Air pollution, mobility, remote work and the Great Lockdown

Miquel-Àngel Garcia-López[*†]
Universitat Autònoma de Barcelona and *Institut d'Economia de Barcelona*

Hugo Carpena Barranco[*‡]
Universitat Autònoma de Barcelona

January 2026
Do not cite without permission.

Abstract: This paper investigates the impact of mobility on pollution. To do so, we take advantage of the natural experiment provided by the COVID-19 pandemic to assess the extent to which pollution levels can be reduced when mobility restrictions are implemented and technology remains unchanged. Thanks to the use of high-frequency data for Spain's major cities, we also analyze the impacts during different sub-periods of the pandemic (first wave, new normality, and other waves) as well as across different hours of the day. Overall, the results of these analyses can be interpreted as an approximation of the potential effects of increasingly relevant phenomena in our lives, such as teleworking and e-commerce.

JEL classification: R41, Q53, L86
Key words: Pollution, mobility, teleworking, COVID-19

[*]Financial support from Ministerio de Ciencia e Innovación (PID2021-128227OB-I00, TED2021-132184B-I00), Generalitat de Catalunya (2021SGR00189), i Fundació La Caixa (Social Research Call 2021 LCF/PR/SR21/52560001).

[†]Departament d'Economia Aplicada, Universitat Autònoma de Barcelona, Edifici B, Facultat d'Economia i Empresa, 08193 Bellaterra (Cerdanyola del Vallès) (e-mail: miquelangel.garcia@uab.cat; Telèfon: +34 93 581 4584; website: https://miquelangelgarcialopez.wordpress.com).

[‡]Departament d'Economia Aplicada, Universitat Autònoma de Barcelona, Edifici B, Facultat d'Economia i Empresa, 08193 Bellaterra (Cerdanyola del Vallès) (e-mail: hugo.carpena@uab.cat).

1. Introduction

According to World Health Organization (2022), air pollution in cities causes the death of 4.2 million people every year. This exceeds the number of deaths caused by HIV, malaria, and influenza combined. European Environment Agency (2019) estimates that in 2016 alone, $PM_{2.5}$ emissions were responsible for 324,000 premature deaths in Europe and 24,100 in Spain. Overall, at least three percent of annual mortality in Spain is caused by air pollution—eight times higher than mortality from traffic accidents. In addition to causing premature deaths, air pollution also reduces the general quality of life by worsening asthma and allergies, increasing cases of bronchitis in children, and raising the incidence of viral infections.

Emissions of air pollutants are partly determined by mobility patterns in our cities. According to the European Commission, travel using gasoline and diesel-powered vehicles is responsible for up to 70% of emissions of pollutants such as nitrogen oxides (NO_x), particulate matter (PM), and sulfur dioxide (SO_2), among others (European Comission, 2021).

Urban mobility is shaped by how we live, work, and consume. Whether we live near or far from our workplace, work remotely, consume local or imported goods, and shop online or in person —all of these decisions influence how and how much we travel.

In response to growing concerns about the effects of pollution, public authorities have implemented policies aimed at reducing air pollutants. Most of these policies target vehicle fleets and/or impose mobility restrictions. At the supranational level, the European Union has regulated urban air quality standards through initiatives such as the Clean Air for Europe program and the European Green Deal. At the national and regional levels, various countries and regions have introduced environmental labels for vehicles and launched plans to renew combustion vehicle fleets and incentivize the transition to electric vehicles. At the local level, many cities are implementing low-emission zones and congestion charges, as well as urban planning policies that prioritize pedestrian spaces over private transport and promote public transit.

Recent academic literature has explored the interconnections between cities, mobility, and pollution, highlighting how urban form and mobility patterns shape air quality and, consequently, public health.

Regarding urban form, several studies have examined the impact of population density on pollutant concentrations. Carozzi and Roth (2023) find that increased urban density significantly raises $PM_{2.5}$ levels, with measurable implications for mortality and associated social costs. Complementarily, Borck and Schrauth (2021) show a positive correlation between density and concentrations of NO_2 and PM_{10}. However, Castells-Quintana, Dienesch, and Krause (2021) argue that within cities, densification can reduce per capita emissions, especially in polycentric urban contexts, thereby qualifying the overall effects of density.

In terms of mobility and traffic regulation policies, multiple studies have shown the effectiveness of measures such as congestion charges and low-emission zones in reducing vehicle volume, road congestion, and environmental pollution. For example, Wolff (2014) and Malina and Scheffler (2015) report substantial emission reductions in areas affected by these policies. Conversely, Bernardo, Fageda, and Flores-Fillol (2021) find that low-emission zones are effective in reducing pollution but not traffic congestion. In the case of Madrid, Tassinari (2024) finds that its low-emission zone effectively reduces traffic within the restricted area but displaces it to other parts of the city, where congestion increases.

