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To cite this article: Ákos Gosztonyi *et al* 2026 *Environ. Res. Commun.* **8** 015021

View the article online for updates and enhancements.

Environmental Research Communications

OPEN ACCESS

RECEIVED
30 May 2025

REVISED
12 December 2025

ACCEPTED FOR PUBLICATION
23 December 2025

PUBLISHED
23 January 2026

PAPER

Divergent NO_2 air pollution trends during the COVID-19 pandemic in Helsinki Metropolitan Area

Ákos Gosztonyi[1,2,3,*], **Aleksi Karhula**[4,5], **Sirkku Juhola**[1,2] and **Sanna Ala-Mantila**[1,2]

[1] Ecosystems and Environment Research Programme (ECOENV), Faculty of Biological and Environmental Sciences, University of Helsinki, Finland
[2] Helsinki Institute of Sustainability Science (HELSUS), University of Helsinki, Finland
[3] Helsinki Inequality Initiative (INEQ), University of Helsinki, Finland
[4] INVEST Research Flagship Centre, University of Turku, Finland
[5] Turku Institute for Advanced Studies (TIAS), University of Turku, Finland
[*] Author to whom any correspondence should be addressed.

E-mail: akos.gosztonyi@helsinki.fi

Keywords: environmental inequality, COVID-19, air pollution

Abstract

Measures taken during the COVID-19 pandemic reduced key air pollutant concentrations worldwide and highlighted socio-economic disparities in their distribution. While most studies report temporary air quality improvements for lower socio-economic status (SES) groups, we show—using high-resolution spatial socio-economic and air pollution (NO_2, nitrogen dioxide) data from the Helsinki Metropolitan Area (HMA), Finland, and applying a generalized difference-in-differences approach—that locations with higher shares of upper-level employees and high-income households experienced the largest reductions in NO_2 in 2020, while areas with higher shares of low-income households, lower-level employees, manual workers and social-housing renters saw smaller reductions or non-significant changes in NO_2 concentrations. By spring 2021, under less strict containment response policies, NO_2 levels rose relative to 2020, though remained below 2019 levels, and the socio-economic pattern partly shifted: higher SES areas showed larger year-on-year increases. However, when compared with pre-pandemic trends, shares of upper-level employees and high-income households were associated with more substantial air quality improvements in 2021 too, whereas most lower SES indicators were associated with weaker improvements or non-significant changes. Taken together, the two spring periods reveal a rather consistent socio-economic stratification in NO_2 air pollution trajectories: higher SES locations experienced more significant reductions in NO_2 in most instances, whereas most lower SES characteristics were associated with smaller reductions or non-significant changes, indicating more stable air pollution levels. Shares of car owners and private renters are found to exhibit distinct relationships with air pollution changes. As our findings differ from and complement earlier findings from across the globe, we stress the need for more localized research to inform policies aiming to reduce air pollution in an equitable manner in the long run.

1. Introduction

The onset of the COVID-19 pandemic brought about considerable improvements in outdoor air quality on a global scale (Dang and Trinh 2021). As economic activity declined due to widespread lockdowns and mobility restrictions, the concentrations of most air pollutants also decreased, with notable evidence on the link between mobility trends and traffic-related pollutants (Venter *et al* 2020). However, the environmental gains were not evenly distributed. While research on potentially averted premature deaths and health improvements due to air pollution reduction during the COVID-19 pandemic are estimated to be highly significant (Liu *et al* 2021), the spatial distribution of air pollution change, and consequently its health impacts have been suggested to follow heterogeneous patterns across different geographical contexts (e.g., Giani *et al* 2020, Zhang *et al* 2022). At the same time, limited research has examined how such changes were experienced across different socio-economic groups, particularly from European urban settings.

In the U.S., Kerr *et al* (2021) show at urban neighbourhood level that more non-white, lower income, and lower educational attainment neighbourhoods still experienced a higher exposure to air pollution in absolute terms during the lockdowns, even when the largest lockdown-related nitrogen dioxide (NO_2) reductions were measured in such neighbourhoods. In a state-wide analysis, lower income of neighbourhoods, as well as higher shares of non-white residents were also associated with higher air pollution reductions in California, U.S. (Bluhm *et al* 2022). Similarly to findings from the U.S., lower socio-economic status areas in the Greater London Area were found to enjoy larger air pollution exposure reductions in March and April of 2020 (Kazakos *et al* 2021). In all three papers, the role of traffic reduction in air pollution change was highlighted as a key driver. Contrary to global findings on air pollution reductions, but in line with findings on larger decrease among lower socio-economic status groups, in South-Central Chile, fine particulate matter ($PM_{2.5}$) rose overall —mainly in middle-income and commercial areas—but decreased in low-income residential areas during lockdown (Martinez-Soto *et al* 2021). Martinez-Soto *et al* (2021) attribute such tendencies to the prevalence of wood heating and the decreased capacity of energy-vulnerable households to heat their homes. As Nwosu *et al* (2022) have highlighted, the ability to work from home (WFH) may also be subject to disparities based on socio-economic background, ability to WFH being pro-rich. Although the COVID-19 pandemic led to relatively short-term changes in the levels of air pollution, a deeper understanding of how air pollution changed due to lockdown measures, reduced mobility and reduced economic activity in local contexts is crucial in order to implement effective and just long-term air pollution mitigation strategies.

Regarding air pollution-related inequalities, in contrast to most studies across the world, European contexts often show non-linear relationships between socio-economic status and air pollution (Hajat *et al* 2015), including in Helsinki Metropolitan Area, Finland (HMA) (Gosztonyi *et al* 2023). Global data indicates that reduction in air pollution due to mobility restrictions is expected to be the largest in Europe (Barua and Nath 2021), underlining the role of the transportation sector in shaping the picture of air pollution in Europe. Indeed, among the main sources of air pollution in Helsinki as well, local traffic and long-range transportation have been identified as key contributors (Teinilä *et al* 2019). The COVID-19 pandemic-related containment response measures, similarly to other locations, heavily affected transportation and traffic in HMA, with arguably the strictest local measure being the temporary closure of the Uusimaa region's borders—where HMA is also located—in the spring of 2020 (Finland, Government Decree No. 146/2020, Finland, Government Decree No. 217/2020). At the regulatory level, this restriction effectively halted most interregional travel and long-distance commuting, and public events were suspended or limited. At the public adjustment level, WFH and distance learning were widely, but flexibly adopted, which substantially reduced daily commuting and school-related trips. At the individual level, many residents avoided public transport which resulted in an approximately 70 percent drop in passenger numbers in HMA in 2020 (HKL 2020), road traffic volumes for passenger vehicles and vans also decreased, particularly in the spring of 2020 across Finland (Traficom 2022), and, when possible, residents temporarily relocated to secondary homes (Willberg *et al* 2021). While Finland's restrictions were less stringent than in many locations imposing nationwide stay-at-home orders, the combination of voluntary compliance and targeted regulations impacted the transport sector heavily. Compared with spring 2020, the situation in spring 2021 was somewhat looser. While a state of emergency was declared again (Finnish Government 2021), there were no regional travel restrictions introduced this time, however, remote work and distance learning recommendations remained in place. By 2021, road traffic in the urban regions of Finland, including in the Helsinki region, began to grow (Traficom 2021). Consequently, although NO_2 concentrations had been on the decline in HMA due to more fuel-efficient vehicles, a dramatic drop in air pollution was observed in this period, and particularly in the spring of 2020. This large drop can be attributed to the decreased road traffic together with the higher number of people staying at home.

