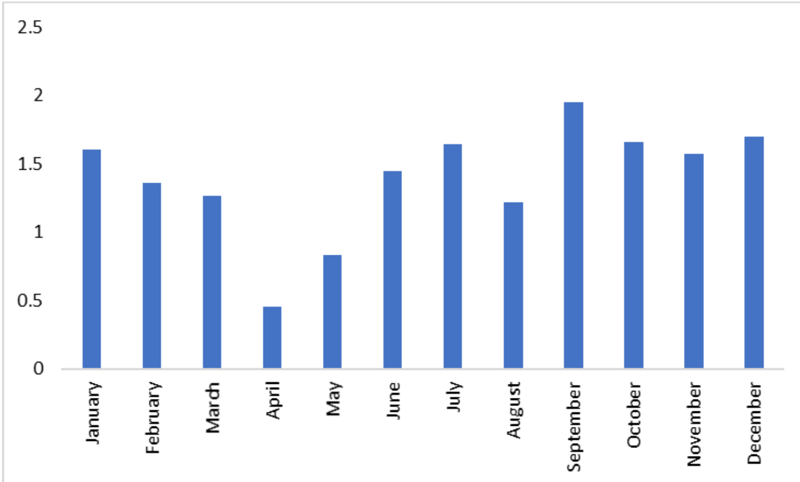
Figure 5: Distribution of cities requiring facial covering



Source: Hale *et al.* (2020)

Figure 6 provides some insights of the extent of modal competition during and after the pandemic, as indicated by the new car registration per capita. This indicator displays a significant drop during the month of April to then reach a peak in the month of September and continuing at a level above the pre-pandemic levels also for the remaining months of the year. This is a trend completely different than the one recorded for public transit, which were still suffering a significant decrease in the ridership, confirming a tendency to rely more on private transport.

Figure 6: New car registration for the sample of countries



Source: Elaboration from country level statistics

3. Results

In this section, we estimate a baseline model that relates the changes in mobility and congestion to the evolution of the pandemic and the lockdowns, and a range of controls. Our model accounts for differences in weather conditions, as well as the changes in mobility during the national holidays.

3.1 Econometric model and testable hypotheses

The basic specification of the model used is as follows:

(1M) $$M_{ij,,t} = \beta L_{j,t} + \omega P_{J,t} + +\vartheta U_{i,t} + \theta W_{i,t} + \Phi T_{i,t} + \epsilon_{i,t}$$

(1C) $$C_{i,j,t} = \beta L_{j,t} + \omega P_{J,t} + +\vartheta U_{i,t} + \theta W_{i,t} + \Phi T_{i,t} + \epsilon_{i,t}$$

where:

- $M_{c,t}$ is the mobility average change in time spent respectively in public transit compared to the selected baseline in city *i* of country j at time *t*.
- $C_{c,t}$ is equal to 1 if it identifies for each city a day in 2020 with the congestion level that is at least 50% lower than the congestion level on the corresponding day in the previous year (0 otherwise).
- $L_{i,t}$ is the indicator capturing the severity of lockdown, capturing both generic and sector specific indices, which are introduced separately in the regressions.

- $P_{i,t}$ is the indicator capturing the evolution of the pandemic through the daily number of infected cases and deaths per million due to COVID-19.
- $U_{i,t}$ are the monthly per capita registration of new cars in each country.
- $W_{i,t}$ is equal to one if date *t* is a working date (that is, excluding national holidays or nonworking days such as weekends).
- $T_{i,t}$ represents the variables capturing for each city the minimum and average temperature as well as the level of precipitation.
- $\epsilon_{i,t}$ is an i.i.d. innovation term.
- $\beta, \omega, \theta, \vartheta, \ \pi, and\ \gamma$ are the estimated parameters.

This model can be used to test the following hypotheses.

Hypothesis 1: *Countries where the lockdown measures were effectively enforced were characterized by a greater decline in public transport mobility and urban congestion, with a differential impact of sectoral and cross sectoral measures.*

This first hypothesis tests whether the reduction in mobility of public transport reflects the severity of the lockdown measures. In terms of equation (1), this translates into a coefficient value β<0. Since the stringency of the national lockdowns can be measured both using sectoral and cross sectoral indicators, as noted above, the econometric model can also be used to explore which of these has the most influence on the change in mobility and traffic congestion. Sector specific restrictions such as closures of public transport are expected to have a much higher impact on public transport mobility. More effective safety measures such as requirements to use face masks, on the other hand, are expected to be effective in terms of encouraging use of public transport.