This paper examines the impact of mobility on pollution by leveraging the natural experiment created by the COVID-19 pandemic. Specifically, we assess the extent to which pollution levels can be reduced when mobility is restricted, while technological conditions remain constant. Using high-frequency data from Spain's 52 major cities, we analyze the effects across different phases of the pandemic —including the first wave, the new normality, and subsequent waves— as well as variations across different times of day. These findings offer valuable insights into the potential environmental benefits of emerging trends such as teleworking and e-commerce.

The remainder of the paper is structured into five sections. Section 2 describes the data used and the empirical strategy adopted. Section 3 explains why the COVID-19 pandemic provides an ideal setting to analyze the relationship between mobility and air pollution. Section 4 presents the main findings of the study. Finally, Section 7 summarizes the key conclusions drawn from the analysis.

2. Empirical strategy

2.1 Data

Our database includes information on 52 major cities across Spain, disaggregated by the 24 hours of the day and working days of the week, for the period between February 14, 2020, and December 31, 2022. This period includes the COVID-19 pandemic, defined here as the time from the beginning of the first state of alarm in Spain on March 14, 2020, to the end of the third state of alarm on May 8, 2021.

Pollution

This study focuses on four air pollutants. First, primary nitrogen oxides (NO_x) are mainly produced by combustion processes associated with traffic —especially diesel-powered vehicles and transport in general— as well as high-temperature industrial facilities and power generation plants.

Second, we consider two types of suspended particulate matter or atmospheric aerosols: PM_{10} and $PM_{2.5}$. Their origin can be either primary or secondary. Primary sources refer to particles emitted directly into the atmosphere, either naturally (such as dust, soil particles, sea salt, spores, and pollen) or anthropogenically (from human activities), particularly from road traffic and vehicle circulation, industrial combustion processes, or residential and commercial heating systems. Secondary sources arise from chemical reactions in the atmosphere involving precursor gases (SO_2, NO_x, NH_3, etc.) and account for between 40% and 70% of all suspended particles.

Lastly, sulfur dioxide (SO_2) is produced during the combustion of sulfur-containing fossil fuels (such as oil and solid fuels), mainly in high-temperature industrial processes and energy generation. The primary emitter of SO_2 is the industrial sector.

The information on these pollutants comes from the Air Quality e-Reporting database (formerly AirBase), the European air quality database provided by the European Environment Agency. It consists of air quality measurement data and statistics for various atmospheric pollutants from 1969 to 2021. For the whole of Europe, data is provided at the station level for all 24 hours of the day and every day of the year.

Meteorology, demographics, and economic structure

Air pollutant emissions are strongly influenced by meteorological and climatic conditions. To control for their effects, our dataset includes variables calculated at the municipal and daily level, such as temperature, precipitation, humidity, and sunshine hours, based on measurements from stations provided by the Agencia Estatal de Meteorología (AEMET). We also include additional variables on dust episodes (e.g., Saharan dust intrusions) and biomass combustion, published by the Ministerio para la Transición Ecológica y el Reto Demográfico (MITECO) (MITECO).

Given that demographic factors and economic structure also affect pollution levels, we use data from the Instituto Nacional de Estadística (INE) to compute variables related to population and the share of employment in the manufacturing and construction sectors.

2.2 *Main equations*

The main goal of this study is to analyze how mobility affects air pollution. To do so, we use the COVID-19 pandemic period as a natural and exogenous experiment, allowing us to study how the mobility restrictions implemented during that time impacted pollution levels.

We begin by estimating the overall effects of the pandemic using the following empirical model:

$$\ln(\text{Pollutant}_{it}) = \alpha + \beta \times \text{Pandemic}_t + \gamma \times \text{Controls}_{it} + \eta_{i\times t} + \theta_t + \nu_{it} \tag{1}$$

where Contaminantit refers to the air pollutants NOx, PM10, PM2.5, and SO_2 in municipality i at time t. Since we have hourly data, t refers to a specific hour and day.

Pandemic$_t$ is a binary variable indicating the COVID-19 period, taking the value 1 on days between the start of the first state of alarm in Spain on 14/03/2020 and the end of the third state of alarm on 08/05/2021. This variable takes the value 0 during the short pre-pandemic period from 14/02/2020 to 13/03/2020 and the longer post-pandemic period from 08/05/2021 to 31/12/2022. The coefficient of this variable is β and indicates the percentage change in the analyzed pollutant during the pandemic compared to the non-pandemic period.

Controls$_i$ is a vector of control variables related to the climatology and meteorology of the municipalities (temperature, precipitation, humidity, sunshine hours, Saharan dust episodes, biomass combustion), as well as demographic and economic structure (population, and employment shares in manufacturing and construction).

$\eta_{i\times t}$ is the interaction between municipality fixed effects and fixed effects for hour of the day, day of the week, week of the month, and month of the year. θ_t represents year fixed effects. Together, these fixed effects allow us to control for municipality characteristics that do not vary over time, as well as for temporal trends and seasonality. ν_{it} is the error term that captures unobserved effects.