In this paper, we demonstrate differential air pollution change across socio-economic groups during the COVID-19 pandemic in spring 2020, as well as in spring 2021, when looser containment response policies were in place in HMA. We do this by investigating how socio-economic characteristics of areas are associated with air pollution (NO_2) change during the spring months of 2020 and 2021. This is of high relevance, since air pollution started to rebound with easing restrictions (Dong *et al* 2022), and so far, no studies to our knowledge have examined differential air pollution trends across socio-economic groups during the COVID-19 pandemic reaching beyond 2020. Beside singling out spring months of 2020 and 2021, we also present the general trends across the two springs. Our study utilizes exceptionally high-resolution spatial air pollution and socio-economic data aggregated at 250 m × 250 m grid cells unique to environmental inequality research and deploys a generalized difference-in-differences (DID) approach (Bluhm *et al* 2022).

Table 1. Variable names and definitions (Socio-economic variable definitions are based on Statistics Finland's FOLK Basic micro-level database definitions [Statistics Finland 2023]; NO_2 change values are calculated from FMI-ENFUSER [2022]; Road coverage is calculated from HSY [2022]).

Name	Definition
NO_2 change ($\mu g/m^3$)	Change in monthly mean NO_2 compared to the previous year's value within grid cells (spring months of 2018–2021, March values are indicative of the second half of each year's March)
Share of car owners (%)	Share of car owner households within grid cells
Share of homeowners (%)	Share of adult residents in homeownership within grid cells
Share of private renters (%)	Share of adult residents in private rental dwellings within grid cells
Share of social housing renters (%)	Share of adult residents in rental social housing within grid cells
Share of manual workers (%)	Share of manual workers of adult population within grid cells (workers in agriculture, forestry and commercial fishing; manufacturing workers; other production workers; distribution and service workers; other workers)
Share of upper-level employees (%)	Share of upper-level employees of adult population within grid cells (senior officials and upper management; senior officials and employees in research and planning; senior officials and employees in education and training; other senior officials and employees)
Share of lower-level employees (%)	Share of lower-level employees of adult population within grid cells (supervisors; clerical and sales workers, independent work; clerical and sales workers, routine work; other lower-level employees)
Share of high-income households (%)	Share of households belonging to the highest two income deciles within grid cells based on disposable money income
Share of low-income households (%)	Share of households belonging to the lowest two income deciles within grid cells based on disposable money income
Road coverage (%)	Percentage of the grid cells' land surface covered by paved roads

2. Materials and method

2.1. Data sources and variables

We integrate various spatial datasets at the resolution of 250 m × 250 m grid cells across HMA. We use annual geo-coded micro-level data on the inhabitants' and households' socio-economic characteristics based on their location of residence (Statistics Finland 2023). We aggregate this data to the 250 m × 250 m grid cells' level, and remove grid cells with too few observations, as well as grid cells that are not consistently present across our study period between 2017 and 2021 (e.g., new residential areas). The variables of interest are related to the income status, housing type, occupational type, and car ownership of residents (table 1). We select these variables based on recent research indicating environmental inequalities in HMA (Gosztonyi *et al* 2023), and research highlighting occupational types' influence on mobility change during the pandemic (Borkowski *et al* 2021).

We utilize the high-resolution air quality dataset of the Finnish Meteorological Institute (FMI-ENFUSER 2022). This dataset is based on observation stations' measurements. The method of producing the raw hourly air quality data at 10 to 15 m resolution combines dispersion modelling techniques, information fusion algorithms, and additional statistical methods (Johansson *et al* 2015, Johansson *et al* 2022). We aggregate the NO_2 component of this dataset at outdoor locations at the spatial resolution of the socio-economic grid cells, and by temporally averaging for each April and May between 2017 and 2021. As the first state of emergency in Finland was declared on the 16th of March, 2020, for each March we average only the second halves of the month. From these values we calculate the annual change in NO_2 between 2018 and 2021 for each spring month, compared to the previous year's same month. Similarly, we also calculate the change between the spring months of 2019 and 2021 to enable a more stringent reflection on air pollution change relative to pre-pandemic trends. Positive change values mean increase in air pollution, while negative change values mean decrease in air pollution. The air quality dataset's spatial coverage accounts for approximately 95% of the socio-economic dataset's grid cells. The grid cells not covered by the air pollution information are located at the margins of HMA and are typically sparsely populated (see the illustrations of the resulting dataset in figures 1 and 2).

While several sources can contribute to NO_2 concentrations, including e.g., industrial activity and maritime traffic (Ramacher *et al* 2020), the spatial distribution of NO_2 in the dataset utilized is majorly shaped by road traffic, considering that the measurement hight of the ENFUSER input values is at two meters, while other sources may contribute to NO_2 concentrations at different altitudes and less granular scale. The importance of road traffic aligns with reduced nitrogen oxides attributed to traffic-related technological improvements and reduced road traffic observed during 2020 and 2021 by the City of Helsinki Environmental report too (City of Helsinki 2023). It is, however, important to recognize that NO_2 is partly a secondary pollutant, and its formation is heavily influenced by sunlight, a temporally variable factor, thus caution is called for when linking

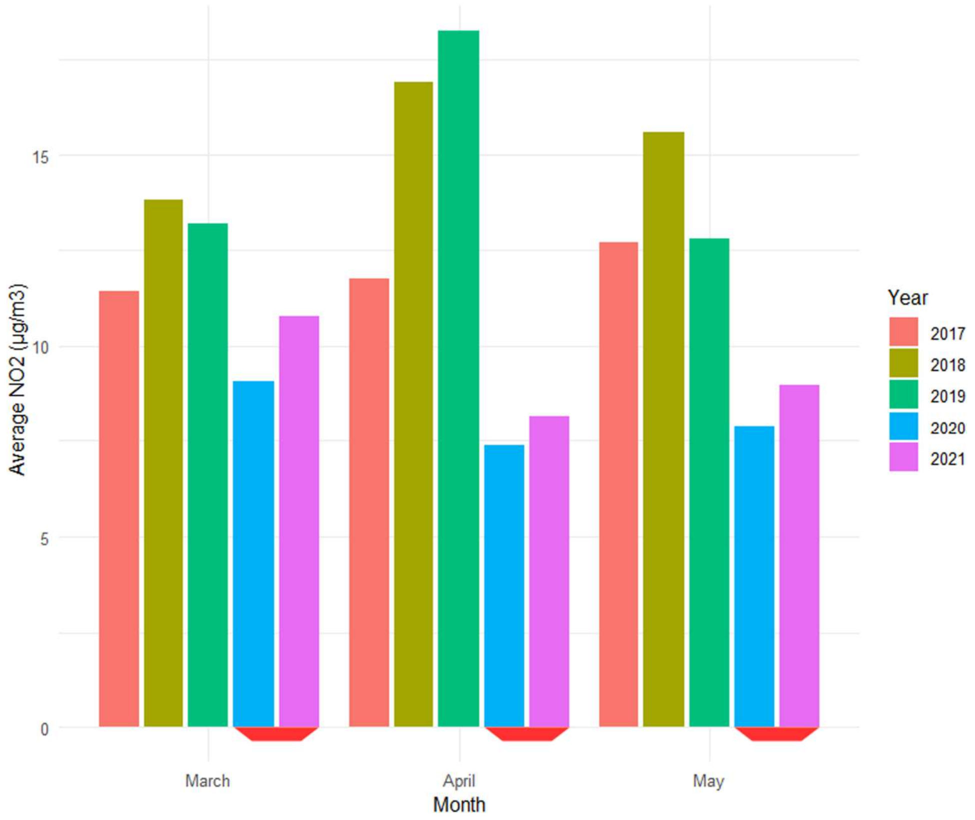

Figure 1. Average NO_2 values in HMA for spring months between 2017 and 2021. Months during the COVID-19 pandemic are underlined with red. March values are indicative of the second half of each year's March.