Hypothesis 2: *Cities where loss of lives was experienced also display a greater decline in mobility and lower congestion.*

The second hypothesis is that evolution of the pandemic, when countries start registering actual cases of death for COVID-19, also has a distinct economic impact over and above the lockdown measures themselves. In terms of equation (1), this would imply a coefficient value $\omega < 0$.

Table 1 *Explanatory Variables Influencing Mobility and Low Congestion*

Variables	Definition	Expected Sign	
		Public transit	Low congestion
PANDEMIC EVOLUTION			
Covid cases	= number of (new) infected cases reported daily (per million)	-	+
Covid deaths	= number of (new) deaths from Covid-19 reported daily	-	+
LOCKDOWN EVOLUTION			
Stringency index	= average value of the government response stringency index based on the policy decisions taken, with the index ranging from 0 (less stringent) to 1 (most stringent).	-	+
Public transit restrictions	= 0 if no measures restricting the use of public transit = 1 if the authorities recommend closing (or significantly reduced volume/route/means of transport available) = 2 if the authorities required closing (or prohibited most citizens from using public transit)	-	+
Facial covering requirement	= 0 if no policy requiring facial covering has been implemented = 1 if facial covering has been recommended = 2 if facial covering has been required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible = 3 if facial covering has been required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible = 4 if facial covering has been required outside the home at all times regardless of location or presence of other people	+	-
Lockdown (April dummy)	= 1 after the month of April	-	+
TRENDS IN MOTORIZATION			
Car registration	= new per capita new registrations of cars	-	+
DAILY CONTROLS			
Working days	= 1 if working day = 0 otherwise (weekends or national holidays)	+	-
Min temperature	= minimum daily temperature	+	-
Avg temperature	= average daily temperature	+/-	-
Precipitation	= average daily temperature	+	-
CITY CONTROLS			
City density	= population per area (km2)	-	-

Hypothesis 3: *The expansion of car registration is expected to lead to a decrease in public transport mobility and an increase in traffic congestion, particularly in mega-cities.*

This third hypothesis examines whether cities that have started experiencing an increase in the use of private cars as soon as restrictions were relaxed have increased intermodal competition away from public transport and have negatively affected congestion.

In addition, the following specification is also estimated.

(2M) $$M_{ij,,t} = \beta L_{j,t} + \omega P_{J,t} + +\vartheta U_{i,t} + \theta W_{i,t} + \Phi T_{i,t} + \pi D_t + \epsilon_{i,t}$$

(2C) $$C_{i,j,t} = \beta L_{j,t} + \omega P_{J,t} + +\vartheta U_{i,t} + \theta W_{i,t} + \Phi T_{i,t} + \pi D_t + \epsilon_{i,t}$$

where the additional variables are:

- D_t is a dummy for the month where all countries in the sample reached the peak of the pandemic.

This specification allows the testing of a fourth hypothesis.

Hypothesis 4: *The pandemic and the associated lockdown measures are associated with a structural break in economic activity across all countries that goes beyond individual countries' specific lockdown measures.*

This fourth hypothesis goes more in depth to determine whether the pandemic and associated lockdown measures caused a structural break in economic activity after a certain threshold for all cities in the sample. To test such a hypothesis, a dummy capturing the peak of the impact is introduced and interacted with the right-hand side variables. This then provides an automatic test of whether the parameters differ before and after this structural break. In equation (2), this would signify a coefficient value of $\pi > 0$.

The full set of explanatory variables is presented in Table 1.

3.2 Empirical results

Table 2 provides the results of the fixed effect regressions, estimating for the basic specification (1), which can be used to test the stated hypotheses. Hypotheses 1 and 2 are validated as the coefficients ω, which can be interpreted as estimates of the effect of the spread of the disease, and the coefficient β, which estimates whether the effect of the lockdown measures are both negative and significant at the 1 percent confidence level. It is also worth noting that in the case of overall lockdown measures β is in absolute terms lower than ω, implying a distinct and higher impact associated to the spread of the disease across all specifications confirming the strong effect of the perception of risks felt by users of public transit.

Table 2

Regression Results of Public Transport Mobility with overall restriction (country fe)

	(1)	(2)	(3)
PANDEMIC & LOCKDOWN EVOLUTION			
Covid deaths (per Million)	-1.035*** (0.023)	-0.945*** (0.022)	-0.945*** (0.022)
Stringency Index	-0.691*** (0.004)	-0.661*** (0.004)	-0.6621*** (0.004)
CONTROLS			
Working days		10.772*** (0.259)	10.772*** (0.259)
Min temperature		0.008 (0.019)	0.008 (0.017)
Avg temperature		-0.065*** (0.017)	0.208*** (0.016)
Precipitation		-1.635*** (0.071)	-1.635*** (0.071)
City density			-0.150 (0.012)
COUNTRY FE			
Country FE	Yes	Yes	Yes
Monthly dummy	Yes	Yes	Yes
Constant	-3.534 (7.417)	-13.999 (7.482)	-26.528*** (7.509)
N	59,777	59,777	59,777
N cities	164	164	164
Wald $\chi 2$	151703.72***	163759.75***	163762.71***
Within R^2	0.7176	0.7329	0.7331
Between R^2	0.6690	0.6636	0.6671
Overall R^2	0.7085	0.7197	0.7204