Next, we analyze the heterogeneity within the pandemic period to examine the differentiated impacts associated with varying degrees of mobility restrictions:

$$\begin{aligned}\ln(\text{Pollutant}_{it}) = \alpha + \beta_1 \times \text{Wave 1}_t + \beta_2 \times \text{Normality}_t + \beta_3 \times \text{Waves 2-3}_t \\ + \gamma \times \text{Controls}_{it} + \eta_{i\times t} + \theta_t + \nu_{it}\end{aligned} \tag{2}$$

where Wave 1_t is a binary variable indicating the period of the first wave of COVID-19, taking the value 1 between the start (14/03/2020) and the end (21/06/2020) of the first state of alarm. During this subperiod, the strictest mobility restrictions were implemented, the most notable being mandatory home confinement.

Normality_t is a binary variable corresponding to the period the Spanish government referred to as the "new normality." It takes the value 1 between 22/06/2020 and 08/10/2020. This subperiod is associated with the end of mandatory home confinement and the gradual easing of mobility restrictions.

Finally, Waves $2\text{–}3_t$ is a binary variable marking the periods of the second and third waves. It takes the value 1 between the beginning of the second state of alarm on 09/10/2020 and the end of the third state of alarm (and the pandemic) on 08/05/2021. During this period, less strict mobility restrictions were in place, such as partial or perimeter lockdowns and a nighttime curfew.

The coefficients of these three variables, β_1, β_2, and β_3, indicate the percentage change in the analyzed pollutant during each respective pandemic subperiod compared to the non-pandemic period.

Finally, we leverage the high temporal resolution of our dataset to analyze the effects across different hours of the day:

$$\begin{aligned}\ln(\text{Pollutant}_{it}) = \alpha + \beta_{0h} \times \sum_{1}^{23} \text{Hour}_h \times \text{No pandemic}_t \\ + \beta_{1h} \times \sum_{0}^{23} \text{Hour}_h \times \text{Wave 1}_t + \beta_{2h} \times \sum_{0}^{23} \text{Hour}_h \times \text{Normality}_t \\ + \beta_{3h} \times \sum_{0}^{23} \text{Hour}_h \times \text{Waves 2-3}_t + \gamma \times \text{Controls}_{it} + \eta_{i\times t} + \theta_t + \nu_{it}\end{aligned} \tag{3}$$

where Hour_h is a binary variable indicating hour h of the day, interacted with the variables for the three pandemic subperiods (Wave 1_t, Normality_t, and Waves $2\text{–}3_t$), as well as with the binary variable for the non-pandemic period (No pandemic_t). The coefficients of these interactions, β_{0h}, β_{1h}, β_{2h}, and β_{3h}, indicate the percentage change in the analyzed pollutant at different hours during the pandemic periods, relative to hour 0 (midnight) of the non-pandemic period.

Taken together, the estimated coefficients from the three equations allow us to analyze the impact of the COVID-19 pandemic on pollution levels. Focusing on the subperiod of the first wave, when the strictest mobility restrictions were implemented (including mandatory home confinement), the estimated coefficients of Wave 1_t in equations (2) and (3) can be interpreted as an approximation of the potential effects of increasingly relevant phenomena in our lives, such as teleworking and e-commerce.

3. Mobility during the pandemic

3.1 Why Study the Pandemic Period?

The COVID-19 pandemic period presents an ideal setting to study how mobility affects pollution. In this context, the political decisions made during the pandemic were not based on environmental criteria, but rather on health, social, and economic considerations. The primary goal of these measures was to contain the spread of the virus and protect public health, especially given the risk of overwhelming healthcare systems. Other factors considered included protecting vulnerable groups, ensuring the continuity of essential services, and mitigating the economic impact of activity restrictions. Therefore, mobility restriction policies were designed in response to a public health emergency rather than with the explicit aim of reducing air pollution.

3.2 Descriptive Evidence

To analyze the impact of the pandemic on mobility, we use data from the Estudio de la Movilidad con Big Data by the Ministerio de Transportes y Movilidad Sostenible. This study is based on anonymized mobile phone data provided by the telecommunications operator Orange and allows for the estimation and quantification of hourly mobility patterns between municipalities throughout Spain starting from February 14, 2020.

Specifically, the dataset includes detailed information on the number of origin-destination trips, classified into three categories: (1) internal trips, i.e., movements within the same municipality; (2) outbound trips, originating in the municipality under analysis and ending in another; and (3) inbound trips, originating in other municipalities and ending in the municipality in question.

Table 1 presents the evolution of the number of trips during different periods: the pre-pandemic period (14/02/2020–13/03/2020), three phases within the pandemic period (first wave: 14/03/2020–21/06/2020; new normality: 22/06/2020–08/10/2020; other waves: 09/10/2020–08/05/2021), and finally, the post-pandemic period (09/05/2021–31/12/2022). The table is organized into two panels: Panel A shows the daily average of trips, and Panel B shows the hourly average. In both cases, the distinction between internal, outbound, and inbound trips is maintained.