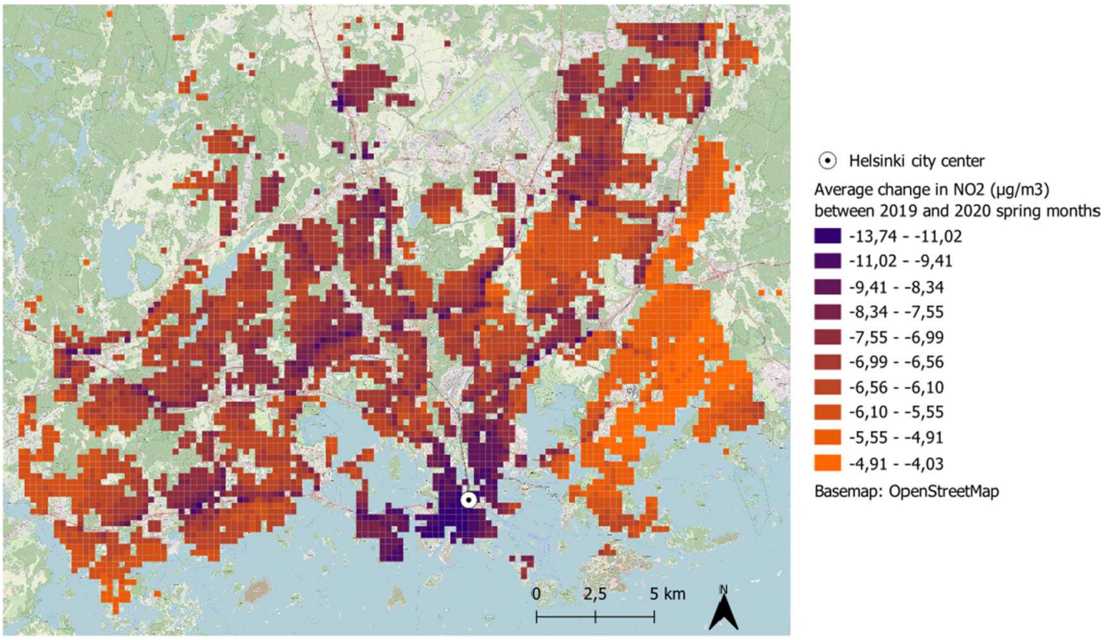

Figure 2. Average monthly change in NO_2 between the spring months of 2019 and 2020 in populated, 250 m × 250 m grid cells across HMA.

concentration changes directly to road traffic. In our case this concern is eased by calculating averages from the same months. Further, although the ENFUSER model does not explicitly utilize photochemical information, it does utilize meteorological inputs and data assimilation with observed concentrations (Johansson *et al* 2022) that may indirectly capture chemical and atmospheric processes. Still, the NO_2 values are modelled estimates, and, as inferred from Johansson *et al* (2022), their accuracy depends on the quality of emission inventories, input data, and monitoring coverage, which may limit precision during periods of rapid emission change. As this paper focuses on relative change, systemic model biases emerging from the ENFUSER dataset are expected to even out. Nevertheless, the findings of this paper should be interpreted with caution, as they rely on average estimates that may smooth variability in air pollution changes.

Additionally, we include paved road information from the Helsinki Region Environmental Services (HSY 2022). From this, we calculate the percentage of each 250 m × 250 m grid cell's land surface covered by roads. Including this information helps separate the effects of the built environment from the effects of socio-economic characteristics in explaining differential changes in NO_2. The variables and their descriptions included in the analysis are presented in table 1.

2.2. Methodological approach

To understand the differential effects of the COVID-19 pandemic on air pollution change across socio-economic gradients, we utilize a generalized difference-in-differences (DID) approach, as proposed by e.g., Bluhm *et al* (2022). DID is a well-established, and commonly used method to evaluate the heterogeneous effects of policy interventions, shocks, or treatment effects, where classically one group is exposed to the intervention over time, and another—the control group—is not (e.g., Liu *et al* 2021, Meriläinen *et al* 2024). The challenge of evaluating the effects of the COVID-19-related measures lies in the difficulty to identify a control group in a traditional way within a relatively small study area, as everyone is affected by the intervention (i.e., the pandemic). Thus, applying a generalized DID approach enables the identification of differential trends across socio-economic groups even in this scenario (see Bluhm *et al* 2022).

In our case, we interpret the treatment effect in four different sets of models. The **first** set of models considers values only from spring 2020 falling under the treatment effect, quantifying the immediate impact of the shutdown; the **second** set of models considers values only from spring 2021 falling under the treatment effect, evaluating the year-on-year differential trends experienced during the loosening of restrictions; the **third** set of models considers values from 2020 and 2021 together falling under the treatment effect, exploring the longer lasting, or 'generalized average' impact of the pandemic; and the **fourth** set of models considers the change in 2021 compared to 2019, evaluating the distance from pre-covid trends experienced in 2021. The sets of models are expressed in a simplified Fixed Effects Ordinary Least Squares model as the following:

$$\begin{aligned} Change\ inNO_2 = {} & \beta_1 \times Socio - economic \quad variable \\ & + \beta_2 \times (Binary\ treatment\ effect \times Socio - economic\ variable) \\ & + \beta_3 \times (Binary\ treatment\ effect \times Road\ coverage) + \lambda + \delta + \mu + e \end{aligned}$$

Where *Binary treatment effect* is the indicator of the period we consider as being treated, *Road coverage* is a control variable for the percentage of roads' surface within grid cells, λ are year fixed effects, δ are month fixed effects, μ are grid cell fixed effects, and e is an error term. The inclusion of year, month and grid cell fixed effects helps isolate the pandemic-related signal by absorbing recurring seasonal patterns and location-specific meteorological differences. We cluster the standard errors by postal code areas within HMA. The key variables of interest are the interacted *Socio-economic variables*, which can be interpreted as the association between the presence of certain socio-economic groups' residence in percentage terms and the change in air pollution levels at given time periods.