Note: *, **, *** indicate respectively level of significance of 10, 5 and 1 percent

Table 3
Regression Results of Public Transport Mobility with sectoral restriction (country fe)

	(2.a)		(2.b)
PANDEMIC & LOCKDOWN EVOLUTION			
Covid death (per Million)	-1.480*** (0.025)	-1.304*** (0.025)	-1.260*** (0.026)
Public transport closure	-12.669*** (0.155)	-11.974*** (0.136)	-11.996*** (0.136)
Public transport facial covering	1.170*** (0.080)	1.239*** (0.059)	1.219*** (0.077)
CONTROLS			
Working days		12.408*** (0.287)	12.439*** (0.287)
Min temp		0.092*** (0.019)	0.093*** (0.019)
Avg temp		0.229** (0.018)	0.232*** (0.018)
Precipitation		-1.378*** (0.079)	-1.363*** (0.071)
City density			-0.016 (0.012)
TRENDS IN MODAL COMPETITION			
Car registration			0.544*** (0.012)
COUNTRY FE			
Country FE	Yes	Yes	Yes
Monthly dummy	Yes	Yes	Yes
Constant	-4.010 (7.454)	-21.899 (7.513)	-21.515*** (7.348)
N	59,777	59,777	59,777
N cities	186	186	186
Wald $\chi 2$	110836.80***	122569.48***	122635.90***
Within R^2	0.6498	0.6724	0.6725
Between R^2	0.6677	0.6573	0.6610
Overall R^2	0.6536	0.6697	0.6706

Note: *, **, *** indicate respectively level of significance of 10, 5 and 1 percent.

When we turn to introduce sector specific restrictions in Table 3, results are significantly different. The impact of restrictions on public transit has clearly the highest impact, much higher than the spread of the disease. More effective safety measures, such as those related to the use of facial covering are positively and significantly associated to the use of public transport, though their magnitude is small.

Hypothesis 3 is not validated across all specifications, implying that intermodal competition has not taken place. All the coefficients ϑ capturing the extent of intermodal competition coming from the increase in new car registration impacted positively rather than negatively public transit mobility. The use of car registration in Table 2 could introduce an endogeneity issue, as the specification does not control for public transport closure which could simultaneously affect public transport mobility and the purchase of cars as measured by car registrations. Accordingly, in Table 2 such a variable has been dropped, and has been added only in Table 3, where the introduction of public transport closure as an explanatory variable provides a way to address the endogeneity issue.

Among the other controls that are included in Tables 2 and 3, it is worth noting the expected positive sign of higher mobility during working days, and as the average temperature is decreasing or precipitation are lower. Robustness checks have also been undertaken, including additional control variables, such as city density. The idea is to control for the more intense supply of public transport as well as greater congestion ceteris paribus in denser cities.

Tables 4 and 5 replicate the same regressions using as independent variable capturing the change in congestion compared to the pre-pandemic period. As the variable is a dummy, equal to 1 if it identifies a day in 2020 with the congestion level that is at least 50% lower than the congestion level on the corresponding day in the previous year (0 otherwise), we perform probit regressions.

Hypotheses 1 and 2 are validated as the coefficients ω, which can be interpreted as estimates of the effect of the spread of the disease, and the coefficient β, which estimates whether the effect of the lockdown measures are both positive and significant at the 1 percent confidence level. It is also worth noting that β and ω display similar size, implying a distinct and higher impact associated to the spread of the disease across all specifications.

When we turn to introduce sector specific restrictions, as expected, the impact of restrictions on public transit has clearly the highest impact, much higher than the spread of the disease, and acts indirectly as a disincentive also to move on the road. More effective safety measures, such as those related to the use of facial covering are associated to higher use of public transport and an increase in the likelihood of low congestion.

Hypothesis 3 is also confirmed across all specifications. All the coefficients ϑ capturing the increase in new car registration negatively impacted the probability of low traffic congestion. Among the other controls that are included in Tables 1 and 2, it is worth noting the expected negative sign of lower congestion during working days, and as the negative impact on congestion as the average temperature is increasing or precipitation are intensified.

Robustness checks have also been undertaken, including additional control variables. It is also worth noting that city density is negatively associated to lower level of congestion, confirming that denser cities are more congested.