According to Panel A, before the onset of the pandemic, the average number of internal trips in Spain was around 37 million per day. This figure dropped sharply during the pandemic: a 41% decrease during the first wave, and 25% and 20% decreases during the new normality and the subsequent waves, respectively. In the post-pandemic period, internal mobility gradually recovered, reaching levels nearly identical to those observed before the health crisis.

As for outbound and inbound trips, the figures show the expected symmetry: trips departing a municipality during a given time slot (e.g., 7 a.m.) often correspond to return trips recorded later (e.g., 5 p.m.). Both types of trips were around 5 million daily in the pre-pandemic period. This mobility also experienced a significant drop of 51% during the first wave, and 19% during the later stages. In the post-pandemic period, the numbers recovered and stabilized at approximately 4.8 million daily.

Panel B of Table 1 shows results consistent with Panel A but expressed in hourly terms. It reveals an average reduction of 40% in internal hourly trips and 50% in inbound and outbound hourly trips during the first wave. In the subsequent phases of the pandemic, the reduction moderated to around 23% for internal trips and 25% for inter-municipal movements. With the lifting of restrictions, hourly values returned to levels very close to, and even slightly above (in the case of internal trips), those of the pre-pandemic period.

Table 1: Trips by period and type

	Pre-pandemic	Pandemic			Post-pandemic
		First wave	New normality	Other waves	
	14/02/2020-13/03/2020	14/03/2020-21/06/2020	22/06/2020-08/10/2020	09/10/2020-08/05/2021	09/05/2021-31/12/2022
Panel A: Daily average					
Internal	37,540,623	21,974,232	28,237,433	29,948,247	35,431,229
Outbound	9,654,724	4,726,297	7,801,015	7,191,453	8,822,996
Inbound	9,656,810	4,727,795	7,821,403	7,196,196	8,836,362
Panel B: Hourly average					
Internal	30,081	17,615	22,626	24,002	28,390
Outbound	7,754	3,841	6,276	5,803	7,075
Inbound	7744	3841	6288	5,800	7,084

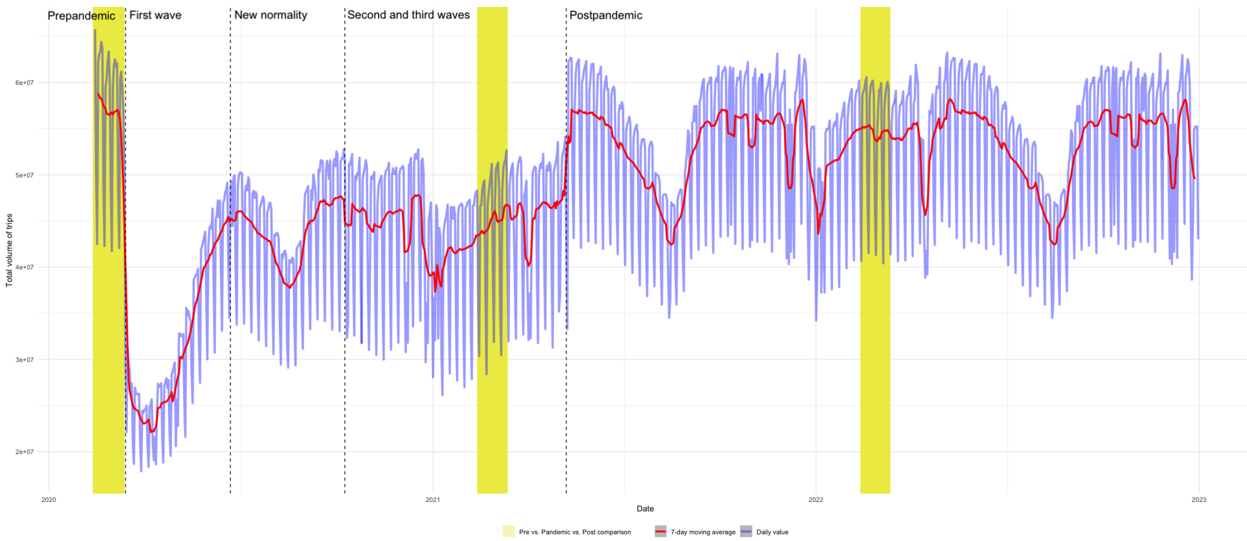
Figure 1 graphically depicts the evolution of the total number of trips between 2020 and 2023. The blue line shows the average value for each day, clearly highlighting weekly and seasonal variability, influenced by work activity and the holiday calendar (with systematic decreases during weekends, holiday periods, and public holidays). The red line represents the 7-day moving average, which helps smooth out short-term fluctuations and capture the overall trend.