We run the models for each socioeconomic variable separately. Utilizing this model structure, we run **four** sets of models with three different treatment effects. **First**, we contrast air pollution change in 2020 to the changes in air pollution in 2018 and 2019 (i.e., Binary treatment effect is = 0 for the spring months of 2018 and 2019, and Binary treatment effect is = 1 for the spring months of 2020). This tells us how the change in air pollution was divergent for each socioeconomic variable in the spring of 2020 (blue in figures 3 and 4). **Second**, contrasting the changes during the spring months of 2021 to the changes in the previous years' spring months (i.e., Binary treatment effect is = 0 for the spring months of 2018, 2019 and 2020, and Binary treatment effect is = 1 for the spring months of 2021) we analyse how the trends in air pollution change differed during the second spring of the pandemic with loosening restrictions when air pollution change is conceptualized to be successive, i.e., testing if the change in 2020 persisted or diverged dissimilarly across socio-economic groups (red in figure 3). **Third**, by contrasting the changes during the spring months of both 2020 and 2021 (Binary treatment effect = 1) to the changes in 2018 and 2019 (Binary treatment effect = 0) we show how the changes during the COVID-19 pandemic's two springs overall differed for each socioeconomic variable (yellow in figure 3). And **fourth**, we contrast the changes during 2021 (Binary treatment effect = 1) to pre-pandemic trends (Binary treatment effect = 0 for spring months of 2018 and 2019). In this case the change in 2021 is calculated compared to the spring months of 2019 (red in figure 4). The **first** set of models corresponds to the striking decrease in air pollution in spring 2020. By presenting the results of the **second** set of models, where the spring months of 2021 are considered the treatment period, we reflect more explicitly on how—and how

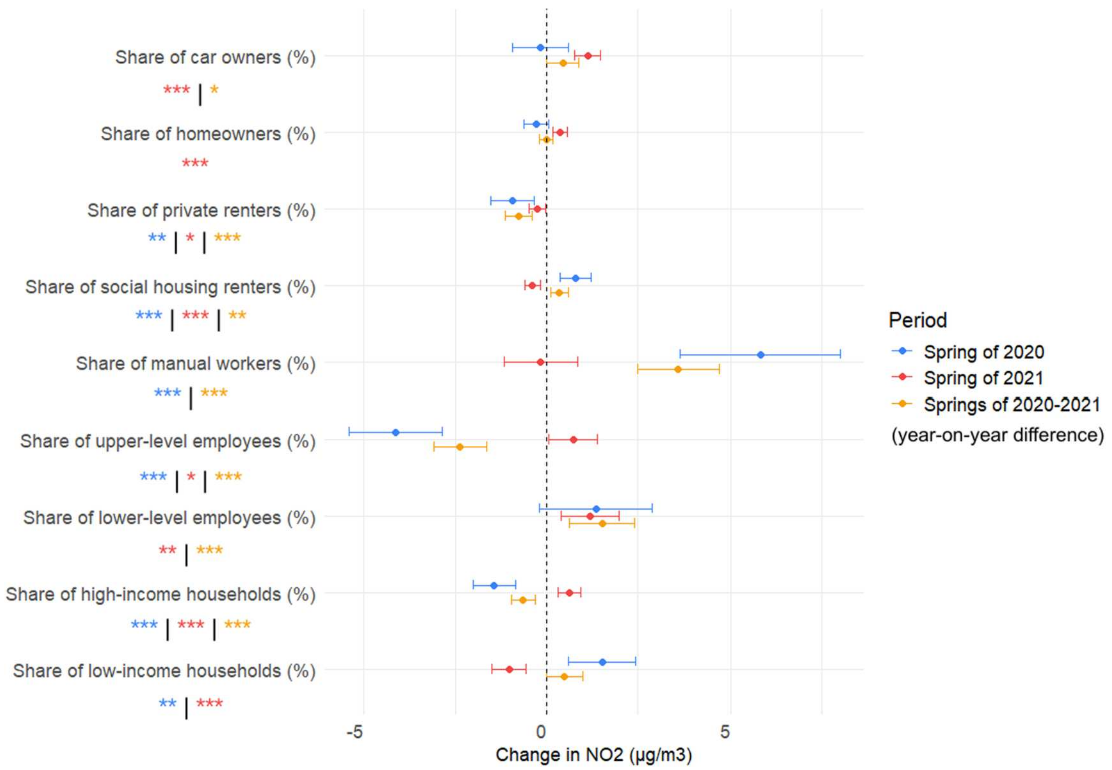

Figure 3. Differential year-on-year changes in NO_2 concentrations across socio-economic characteristics of 250 m × 250 m grid cells in HMA during the spring months of 2020 and 2021, with 95% confidence intervals for the coefficients. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Colour-coded according to time period.

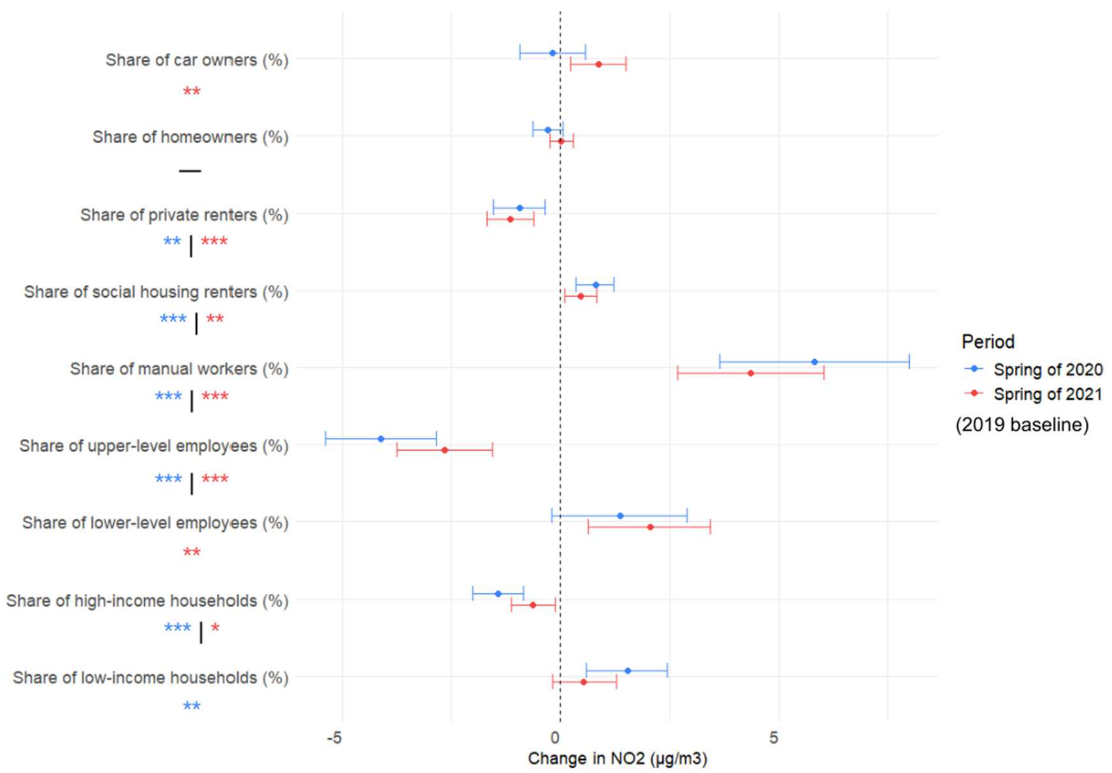

Figure 4. Differential changes in NO_2 concentrations across socio-economic characteristics of 250 m × 250 m grid cells in HMA during the spring months of 2020 and 2021 (2019 baseline), with 95% confidence intervals for the coefficients. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Colour-coded according to time period.

Table 2. Summary table of change in NO_2 levels within grid cells in spring 2020, spring 2021 and springs of 2020–2021 together (year-on-year [YoY]), and in spring 2021 compared to 2019 ($\mu g\ m^{-3}$).