Table 4
Regression Results of Low Congestion with overall restriction (country fe)

	(1)	(2)	(3)
PANDEMIC & LOCKDOWN EVOLUTION			
Covid death (per Million)	0.053*** (0.003)	0.048*** (0.003)	0.090*** (0.0036)
Stringency Index	0.040*** (0.0004)	0.040*** (0.0005)	0.077*** (0.001)
CONTROLS			
Working days		-1.617*** (0.030)	-3.018*** (0.060)
Min temp		0.0007 (0.003)	0.002 (0.005)
Avg temp		-0.012*** (0.002)	-0.022*** (0.005)
Precip		-0.048*** (0.010)	-0.098*** (0.020)
City density			-0.003** (0.001)
COUNTRY FE			
Country FE	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes
Constant	-1.541*** (0.385)	-0.859** (0.427)	-3.472*** (0.877)
N	68076	68076	68076
N cities	186	186	186
Wald $\chi 2$	16227.92***	16319.18***	12899.60***
Log likelihood	-19162.402	-17563.367	-17343.466
LR (chi2)	1996.67***	2349.993***	2361.97***

Note: *, **, *** indicate respectively level of significance of 10, 5 and 1 percent.

Table 5
Regression Results of Low Congestion with sectoral restriction (country fe)

	(2.a)		(2.b)
PANDEMIC & LOCKDOWN EVOLUTION			
Covid death (per Million)	0.093*** (0.002)	0.080*** (0.003)	0.064*** (0.003)
Public transport closure	0.595*** (0.013)	0.629*** (0.015)	0.598*** (0.015)
Public transport facial covering	0.110*** (0.005)	0.107*** (0.009)	0.105*** (0.005)
CONTROLS			
Working days		-1.670*** (0.030)	-1.666** (0.030)
Min temp		-0.003 (0.002)	-0.002 (0.002)
Avg temp		-0.016*** (0.002)	-0.017*** (0.002)
Precipitation		-0.061*** (0.009)	-0.064*** (0.071)
City density			-0.001* (0.0007)
TRENDS IN MOTORIZATION			
Car registration			-0.226*** (0.015)
COUNTRY FE			
Country FE	Yes	Yes	Yes
Monthly dummy	Yes	Yes	Yes
Constant	-1.377 (0.295)	-0.862** (0.431)	-0.610 (0.431)
N	68076	68076	68076
N cities	186	186	186
Wald χ2	9068.76***	15739.15***	15825.39***
Log likelihood	-26248.126	-18961.454	-18839.815
LR (chi2)	1506.92***	2276.12***	2227.78***

Note: *, **, *** indicate respectively level of significance of 10, 5 and 1 percent.

To further test Hypothesis 3 we run separate regressions depending on the size of the cities. We classify mega-cities as those cities where population is above 8 million people, intermediate when it is between 800,000 and 8 million, and small when lower than 800,000 people. As we know, some organizational and management problems are common to most cities in the world, whatever their size. The most obvious similarity is that all are too dependent on road transport. The burden of rising levels of car ownership is growing throughout the countries. The commensurate increase in congestion on already crowded streets is threatening to incapacitate the bus systems that many middle- to low-income commuters still rely on.

Increase in motorization through new car registration has a differential impact depending on city size, as shown in Tables 6 and 7. The most significant effect of higher car registration level is displayed in mega-cities, who experience both an increase in public transit mobility and an increase in traffic congestion. The increase in traffic congestion in mega-cities not only aggravates commuters but also isolates them with time-consuming, unreliable, and expensive commutes.

Another interesting result concerns the differential impact of city density within different types of cities. The increase in city density is worsening the decline in public transport significantly only in mega-cities. The different coefficients across groups of cities based on density could capture behavioral aspects (e.g. fear to ride public transport may be greater due to an increased risk of contamination in denser urban contexts). Also, the likelihood of low congestion in mega-cities as well as in intermediate cities is lower as city density increases. Surprisingly, the evolution of the pandemic in terms of Covid deaths is showing a higher coefficient in smaller cities.