The vertical dashed black lines mark the boundaries of the different periods analyzed: pre-pandemic, first wave, new normal, subsequent waves, and post-pandemic. Additionally, the period between February 14 and March 13 is specifically highlighted to facilitate interannual comparison across the years 2020 (pre-pandemic), 2021 (pandemic), and 2022 (post-pandemic).

The results show high and stable levels of mobility before the pandemic, followed by a sharp drop during the first wave due to lockdown measures. This is followed by a partial and gradual recovery during the new normality and subsequent waves, culminating from May 2021 onward in a sustained recovery trend toward levels similar to those observed before the health crisis.

Comparing the same period (14/02–13/03) across years clearly illustrates the initial impact of the pandemic on mobility and the subsequent restoration of usual travel behavior.

Figure 1: Total trips



4. Pollution and mobility restrictions

4.1 *Results*

This section presents the results derived from applying the empirical strategy described in Section 2, which allows for the analysis of the impact of mobility on air pollution levels in Spanish cities. The COVID-19 pandemic period acts as a natural experiment, as the mobility restrictions implemented during this time offer a unique opportunity to evaluate this causal relationship.

First, we examine the overall effects of the mobility restrictions applied throughout the pandemic period by estimating Equation 1. Table 2 presents the results using the logarithm of emissions of NO_x (Column 1), PM_{10} (Column 2), $PM_{2.5}$ (Column 3), and SO_2 (Column 4) as the dependent variable.

Overall, the estimated coefficients show a reduction in pollution during the pandemic period. This reduction and its statistical significance vary depending on the pollutant. The most pronounced decrease is observed in NO_x, with a significant 33% reduction compared to the non-pandemic period, which is consistent with the sharp drop in road traffic — the main source of this pollutant. For PM_{10}, a marginally significant 7% reduction is estimated, while $PM_{2.5}$ shows a non-significant 24% decrease. Finally, SO_2 emissions decline by 16%.

Table 2: Pollution and COVID-19: Global effects

Dependent variable:	log(Pollutant)			
	NO_x [1]	PM_{10} [2]	$PM_{2.5}$ [3]	SO_2 [4]
Pandemic period (14/03/2020-08/05/2021)	-0.331[a]	-0.071[c]	-0.243	-0.164[a]
	(0.037)	(0.041)	(0.157)	(0.040)
Year fixed-effects	✓	✓	✓	✓
Interacted fixed-effects of Municipality, Month, Week, Day and Hour	✓	✓	✓	✓
Demographic and Economic Structure controls	✓	✓	✓	✓
Climatic-Meteorologic controls	✓	✓	✓	✓
Adjusted R^2	0.755	0.630	0.597	0.789
Observations	394,764	433,245	209,161	459,849

Notes: Robust standard errors clustered at the municipality-date level in parentheses. [a], [b] i [c] indicates significant at 1, 5, and 10 percent level, respectively.

Next, we estimate Equation 2, where the pandemic period is disaggregated into three subperiods reflecting varying degrees of mobility restrictions: First Wave (14/03/2020–21/06/2020), New Normality (22/06/2020–08/10/2020), and Second and Subsequent Waves (09/10/2020–08/05/2021). Table 3 presents the results of this disaggregated analysis, revealing significant heterogeneity in the impacts.

Table 3: Pollution and COVID-19: Waves and new normality

Variable dependent:	log(Pollutant)			
	NO_x [1]	PM10 [2]	PM2.5 [3]	SO_2 [4]
First wave (14/03/2020-21/06/2020)	-0.564[a]	-0.316[a]	-0.349[b]	-0.103[b]
	(0.040)	(0.045)	(0.170)	(0.044)
New normality (22/06/2020-08/10/2020)	-0.066[c]	0.160[a]	-0.054	-0.182[a]
	(0.039)	(0.043)	(0.222)	(0.044)
Other waves (09/10/2020-08/05/2021)	-0.263[a]	0.017	0.075	-0.255[a]
	(0.042)	(0.049)	(0.194)	(0.050)
Year fixed-effects	✓	✓	✓	✓
Interacted fixed-effects of Municipality, Month, Week, Day and Hour	✓	✓	✓	✓
Demographic and Economic Structure controls	✓	✓	✓	✓
Climatic-Meteorologic controls	✓	✓	✓	✓
Adjusted R^2	0.764	0.631	0.600	0.789
Observations	394,764	433,245	209,161	459,849

Notes: Robust standard errors clustered at the municipality-date level in parentheses. [a], [b] i [c] indicates significant at 1, 5, and 10 percent level, respectively.

NO_x shows a substantial reduction of 56% during the first wave, when restrictions were most stringent. This effect decreases to 7% during the new normality and remains at 26% in the subsequent waves, indicating a sustained impact from reduced mobility. The effects on PM_{10} are less consistent: an initial drop of 32% is followed by a 16% increase during the new normality, with no effect observed in the later phases. $PM_{2.5}$ declines by 35% during the first wave, with non-significant effects for the remainder of the period. SO_2 emissions show a gradual decrease:

10% during the first wave, 1% in the new normality, and up to 26% in the subsequent waves, suggesting a more persistent impact on the economic activities that generate this pollutant.