	Spring of 2020 (compared to 2019)	Spring of 2021 (compared to 2020)	Springs of 2020–2021 (YoY)	Spring of 2021 (compared to 2019)
Min.	−21.69	−4.768	−21.69	−22.491
20th Percentile	−10.639	−0.186	−6.371	−9425
40th Percentile	−6.371	−1.037	−3.788	−5.022
60th Percentile	−4.827	1.67	0.185	−3.43
80th Percentile	−3.785	2.138	1.67	−2.425
Max.	−0.411	3.844	3.844	2.095
Mean	−6.623	1.179	−2.722	−5.444
Observations < 0	12 891	2157	15 048	12 378
Observations > 0	0	10 734	10 734	513

divergently across socio-economic groups—the somewhat loosening restrictions resulted in divergent trends across socio-economic groups with 2020 changes conceptualized as accelerated decrease, and the changes in 2021 compared to 2020 as the divergence from this trend. Thus, we can reflect on what socio-economic characteristics may have been associated with the slight uptick in 2021 (as seen in figure 1), and on the persistence or the reversal of the pandemic's impact. The **third** set of models corresponds to the longer-term shock of the COVID-19 pandemic, showing how different socio-economic characteristics of neighbourhoods may have played a role in air pollution change during the two springs of the pandemic together. The **fourth** set of models approaches the changes experienced in 2021 differently compared to the second set of models. As in this case the change in 2021 is calculated by comparing the NO_2 values to 2019 levels, we can reflect on whether 2021 trends differ from the pre-pandemic experience. We visualize the effects of the key variables of interest from the **first three** sets of models in figure 3. In addition, we visualize the **second and** the **fourth** sets of models in figure 4 to better outline the distance from pre-pandemic trends. We report the full regression tables in appendix A–D.

3. Results

In figures 3 and 4, we present our difference-in-differences estimates for the changes in NO_2 concentrations across socioeconomic groups within grid cells caused by the COVID-19 pandemic. Positive estimates indicate an upward shift in the change in NO_2 concentrations, while negative estimates indicate a downward shift in the tendency, compared to the pre-pandemic baseline trend, and in the case of 2021, to the baseline trend including the early pandemic phase as well. In other words, if the estimate is positive, ΔNO_2 is higher than expected based on past trends. If the estimate is negative, ΔNO_2 is lower than expected based on past trends. We focus on three distinct periods in four distinct settings: the spring of 2020, corresponding to the immediate impact of the pandemic (full table in appendix A); the spring of 2021, corresponding to the loosening restrictions as successive change (Appendix B) and corresponding to distance from pre-pandemic trends (Appendix D); and the springs of 2020 and 2021 combined (Appendix C). In table 2, we summarise the changes in NO_2 levels in the entire study area to provide a reference point for interpreting the results. For example, as all grid cells showed air pollution decrease during the spring months of 2020, a positive coefficient estimate in this period suggests smaller than expected NO_2 decrease.

3.1. Properties: Car ownership and homeownership associated with upward spring 2021 air pollution change

Our results indicate that the share of car owners within grid cells during the first spring of the pandemic had no statistically significant effect on the change in NO_2 levels, however, it did have a small positive effect on the change in NO_2 levels when we consider the general trend across the springs of 2020 and 2021 together. When we specifically isolate the spring months of 2021 as year-on-year change, car ownership has a very strong positive effect on air pollution change. A 10-percentage-point increase in the households' share owning at least one car within grid cells predicts an approximately 0.1 $\mu g\ m^{-3}$ increase in NO_2 change in spring 2021. When the change in 2021 is contrasted against 2019, car ownership, yet again, is found to have a slightly more moderate, but still positive effect on air pollution change. Considering that the majority of the grid cells showcased a generally positive year-on-year trend in 2021, this result indicates that car ownership played an important role in halting air pollution decrease following the loosening restrictions. Compared to 2019, although most cells show (less intense than in 2020) decrease in NO_2 concentrations in 2021, car ownership's positive effect indicates that areas with higher shares of private vehicles experienced a significantly lower rate of air pollution improvement in 2021. The non-significant finding for spring 2020 indicates that the share of car owners within grid cells has no explanatory power to explain the overwhelmingly decreasing trend in NO_2 levels in the spring of 2020.

Similarly, however, less pronouncedly, share of homeowners shows a statistically significant, positive effect on air pollution change in 2021, but only when year-on-year change is investigated. A 10 percent increase in the share of homeowners within grid cells predicts a small, 0.04 $\mu g\ m^{-3}$ increase in the change of NO_2 levels, contributing to the temporary upward trend of air pollution change in spring 2021. In parallel with the share of car owners, homeownership rates lack explanatory value in explaining the decreasing tendency in spring 2020.

3.2. Tenancy: More substantial decrease in air pollution for private renters, more stable air pollution levels for social housing renters

The share of private renters within grid cells shows a similar pattern to the share of homeowners and the share of car owners regarding the relative positions of the estimated effects according to time periods. It is statistically significant for explaining change in NO_2 levels in spring 2020, and even more strongly significant for explaining the change during both springs together in a year-on-year change framework. I.e., each additional 10 percent increase in the share of private renters is associated with approximately 0.1 $\mu g\ m^{-3}$ decrease in the change in NO_2 levels in 2020, and 0.08 $\mu g\ m^{-3}$ decrease when 2020 and 2021 are accounted for jointly. The significance of the decreasing tendency still holds for explaining the changes in spring 2021, both when year-on-year change is considered, and even more when 2019 NO_2 values are used as the baseline. Put differently, considering the strongly decreasing tendency of NO_2 levels in 2020 (table 2), we can conclude that the higher the share of private renters within grid cells, the larger the decrease in air pollution was during the spring months of 2020, and this tendency persisted beyond the spring of 2020; and as figure 4 shows, even intensified when 2019 is considered as the baseline.

The share of social housing renters within grid cells shows a markedly different pattern regarding the relative position of the estimated effects. While the previous variables under investigation show more (relatively) positive estimates in 2021 (coloured red in figure 3) and less (relatively) positive results in 2020 (coloured blue in figure 3), this pattern reverses for social housing renters. The share of social housing renters is associated with more positive change values in spring 2020 and more negative change values in spring 2021 in a year-on-year framework. Springs of 2020 and 2021 jointly considered falls in-between, but on the generally positive side. Hence, a 10-percentage-point increase in the share of social housing renters within grid cells is associated with approximately 0.08 $\mu g\ m^{-3}$ higher (less negative) change in NO_2 levels in 2020, and a more modest, but still strongly significant decrease of approximately 0.04 in 2021 when year-on-year change is calculated. Considering the principally negative trend for spring 2020, we can state that a larger share of social housing renters within grid cells is associated with a significantly lower decrease in air pollution during the spring months of 2020. When the change in spring 2021 is contrasted against the 2019 baseline, similarly to the change in 2020, we find that the share of social housing renters is associated with an upward (less negative) change. These findings together indicate that the air pollution reduction in locations with larger shares of social housing renters in 2020 was less pronounced, but by 2021 (compared to 2020) the decrease began to intensify. However, as figure 4 shows, compared to 2019, we still find that locations with higher shares of social housing renters face significantly less intense NO_2 reductions, although less markedly than in 2020.