Table 6

Regression Results of Public Transport Mobility depending on size of cities (country fe)

	(Megacities)	(Small cities)	(Intermediate)
PANDEMIC & LOCKDOWN EVOLUTION			
Covid death (per Million)	-0.474*** (0.079)	-1.241*** (0.036)	-1.273*** (0.044)
Public transport closure	-13.166*** (0.369)	-16.012*** (0.246)	-8.216*** (0.179)
Public transport facial covering	-0.498*** (0.209)	1.206*** (0.132)	1.501*** (0.104)
CONTROLS			
Working days	11.365*** (0.666)	12.932*** (0.527)	12.042*** (0.189)
Min temperature	-0.459*** (0.055)	0.361*** (0.031)	0.012 (0.026)
Avg temperature	0.488*** (0.056)	0.013 (0.029)	0.322*** (0.025)
Precipitation	-1.132*** (0.158)	-1.462*** (0.141)	-1.245*** (0.109)
City density	-0.008*** (0.001)	-0.234 (0.424)	-0.330 (0.380)
TRENDS IN MODAL COMPETITION			
Car registration	1.521*** (0.399)	0.720*** (0.165)	0.410*** (0.189)
COUNTRY FE			
Country FE	Yes	Yes	Yes
Monthly dummy	Yes	Yes	Yes
Constant	-58.712*** (1.986)	-32.630** (7.918)	-72.216*** (5.410)
N	6588	27,992	25,197
N cities	18	77	69
Within R^2	0.7495	0.6704	0.6828
Between R^2	0.9327	0.4666	0.8778
Overall R^2	0.7844	0.6434	0.7315

Note: *, **, *** indicate respectively level of significance of 10, 5 and 1 percent

Table 7
Regression Results of Low Congestion depending on size of cities (country fe)

	(Megacities)	(Small cities)	(Intermediate)
PANDEMIC & LOCKDOWN EVOLUTION			
Covid death (per Million)	0.060*** (0.018)	0.150*** (0.009)	0.072*** (0.011)
Public transport closure	1.056*** (0.061)	1.041*** (0.056)	1.167*** (0.042)
Public transport facial covering	0.453*** (0.041)	-0.112*** (0.034)	0.205*** (0.025)
CONTROLS			
Working days	-2.671*** (0.123)	-3.683*** (0.111)	-2.983*** (0.082)
Min temp	0.019* (0.012)	-0.016** (0.007)	0.003 (0.007)
Avg temp	-0.051*** (0.011)	-0.010 (0.007)	-0.017*** (0.004)
Precip	-0.020 (0.031)	-0.224*** (0.039)	-0.041*** (0.006)
City density	-0.002** (0.001)	-0.010 (0.023)	-0.050 (0.055)
TRENDS IN MOTORIZATION			
Car registration	-1.155*** (0.139)	-0.168*** (0.037)	-0.518*** (0.005)
COUNTRY FE			
Country FE	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes
Constant	2.557*** (0.731)	2.064*** (0.427)	1.327*** (0.491)
N	9882	28182	30012
N cities	27	77	82
Wald $\chi 2$	2022.59***	5586.96***	5158.68***
Log likelihood	-3046.4335	-7540.9512	-7626.5672
LR (chi2)	228.28***	861.46***	674.77***

Note: *, **, *** indicate respectively level of significance of 10, 5 and 1 percent.

To start to test hypothesis 4 and identify signs of structural break in the data before and after a threshold date, we first report below the values of monthly dummies in Table 8 for the regressions of Tables 3 and 5. As we can see, the sign associated with the dummy variable capturing the month of April is the highest in absolute terms and is negative (positive) and statistically significant at the 1 percent confidence level in the case of mobility (low congestion).

Table 8 Values of monthly dummies

Feb-20	6.727***	0.151***
Mar-20	-2.272***	1.393***
Apr-20	-10.948***	1.74***
May-20	-5.896***	1.167***
Jun-20	-0.113***	0.448***
Jul-20	3.548	-0.005
Aug-20	6.390***	-0.221***
Sep-20	7.233***	-0.244***
Oct-20	10.453***	-0.327***
Nov-20	8.588***	-0.218***
Dec-20	11.762***	-0.712***

To go further in identifying the structural break, Table 9 interacts all variables with a dummy for the break and interacts it with the right-hand side variables. The first and third columns report the coefficients associated to the right-hand side variables as in specification (2M) and (2C) respectively, whereas the second and fourth reports the coefficients associated to the interacted variable of the "break" dummy and the respective right-hand side variables.

As all variables and their respective interacted terms are significant and in almost all cases at the 1 percent confidence level, this means that the parameters differ significantly before and after the break, validating Hypothesis 2 and confirming the presence of a structural break. In terms of interpreting the sign of the interacted terms, the impact of the pandemic evolution is somewhat smoothened after the structural break. On the other hand, the increase in the stringency of the lockdown measure is instead strengthened, confirming that mobility is significantly affected by restrictions. The fact that the stringency of restrictions had greater impacts after the peak of the pandemic may be due to an increased compliance due to peer effects or learning about the seriousness of the disease. New car registration after the structural break is also reducing the days with low congestion after the peak of the pandemic.

Whereas this result provides strong evidence of the presence of a structural break in the short term, we are not yet in a position to answer whether this structural break will persist in the long-run.