Finally, we estimate Equation 3 to analyze the hourly evolution of pollution and, in particular, the hourly impact of mobility restrictions introduced during the COVID-19 pandemic. Specifically, Figure 2 presents the estimated coefficients for the non-pandemic period (in blue) and the most severe pandemic period of the first wave (in red) in the graphs on the left (Figures 2a, 2c, 2e, and 2g), as well as the differences in the coefficients in the graphs on the right (Figures 2b, 2d, 2f, and 2h). As detailed in Section 2, these coefficients are relative to hour 0 (midnight) in the non-pandemic period and thus represent percentage variations between the analyzed hour and midnight.

In general, during the non-pandemic period, pollution (1) decreases during the early hours of the day (1–5 a.m.), and (2) is higher than at midnight from around 7–8 a.m. until 11 p.m., with peak pollution levels occurring at 9–10 a.m. and 8–9 p.m. During the first wave of the pandemic, a similar hourly pattern is observed, though accompanied by a general reduction in pollution levels compared to the non-pandemic period. Notably, there is a significant reduction in pollution during traditional traffic peak hours (morning and evening).

In the specific case of NO_x, the comparison of estimated coefficients between the two periods (Figure 2a) shows a clear reduction in this pollutant during peak mobility hours (around 8–11 a.m. and 6–8 p.m.), which coincide with typical commuting times. The difference in coefficients (Figure 2b) indicates a drop of more than 60 percentage points at some of these peak times, reflecting the strong link between this pollutant and mobility.

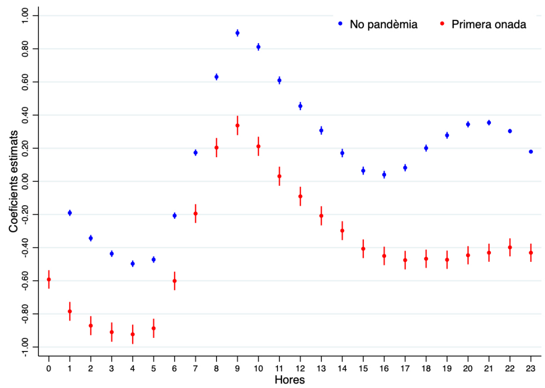
A notable decrease in PM_{10} is also observed during the pandemic period (Figure 2c), especially in the early morning and evening. The difference in coefficients between periods (Figure 2d) shows declines ranging from 20 to 40 percentage points.

The reduction in $PM_{2.5}$ is slightly less pronounced than that of PM_{10}, but it follows a similar pattern, with the most marked and significant decreases occurring from 11 a.m. onwards (Figure 2e). The difference in coefficients (Figure 2f) ranges between 30 and 50 percentage points.

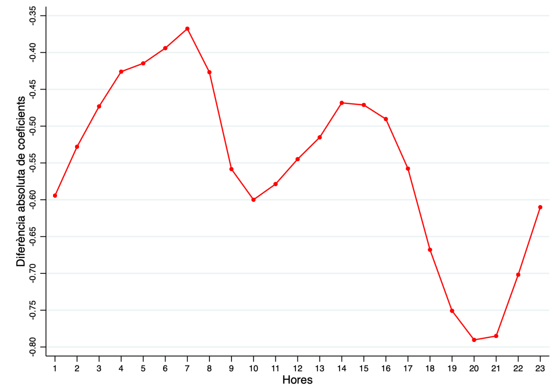
Finally, the impact of mobility restrictions during the first wave on SO_2 is much more modest and irregular. Nevertheless, the estimated coefficients show significant reductions during the morning and late afternoon peak hours (Figure 2g). The difference in coefficients between periods (Figure 2h) shows decreases ranging from 5 to 17 percentage points. This is likely due to the fact that SO_2 mainly originates from industrial processes rather than urban traffic.