3.3. Occupation: striking differences according to occupation-related socio-economic status

Shares of manual workers, upper-level employees and lower-level employees also show divergent trends. Yet again, the variable associated with higher socio-economic status, the share of upper-level employees within grid cells shows a similar pattern to previously discussed variables commonly linked to higher socio-economic status: a more substantial decrease in air pollution during spring 2020, this time with strong statistical significance, and a more positive tendency in spring 2021 when year-on-year change is considered. The joint effect of 2020 and 2021 is also found to be strongly significant. In other words, a 10 percent increase in the share of upper-level employees predicts a relatively large, approximately 0.41 $\mu g\ m^{-3}$ additional decrease in NO_2 levels during spring 2020. When the springs of 2020 and 2021 are investigated together, each additional 10 percent increase in their share is associated with approximately 0.24 $\mu g\ m^{-3}$ decrease in air pollution change. When spring 2019 is considered to be the baseline for the 2021 change values (figure 4), we find that the decreasing tendency is less intense compared to the change in 2020, which cognates with the positive year-on-year change (figure 3).

The share of manual workers and the share of lower-level employees, similarly to the share of social housing renters, typically associated with lower socio-economic status, change patterns compared to the share of upper-level employees. Less marked or non-significant air pollution decreases in the spring of 2020 and more upward change in the spring of 2021. In the case of the share of manual workers, a 10 percent increase is associated with a statistically strongly significant, approximately 0.58 $\mu g\ m^{-3}$ positive change in NO_2 levels and we find no statistically significant trend in the case of lower-level employees in the spring of 2020. Considering the crude values for change in NO_2 levels (table 2), this means that during the spring of 2020 grid cells with higher shares of lower-level employees and manual workers experienced a less substantial or non-detectable air pollution decrease. When the springs of 2020 and 2021 are investigated jointly, both variables show statistically significant positive trends, in other words, less intense air pollution decreases during the two springs of the pandemic. The share of lower-level employees shows a statistically significant relationship with the change in NO_2 levels during 2021 too, when year-on-year change is considered. When spring 2019 is taken as the baseline for calculating change in spring 2021, we find that the NO_2 change becomes significantly positive for the share of manual workers - although less positive than its estimate for 2020 - and in the case of lower-level employees, while the change in 2020 is found to be non-significant, the positive change in 2021 is even more pronounced than in the case of year-on-year change.

3.4. Income: opposing trends for high- and low-income households

Regarding the shares of low- and high-income households within grid cells we observe a familiar pattern: the share of high-income households, a variable associated with higher socio-economic status, has a negative relationship with change in NO_2 values in spring 2020. This means that the higher the share of high-income households, the sharper the decrease in NO_2 levels was during the first spring of the pandemic. To quantify it, a 10 percent increase in the share of high-income households is associated with approximately 0.14 $\mu g\ m^{-3}$ more decrease in NO_2 levels. However, the relationship changes direction in the spring of 2021 when year-on-year change is considered: each additional 10 percent increase in the share of high-income households within grid cells is associated with a positive change in NO_2 levels by 0.06 $\mu g\ m^{-3}$. Jointly investigating 2020 and 2021, the share of high-income households has a negative effect on the change in NO_2 levels, retaining more substantial air pollution reduction throughout the pandemic's two springs in general. When the 2021 change is contrasted against 2019, the share of high-income households within grid cells is still associated with a larger decrease in NO_2, however, in accordance with the year-on-year change, this decrease is less striking than the change in 2020.

The share of low-income households within grid cells variable is like the mirror image of these trends. In spring 2020, a 10 percent increase in the share of low-income households is associated with approximately 0.15 $\mu g\ m^{-3}$ smaller decrease in NO_2 levels. When year-on-year change is considered, the share of low-income households in spring 2021 is associated with approximately 0.1 $\mu g\ m^{-3}$ lower change in NO_2 levels. When the springs of 2020 and 2021 are jointly considered, the share of low-income households has a positive relationship with change in NO_2 levels, although on the verge of statistical significance. When the change in 2021 is calculated against the 2019 baseline, we find no significant relationship. To put it another way, the higher the share of low-income households within grid cells, the less did they benefit from air quality improvements during the pandemic's first spring, and although compared to 2020, some air quality improvement trends are detectable in 2021, this improvement is not significant when contrasted against 2019.

4. Discussion

4.1. Who and where are the beneficiaries of air quality improvements?

While earlier findings from across the world indicate larger drops in air pollution in less affluent locations during the first year of the pandemic (Kazakos *et al* 2021, Kerr *et al* 2021, Martinez-Soto *et al* 2021, Bluhm *et al* 2022), our results show the opposite in spring 2020. Previous research from Finland utilizing mobile phone data has detected a population decrease in densely populated urban centres, and a population increase in rural areas, as well as a reduction in inter-municipality mobility during the pandemic's first year (Willberg *et al* 2021). They also found that such dynamics were strongly correlated with access to secondary housing. I.e., those who possess a secondary home were found to be likely to relocate from urban areas to WFH from their secondary homes. Considering that income correlates positively with having access to and possessing secondary homes, with more than 80% of households earning at least EUR 90,000 a year having access to secondary homes in 2015 (Adamiak *et al* 2015), the interpretation of our results becomes more nuanced. Although our models do not incorporate data on relocations, the more striking air pollution decrease in higher income areas during spring 2020 could be linked to the phenomenon described above (Willberg *et al* 2021). In this sense, although air pollution indeed decreased more in more well-off locations, the number of households enjoying the benefits of reduced local air pollution in HMA may be tapered due to such migration patterns in spring 2020, and reversed relocation patterns could very well explain the upward change in spring 2021 compared to 2020, and the less intense decrease compared to 2019. As secondary homes in Finland are typically cottages located in the countryside, this would indicate an even sharper decrease in the air pollution exposure for the high-income population. Future research may also focus on how more remote, secondary home-rich locations' air pollution levels could have been influenced by this temporary residential migration.

4.2. Private renters: the exceptions to the rule?

We conclude that areas of lower socio-economic status experienced more stable air pollution levels, while areas with higher socio-economic status saw more substantial changes. Considering that arguably the most impactful policies in place were the travel restrictions, physical distancing and WFH, higher socio-economic locations showcased higher levels of agility to the shocks of the pandemic, that is reflected in the rapid and more substantial changes in NO_2 levels throughout the years. On the other hand, the more stable air pollution levels in lower socio-economic status locations indicate that it was more likely that in these locations activities associated with emitting NO_2 remained (or had to remain) closer to the business-as-usual.

Perhaps one exception among the variables under investigation often associated with lower socio-economic status is the share of private renters. In their case the air pollution change trends are closer to variables associated with higher socio-economic status, and they are the only group whose change in 2021 compared to 2019 not only remained negative, but showed even larger relative decrease compared to the change between 2019 and 2020. Research from the U.S. have indicated that private renters' residential relocations during the pandemic slowed down or countered the gentrification of certain neighbourhoods via their relocations from places with high connectivity, dense road network and proximity to roads and jobs, to more remote locations formerly less in demand (Ding and Hwang 2022, Li and Su 2023). This could be explained by the relatively higher flexibility embedded in their tenure status and their potential overlap with higher and middle-income categories, as well as by having more opportunities to WFH. Our dataset shows the largest air pollution decrease in central, highly dense locations and near roads (figure 2). Since we do not incorporate information on residential relocations into our models, we cannot conclude that similar de-gentrification happened in HMA. However, future research may find our results useful as a potential vantage point for understanding how cities' population may have been reshuffled during the pandemic, and what its impact on the environment could be.