Table 9
Regression Results of structural break in public transport and congestion

	(Transit)var	(Transit)int	(Lowcong)var	(Lowcong)int
PANDEMIC & LOCKDOWN EVOLUTION				
Covid death (per Million)	-2.289*** (0.066)	2.148*** (0.069)	0.530*** (0.048)	-0.549*** (0.048)
Stringency Index	-0.711*** (0.005)	-0.047*** (0.007)	0.039*** (0.001)	0.006*** (0.001)
COUNTRY LEVEL CONTROLS				
Working days	10.848*** (0.604)	2.880*** (0.675)	2.404*** (0.059)	0.984*** (0.066)
Min temperature	0.429*** (0.034)	-0.290*** (0.036)	-0.022*** (0.006)	0.014** (0.006)
Average temperature	-0.225*** (0.033)	0.352*** (0.034)	0.021*** (0.005)	-0.025** (0.005)
Precipitation	-0.546*** (0.156)	-1.064*** (0.177)	-0.099*** (0.029)	0.047 (0.003)
City density	0.0003 (0.012)	-0.021*** (0.002)	-0.001 (0.001)	-0.0002 (0.0004)
TRENDS IN MOTORIZATION				
New car registration	-5.412*** (0.121)	-0.014 (0.104)	-0.381*** (0.021)	-0.375*** (0.020)
COUNTRY FE				
Country and monthly FE	Yes	Yes	Yes	Yes
Constant	-8.984 (7.069)		0.0176 (0.0178)	
N	59777		68076	
N cities	164		186	
Wald χ2	135765.34***		14048.20***	
Within R^2	0.6946		na	
Between R^2	0.6669		na	
Overall R^2	0.6895		na	

Note: *, **, *** indicate respectively level of significance of 10, 5 and 1 percent.

4. Conclusions

Empirical estimates of the size of the economic shocks triggered by the pandemic and lockdown evolution have been scarce since official economic indicators are only made available with a significant lag. In this paper, we provide an illustration by tracking the evolution of high-frequency variables, related to the trends in public transit data as well as traffic congestion.

The availability of such high-frequency variables allows us to investigate the economic impact of lockdowns, which have been the main public health policy implemented by governments around the world to contain the pandemic. It has been argued that these measures, which are useful in "flattening the curve" of health costs, may come at high economic costs, but also that a silver lining of reduction in congestion is only a temporary result, reverted by the increase in motorization,

The analysis in this paper also confirms the significant cost of such measures in terms of reduction in urban mobility in terms of public transport and traffic congestion. Interestingly, it shows that beyond the impact of the lockdowns, also the spread of the disease itself has an economic impact distinct from that of lockdown measures, as the incidence of death per population increases the drop in activity associated with the spread of the disease, and is statistically highly significant, both in terms of reduction in urban mobility by public transport and a reduction in traffic congestion.

We also find different results on the magnitude of impact of cross sectoral vis-à-vis sectoral restrictions on urban mobility and congestion. Whereas the magnitude of the spread of the disease is higher than the overall stringency of the lockdown, we turn to introduce sector specific restrictions and, as expected, results are significantly different. The impact of restrictions on public transit is much higher than the spread of the disease and acts indirectly as a disincentive also to move on the road. More effective safety measures, such as those related to the use of facial covering are associated with higher use of public transport and an increase in the likelihood of low congestion.

We find no evidence of intermodal competition between public transportation and road transport. In particular, the expansion of car registration has not led to a decrease in public transport mobility. Increasing car registration has been, however, significantly associated with an increase in traffic congestion, particularly in mega-cities.

Since the beginning of the pandemic, most public transport operators have quickly stepped up and taken concrete action to make transit systems COVID-safe for staff and passengers. But despite the best efforts of professionals across the sector, as testified by the positive impact of enhanced safety measures, the COVID-19 crisis has dealt a massive blow to public transport, which has not recovered to the pre-Covid levels. On the other hand, congestion has been ramping up, also fueled by the expansion in new car registration.

References

Aletta, Francesco Stefano Brinchi, Stefano Carrese, Andrea Gemma, Claudia Guattari, Livia Mannini & Sergio Maria Patella (2020) Analysing urban traffic volumes and mapping noise emissions in Rome (Italy) in the context of containment measures for the COVID-19 disease *Noise Mapping*, vol. 7, no. 1, pp. 114–122, 2020.