Figure 2: Pollution and COVID-19: Hourly effects

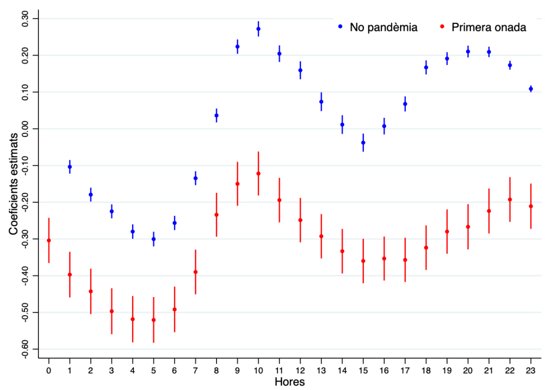
(a) NO_x - Coefficients



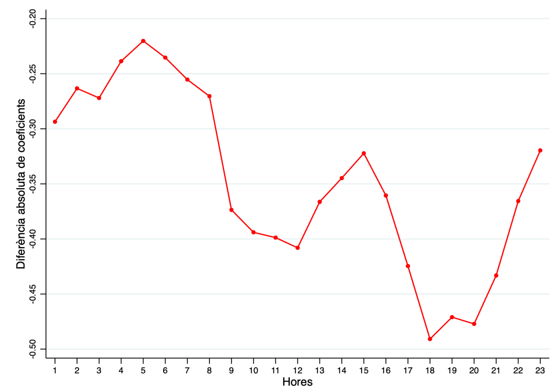
(b) NO_x - Variations



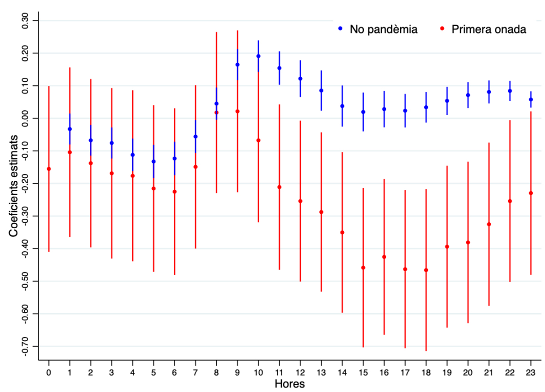
(c) PM_{10} - Coefficients



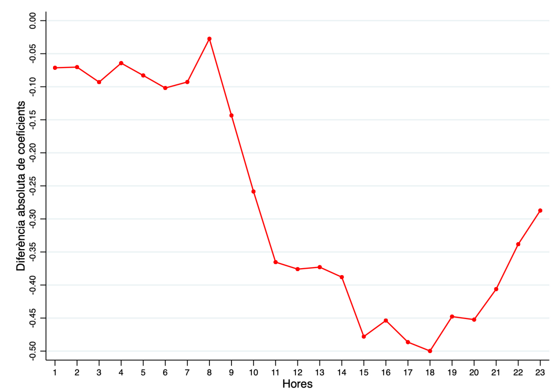
(d) PM_{10} - Variations



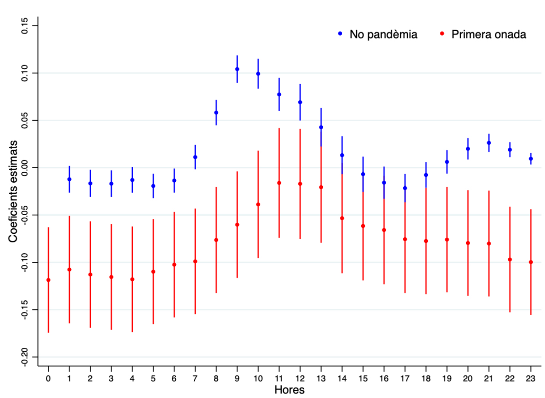
(e) $PM_{2.5}$ - Coefficients



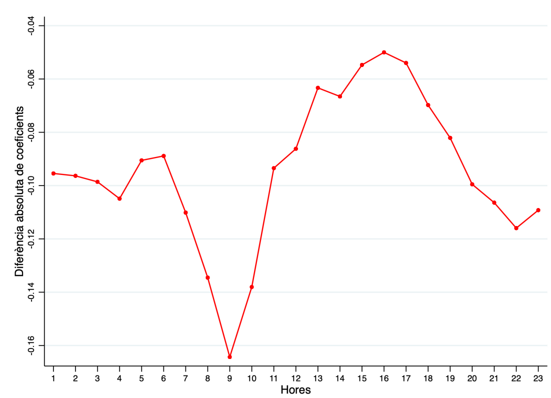
(f) $PM_{2.5}$ - Variations



(g) SO_2 - Coefficients



(h) SO_2 - Variations



4.2 *Interpretation*

The results obtained show a clear relationship between the reduction in mobility during the pandemic period and the decline in various air pollutants. This impact is particularly evident during the first wave and gradually weakens as restrictions are relaxed, highlighting the strong link between human activity —especially mobility and industrial production— and air quality in urban environments.

Moreover, the hourly data reveal that the reduction in mobility not only influenced overall pollution levels but also deeply altered its daily dynamics. The dampening of pollution peaks during rush hours is associated with a significant drop in work-related travel, mainly due to the widespread and forced adoption of remote work. This shift in mobility patterns notably reduced traffic during early morning and late afternoon hours—time frames that show the greatest environmental benefits.

Additionally, the rise in e-commerce as a partial substitute for physical trips to commercial establishments likely contributed to lower individual mobility. However, this effect may have been partly offset by increased delivery vehicle traffic. Nevertheless, the hourly distribution of this logistical activity does not appear to replicate the congestion patterns associated with private vehicle traffic, which helps explain the net reduction in pollution during peak hours.