4.3. Occupation-related socio-economic status and changes in mobility

The most striking differences in air pollution change we detect are among the different occupation-related socio-economic status groups. Locations with higher shares of manual workers and lower-level employees are found to have significantly lower levels of air pollution change during the two springs of the pandemic together, while the most striking air pollution decrease was detected in locations with higher shares of upper-level employees. In the case of manual workers and upper level employees the differences became somewhat moderated in 2021 compared to 2020 when the change is calculated against the 2019 baseline, however, in the case of lower-level employees, while 2020 did not show a significant relationship, it did become positive by 2021 both when calculated as a year-on-year change, and change compared to 2019. Bluhm *et al* (2022) in California, U.S., show that lower-income neighbourhoods, and Borkowski *et al* (2021) in Poland show that blue-collar workers decreased their mobility less compared to higher-income and white-collar and home-office workers respectively. Combined with the larger air pollution reduction in lower-income areas, Bluhm *et al* (2022) conclude that regional economic activity—in contrast to local activity—drives air pollution-related inequities. While we do not incorporate detailed mobility reduction information into our dataset, since the first lockdown in spring 2020 was a regional lockdown—although allowing for freight traffic –, we assume the air pollution changes were more heavily affected by inter-regional passenger car and bus mobility changes. Considering that no regional lockdown was in place in spring 2021, the uptick in air pollution may be partially explained by the reintroduced inter-regional traffic. This is, however, nuanced by our finding on the share of car owners within grid cells having no significant impact on air pollution change in spring 2020, but a strong positive effect in spring 2021: while inter-regional mobility may have influenced the differential changes in spring 2020 more pronouncedly compared to local and regional traffic, the uptick in spring 2021 is likely influenced by local and regional mobility changes as well. Our findings on significantly different air pollution changes between upper- and lower-level employees and manual workers lend additional support to the assumption that higher socio-economic status employees may have reduced their local mobility more during the pandemic's first spring, suggesting potential differential local mobility changes as well. Further research on disentangling the impacts of changes in local, regional and inter-regional traffic may provide insights into the roots of air pollution-related inequities, for which our results offer a solid ground. Investigation towards this direction should also take into consideration how certain travel behavioural changes or behavioural consistencies may relate to occupational and socio-economic constraints and individual choices, especially in light of more stable air pollution levels among lower socio-economic status groups. As in certain neighbourhoods in HMA lower socio-economic status population live closer to the transport infrastructure, changes in the traffic flow may impact their immediate air quality at home more intensely, despite not changing their travel behaviour.

4.4. Whose lives are being saved by air quality improvements?

Our study enters into dialogue with previous research estimating the number of lives potentially saved by reduced air pollution during the pandemic across the globe (Isaifan 2020, Schneider *et al* 2022, Venter *et al* 2021). Via showing how different socio-economic groups experienced air pollution changes during the pandemic at a fine spatial resolution, such estimates may be appended. The improvements in air quality are found to be unequally distributed in spring 2020, and are more pronounced for areas with population of higher socio-economic status, while the uptick in spring 2021 compared to 2020 is also found to be more pronounced in areas of higher socio-economic status in most cases. In contrast, areas with a population of lower socio-economic status are found to showcase more stable air pollution levels across the years. In other words, the impact of higher socio-economic status population may be more significant in shaping the trends of the air pollution landscape in HMA. Their residential areas' more significantly reduced air pollution during the pandemic in general, thus, may have contributed to local residents' health improvements more than to residents in lower socio-economic locations. Lives improved and/or saved during the pandemic due to improved air quality are therefore more likely to be of higher socio-economic status in HMA.

Although the COVID-19 pandemic was a special circumstance, conclusions for policy makers aiming to improve air quality in an equitable manner can be drawn from our study. The evidence on higher socio-economic status locations' more markedly reduced air pollution in spring 2020 and more reactive air pollution change in spring 2021 compared to lower socio-economic status locations' more stable air pollution levels entails that optimizing road traffic for air quality improvement may be most effective by targeting higher socio-economic status population. Combined with the share of car owner's positive association with air pollution change in spring 2021 underlines this: every meter taken by cars matters, and the most significant improvements may be achieved via incentivizing higher socio-economic status households to take less. Conversely, lower socio-economic status areas' air quality changes may be less responsive to such interventions. When designing policies aiming to reduce air pollution in an equitable manner in lower socio-economic status areas as well across the globe, further localised research is needed to better understand the dynamics of inter-regional, regional and local mobility in shaping air pollution, and how the disparate air pollution changes may be a result of inequalities embedded in different urban fabrics, besides being driven by constraints and opportunities arising from properties owned, occupational and tenure types, and income.

5. Conclusions

Our study reveals that socio-economic characteristics played an important role in shaping local air quality trajectories during the spring months of the COVID-19 pandemic in 2020 and 2021. In 2020, NO_2 levels decreased everywhere in the HMA, yet, the magnitude of the improvement was unevenly distributed. Areas with higher shares of upper-level employees and high-income households showed the most pronounced reductions in pollution. In contrast, areas with higher shares of low-income households, lower-level employees, manual workers and social housing renters saw less pronounced reductions. These results suggest that the air quality improvements observed in 2020 did not impact population groups uniformly.

By spring 2021, when air pollution trends generally began to shift upward again compared to 2020, but still below the pre-pandemic levels, the socio-economic characteristics' differential pattern also changed, although most socio-economic characteristics converged toward the pre-pandemic ΔNO_2. Characteristics often associated with higher socio-economic status were strongly associated with greater increases in NO_2 compared to 2020, but when the change is contrasted against 2019, most such characteristics still showed a negative trend, with the notable exceptions of car owners, associated with significantly less intense decreases, and homeowners showing no significant trends. When change is considered against 2020, social housing renters and low-income households show more negative trends, lower-level employees show more positive trends against a non-significant 2020 finding, and manual workers show no significant trends with a highly positive backdrop in 2020. When the change in 2021 is calculated using 2019 as the baseline, we find that areas with higher shares of social housing renters and manual workers still experienced a lower reduction in NO_2, although less markedly than in 2020. In the case of lower level employees the distance from 2019 became larger and significant by 2021, while for low-income households the differential change by 2021 became non-significant.

Examining the two spring periods together reveals a relatively consistent socio-economic stratification in air pollution change. Areas with higher shares of upper-level employees and high-income households show sustained air pollution reductions, while most socio-economic characteristics associated with lower socio-economic status show less intensive NO_2 changes. The shares of car owners falls in line with the latter trend, and the trend for low-income household is non-significant when both springs are jointly considered.

Overall, while air quality improved across the HMA during the first pandemic spring, the gains were distributed unequally. In most instances, the differences persisted, though less sharply, in 2021, indicating that the COVID-19 pandemic reflected and temporarily accentuated air pollution-related environmental inequalities. Considering the differences between our rather unique findings and those reported in other settings, this study highlights the need for locally grounded, context-specific research to inform the development of air pollution mitigation policies that are both effective and equitable over the long term.

Acknowledgments

We thank Lasse Johansson (Finnish Meteorological Institute) for providing us the ENFUSER dataset and answering our questions related to it. A preliminary version of this research, under an earlier title, was presented at the 16th European Sociological Association Conference, 2024, and the presentation's abstract appeared in the Abstract Book of the conference (ISBN: 978-2-9598317-0-6 | EAN: 9782959831706).