Andara, R., Ortego-Osa, J., Gómez-Caicedo, M. I., Ramírez-Pisco, R., Navas-Gracia, L. M., Vásquez, C. L., & Gaitán-Angulo, M. (2021). Behavior of Traffic Congestion and Public Transport in Eight Large Cities in Latin America during the COVID-19 Pandemic. *Applied Sciences*, 11(10), 4703

Bashir, M.F.; Bilal, B.J.; Komal, B.; Bashir, M.A.; Farooq, T.H.; Iqbal, N.; Bashir, M. (2020) Correlation between environmental pollution indicators and COVID-19 pandemic: A brief study in Californian context. *Environ. Res.*, 187, 109652.

Basso, Leonardo J., Felipe A. Sepúlveda and Hugo E. Silva (2020) Public transport policies after Covid-19 confinement (September 15, 2020). Available at SSRN: https://ssrn.com/abstract=3693098

Beck, M. J., & Hensher, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia–The early days of easing restrictions. *Transport Policy*, 99, 95–119.

Berman, J.D.; Ebisu, K. (2020). Changes in U.S. air pollution during the COVID-19 pandemic. *Sci. Total Environ*., 739, 139864.

Bucsky, P. (2020) "Modal share changes due to COVID-19: the case of Budapest," *Transportation Research* Interdisciplinary Perspectives, vol. 8, Article ID 100141.

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira, J. and C. Ratti (2013) "Understanding Individual Mobility Patterns from Urban Sensing Data: A Mobile Phone Trace Example" in *Transportation Research Part C: Emerging Technologies*, vol. 26: 301-313

Chang, Y. S., Lee, Y. J., & Choi, S. S. B. (2017). Is there more traffic congestion in larger cities? -Scaling analysis of the 101 largest U.S. urban centers-. *Transport Policy*, 59, 54–63.

Chen, L.-W.A.; Chien, L.-C.; Li, Y.; Lin, G. (2020). Nonuniform impacts of COVID-19 lockdown on air quality over the United States. *Sci. Total Environ.*, 745, 141105.

Chen, Zhongfei Xinyue Hao, Xiaoyu Zhang Fanglin Chen (2021). Have traffic restrictions improved air quality? A shock from COVID-19 *Journal of Cleaner Production* 279, 123622

Chow, A. H. F., Santacreu, A., Tsapakis, I., Tanasaranond, G., & Cheng, T. (2014). Empirical assessment of urban traffic congestion. *Journal of Advanced Transportation*, 48(8), 1000–1016. https://doi.org/10.1002/atr.1241

Chowdhury, S.; Haines, A.; Klingmueller, K.; Kumar, V.; Pozzer, A.; Venkataraman, C.; Witt, C.; Lelieveld, J. (2021) Global and national assessment of the incidence of asthma in children and adolescents from major sources of ambient NO2. *Environ. Res. Lett.*, 16, 035020.

Cui, Z. (2020) "Traffic performance score for measuring the impact of COVID-19 on urban mobility,", https://arxiv.org/abs/2007.00648.

Devasurendra, K.W. Saeid Saidi, S.C. Wirasinghe , Lina Kattan (2022) Integrating COVID-19 health risks into crowding costs for transit schedule planning, *Transportation Research Interdisciplinary Perspectives*, 13, 100522

Elfar, A., Talebpour, A., & Mahmassani, H. S. (2018). Machine Learning Approach to Short-Term Traffic Congestion Prediction in a Connected Environment. *Transportation Research Record*, 2672(45), 185–195.

Fatmi, M. R. (2020). COVID-19 impact on urban mobility. *Journal of Urban Management*, 9(3), 270–275.

Fang, H., Wang, L. and Y. Yang (2020). Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCOV) in China", *NBER Working Paper* 26906.

Gkiotsalitis, Konstantinos & Oded Cats (2021) Public transport planning adaption under the COVID-19 pandemic crisis: literature review of research needs and directions, *Transport Reviews*, 41:3, 374-392.

Hahn, E., Chatterjee, A., & Sue Younger, M. (2002). Macro-Level Analysis of Factors Related to Areawide Highway Traffic Congestion. *Transportation Research Record*, 1817(1), 11–16. https://doi.org/10.3141/1817-02

Hamra, G.B.; Laden, F.; Cohen, A.J.; Raaschou-Nielsen, O.; Brauer, M.; Loomis, D. Lung (2015). Cancer and Exposure to Nitrogen Dioxide and Traffic: A Systematic Review and Meta-Analysis. Environ. Health Perspect., 123, 1107–1112.

Koźlak, A., & Wach, D. (2018). Causes of traffic congestion in urban areas. Case of Poland. SHS Web of Conferences, 57, 01019.

Lai, Ka, Yan Chris Webster, Sarika Kumari & Chinmoy Sarkar (2020). The nature of cities and the Covid-19 pandemic *Curr Opin Environ Sustain*. Oct;46:27-31.