Overall, the results provide solid evidence of how changes in work and consumption habits can generate significant environmental effects, particularly in improving air quality during times of day with the highest levels of human exposure.

5. Mechanisms

NEXT!

6. Quantifying exercise

NEXT!

7. Conclusions

This paper studies the impact of mobility on air pollution in the 52 major cities of Spain, leveraging the natural experiment created by the COVID-19 pandemic. Although the restrictions imposed during this period were not designed for environmental purposes, they resulted in a drastic and sudden reduction in mobility, offering a unique opportunity to analyze how changes in human activity can influence air quality.

The results show a significant decrease in levels of various air pollutants during the pandemic, particularly during the first wave when mobility restrictions were most severe. Specifically, NO_x levels dropped by 56% during this period, confirming this pollutant's strong dependency on road traffic. Significant reductions were also observed in PM_{10} and $PM_{2.5}$ levels, along with a progressive decline in SO_2, which is more closely linked to industrial activity.

One of the study's key methodological contributions is the use of hourly data, which has made it possible to identify not only overall changes in pollution levels but also alterations in their distribution throughout the day. During periods of tighter restrictions, a clear attenuation of pollution peaks corresponding to rush hours (morning and evening) was observed —times typically associated with commuting. This evidence points directly to the impact of widespread, mandatory teleworking during the pandemic and highlights the importance of such measures in improving air quality.

The impact of e-commerce is also considered as a factor that may have reduced individual mobility. While package deliveries have increased, their timing appears to avoid the most congested periods, potentially contributing to reduced environmental pressure during peak hours. This aspect illustrates how structural changes in consumption habits can have indirect but significant environmental consequences.

The findings have clear implications for public policy design. First, they demonstrate that reducing mobility —especially private vehicle use— can have immediate and measurable positive effects on urban air quality. This supports policies such as low-emission zones, urban tolls, or temporary traffic restrictions, provided they are designed with efficiency and equity in mind.

Second, the study highlights the potential of teleworking as a tool for environmental sustainability. While it may not be universally applicable, its structured promotion can help reduce daily commutes, particularly in dense urban environments. This can yield improvements not only for the environment but also for public health and quality of life.

Finally, the results underscore the importance of addressing mobility management from a comprehensive and preventive perspective. Beyond ad hoc measures, it is essential to promote urban models that reduce the need for long and frequent commutes.

In short, this study shows how drastic but temporary changes in mobility patterns can have substantial effects on air quality. While the pandemic was an extreme and undesirable situation, it has provided a unique window into the magnitude of human influence on the urban environment. Incorporating these insights into public policy and urban planning can decisively contribute to building cleaner, healthier, and more resilient cities in the context of the climate crisis and ongoing social transformation.

References

Bernardo, Valeria, Xavier Fageda, and Ricardo Flores-Fillol. 2021. Pollution and congestion in urban areas: The effects of low emission zones. *Economics of Transportation* 26-27: 100221. URL https://www.sciencedirect.com/science/article/pii/S2212012221000265.

Borck, Rainald and Philipp Schrauth. 2021. Population density and urban air quality. *Regional Science and Urban Economics* 86: 103596. URL https://www.sciencedirect.com/science/article/pii/S0166046220302817.

Carozzi, Felipe and Sefi Roth. 2023. Dirty density: Air quality and the density of american cities. *Journal of Environmental Economics and Management* 118: 102767. URL https://www.sciencedirect.com/science/article/pii/S0095069622001206.

Castells-Quintana, David, Elisa Dienesch, and Melanie Krause. 2021. Air pollution in an urban world: A global view on density, cities and emissions. *Ecological Economics* 189: 107153. URL https://www.sciencedirect.com/science/article/pii/S0921800921002111.

European Comission. 2021. *Developments and Forecasts on Continuing Urbanisation*. Luxembourg: Publications Office of the European Union.

European Environment Agency. 2019. *Air quality in Europe – 2019 reports*. Luxembourg: Publications Office of the European Union.

Malina, Christiane and Frauke Scheffler. 2015. The impact of low emission zones on particulate matter concentration and public health. *Transportation Research Part A: Policy and Practice* 77: 372–385. URL https://www.sciencedirect.com/science/article/pii/S0965856415001159.

Tassinari, Filippo. 2024. Low emission zones and traffic congestion: Evidence from madrid central. *Transportation Research Part A: Policy and Practice* 185: 104099. URL https://www.sciencedirect.com/science/article/pii/S0965856424001472.

Wolff, Hendrik. 2014. Keep your clunker in the suburb: Low-emission zones and adoption of green vehicles. *The Economic Journal* 124(578): F481–F512. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/ecoj.12091.

World Health Organization. 2022. *World health statistics 2022: monitoring health for the SDGs, sustainable development goals*. Geneva: World Health Organization.