Li, J., Xu, P., & Li, W. (2021). Urban road congestion patterns under the COVID-19 pandemic: A case study in Shanghai. *International Journal of Transportation Science and Technology*, 10(2), 212–222.

Liu, Q.; Harris, J.T.; Chiu, L.S.; Sun, D.; Houser, P.R.; Yu, M.; Duffy, D.Q.; Little, M.M.; Yang, C. (2021) Spatiotemporal impacts of COVID-19 on air pollution in California, USA. *Science of The Total Environment*, 750, 141592.

Liu, Feng Meichang Wang & Meina Zheng (2021). Effects of COVID-19 lockdown on global air quality and health, *Science of The Total Environment*, Volume 755, Part 1, , 142533.

Magazzino, Cosimo, Marco Mele & Nicolas Schneider The relationship between air pollution and COVID-19-related deaths: An application to three French cities, *Applied Energy* Volume 279, 1 December 2020, 115835

Manisalidis, I.; Stavropoulou, E.; Stavropoulos, A.; Bezirtzoglou, E. (2020) Environmental and Health Impacts of Air Pollution: A Review. *Front. Public Health*, 8, 14.

Marchant, A. (2020) What Can Traffic Data Tell Us about the Impact of the Coronavirus?, TomTom, Amsterdam, Netherlands, https://www.tomtom.com/blog/moving-world/covid-19-traffic/.

Mele M, Magazzino C. (2021) Pollution, economic growth, and COVID-19 deaths in India: a machine learning evidence. *Environ Sci Pollution* Res. 28, 2669–2677.

Muhammad, S.; Long, X.; Salman, M. (2020) COVID-19 pandemic and environmental pollution: A blessing in disguise? *Sci. Total Environ.*, 728, 138820.

Ortego, J., Andara, R., Navas, L. M., Vásquez, C. L., & Ramírez-Pisco, R. (2021). Impact of the Covid-19 Pandemic on Traffic Congestion in Latin American Cities: An Updated Five-Month Study. In S. Nesmachnow & L. Hernández Callejo (Eds.), Smart Cities (pp. 216–229). Springer International Publishing. https://doi.org/10.1007/978-3-030-69136-3_15

Othman, Murnira & Mohd Talib Latif (2021). Air pollution impacts from COVID-19 pandemic control strategies in Malaysia *Journal of Cleaner Production* 291 125992

Rossi Riccardo, Riccardo Ceccato & Massimiliano Gastaldi (2020). Effect of Road Traffic on Air Pollution. Experimental Evidence from COVID-19 Lockdown *Sustainability*, 12, 8984

Milan Simunek, Zdenek Smutny , and Michal Dolezel (2021). The Impact of the COVID-19 Movement Restrictions on the Road Traffic in the Czech Republic during the State of Emergency *Journal of Advanced Transportation* Volume 2021, https://doi.org/10.1155/2021/6622028.

Taquechel, K.; Diwadkar, A.R.; Sayed, S.; Dudley, J.W.; Grundmeier, R.W.; Kenyon, C.C.; Henrickson, S.E.; Himes, B.E.; Hill, D.A. (2020) Pediatric Asthma Health Care Utilization, Viral Testing, and Air Pollution Changes During the COVID-19 Pandemic. *J. Allergy Clin. Immunol. Pr.*, 8, 3378–3387.

Tian, Xuelin, Chunjiang An, Zhikun Chen &, Zhiqiang Tian (2021). Assessing the impact of COVID-19 pandemic on urban transportation and air quality in Canada, *Science of The Total Environment*, Volume 765, 144270.

Tirachini, Alejandro & Oded Cats (2020). COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs *Journal of Public Transportation*, Vol. 22 No. 1, 1-21

Zangari, S.; Hill, D.T.; Charette, A.T.; Mirowsky, J.E. (2020). Air quality changes in New York City during the COVID-19 pandemic. *Sci. Total Environ.*, 742, 140496.

Zhang, Jian, Houjian Li, Muchen Lei & Lichen Zhang (2021). The impact of the COVID-19 outbreak on the air quality in China: Evidence from a quasi-natural experiment, *Journal of Cleaner Production* 296, 126475.

Xiang, J.; Austin, E.; Gould, T.; Larson, T.; Shirai, J.; Liu, Y.;Marshall, J.; Seto, E. (2020). Impacts of the COVID-19 responses on traffic-related air pollution in a Northwestern US city. *Sci. Total Environ.*, 747, 141325.

Winchester, Alyse K., Ryan A. Peterson, Ellison Carter & Mary D. Sammel (2021). Impact of COVID-19 Social Distancing Policies on Traffic Congestion, Mobility, and NO2 *Pollution Sustainability*, 13, 7275