Conflict of interest

The authors declare no competing interests.

Data availability statement

The data cannot be made publicly available upon publication because they contain sensitive personal information. The data that support the findings of this study are available upon reasonable request from the authors.

Financial disclosure

This research was funded by the Finnish Strategic Research Council at the Academy of Finland (decision no. 365408, 332179, 352450, 352453)

Appendix A. Details of models for change in NO_2 values where treatment effect is considered in spring 2020

	Est.									S.E.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treated × road_pctg	-0.069^{***}	-0.077^{***}	-0.062^{***}	-0.073^{***}	-0.069^{***}	-0.065^{***}	-0.054^{***}	-0.066^{***}	-0.064^{***}	0.011	0.011	0.011	0.010	0.010	0.011	0.009	0.010	0.010
low_income_hh	−1.100+									0.596								
low_income_hh × treated	1.517^{**}									0.462								
high_income_hh		0.121									0.376							
high_income_hh × treated		-1.435^{***}									0.295							
lower_level_empl			0.364									0.544						
lower_level_empl × treated			1.345+									0.784						
upper_level_empl				1.510^{**}									0.505					
upper_level_empl × treated				-4.122^{***}									0.645					
manual_empl_share					-1.796^{**}									0.615				
manual_empl_share × treated					5.819^{***}									1.104				
soc_renters						−0.749+									0.401			
soc_renters × treated						0.793^{***}									0.213			
priv_renters							1.033^{*}									0.410		
priv_renters × treated							-0.937^{**}									0.298		
homeowners								-1.287^{*}									0.518	
homeowners × treated								−0.280									0.177	
carowner_hh									0.216									0.495
carowner_hh × treated									−0.173									0.386
Num.Obs.	38673	38673	38673	38673	38673	38673	38673	38673	38673									
R2	0.725	0.725	0.725	0.727	0.726	0.725	0.725	0.725	0.725									
R2 Adj.	0.690	0.691	0.690	0.692	0.692	0.691	0.690	0.690	0.690									
AIC	191620.6	191546.1	191647.2	191369.6	191443.8	191610.9	191618.8	191642.7	191658.5									
BIC	228483.8	228409.4	228510.4	228232.9	228307.1	228474.1	228482.1	228506.0	228521.8									
RMSE	2.58	2.58	2.58	2.57	2.57	2.58	2.58	2.58	2.58									
Std.Errors	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode									

$+ p < 0.1$, $^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$.

Appendix B. Details of models for change in NO_2 values where treatment effect is considered in spring 2021 (year-on-year)

	Est.									S.E.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treated × road_pctg	−0.019***	−0.018***	−0.024***	−0.022***	−0.024***	−0.023***	−0.021***	−0.019***	−0.010**	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
low_income_hh	−0.244									0.366								
low_income_hh × treated	−1.032***									0.240								
high_income_hh		−0.550*									0.222							
high_income_hh × treated		0.614***									0.160							
lower_level_empl			0.235									0.282						
lower_level_empl × treated			1.194**									0.402						
upper_level_empl				−0.593*									0.291					
upper_level_empl × treated				0.727*									0.336					
manual_empl_share					−0.618									0.413				
manual_empl_share × treated					−0.159									0.510				
soc_renters						−0.252									0.193			
soc_renters × treated						−0.383***									0.102			
priv_renters							0.175									0.209		
priv_renters × treated							−0.259*									0.118		
homeowners								−1.005***									0.275	
homeowners × treated								0.368***									0.099	
carowner_hh									−0.075									0.268
carowner_hh × treated									1.119***									0.177
Num.Obs.	51564	51564	51564	51564	51564	51564	51564	51564	51564									
R2	0.735	0.735	0.735	0.735	0.734	0.735	0.734	0.735	0.735									
R2 Adj.	0.710	0.710	0.710	0.710	0.710	0.710	0.710	0.710	0.711									
AIC	239923.0	239918.5	239936.2	239936.3	239948.2	239934.4	239945.8	239920.1	239870.7									
BIC	278033.6	278029.1	278046.8	278046.9	278058.8	278045.0	278056.4	278030.7	277981.3									
RMSE	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28									
Std.Errors	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode									

$+ p < 0.1$, $^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$.

Appendix C. Details of models for change in NO_2 values where treatment effect is considered in springs of 2020 and 2021

	Est.									S.E.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treated × road_pctg	-0.055^{***}	-0.060^{***}	-0.053^{***}	-0.060^{***}	-0.058^{***}	-0.054^{***}	-0.046^{***}	-0.053^{***}	-0.048^{***}	0.006	0.007	0.006	0.006	0.006	0.006	0.005	0.006	0.006
low_income_hh	−0.618									0.383								
low_income_hh × treated	0.490+									0.249								
high_income_hh		−0.052									0.232							
high_income_hh × treated		-0.638^{***}									0.166							
lower_level_empl			−0.201									0.340						
lower_level_empl × treated			1.518^{***}									0.452						
upper_level_empl				0.934^{**}									0.334					
upper_level_empl × treated				-2.369^{***}									0.362					
manual_empl_share					-1.738^{***}									0.495				
manual_empl_share × treated					3.592^{***}									0.560				
soc_renters						−0.379+									0.220			
soc_renters × treated						0.346^{**}									0.121			
priv_renters							0.740^{**}									0.240		
priv_renters × treated							-0.761^{***}									0.185		
homeowners								-0.947^{***}									0.268	
homeowners × treated								−0.003									0.094	
carowner_hh									−0.083									0.263
carowner_hh × treated									0.440^{*}									0.220
Num.Obs.	51564	51564	51564	51564	51564	51564	51564	51564	51564									
R2	0.736	0.736	0.736	0.737	0.737	0.736	0.736	0.736	0.736									
R2 Adj.	0.712	0.712	0.712	0.713	0.713	0.712	0.712	0.712	0.712									
AIC	239604.8	239568.3	239584.3	239426.7	239445.1	239595.0	239562.8	239604.2	239596.6									
BIC	277715.4	277678.9	277694.9	277537.3	277555.7	277705.6	277673.4	277714.8	277707.2									
RMSE	2.27	2.27	2.27	2.27	2.27	2.27	2.27	2.27	2.27									
Std.Errors	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode									

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix D. Details of models for change in NO_2 values where treatment effect is considered in spring 2021 (2019 baseline).

	Est.	S.E.																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treated × road_pctg	-0.111^{***}	-0.115^{***}	-0.109^{***}	-0.116^{***}	-0.115^{***}	-0.110^{***}	-0.099^{***}	-0.109^{***}	-0.098^{***}	0.010	0.010	0.010	0.010	0.010	0.010	0.009	0.010	0.009
low_income_hh	−0.191									0.500								
low_income_hh × treated	0.546									0.370								
high_income_hh		−0.649+									0.332							
high_income_hh × treated		-0.621^{*}									0.256							
lower_level_empl			0.469									0.490						
lower_level_empl × treated			2.039^{**}									0.707						
upper_level_empl				0.804									0.500					
upper_level_empl × treated				-2.656^{***}									0.552					
manual_empl_share					-1.063^{*}									0.511				
manual_empl_share × treated					4.352^{***}									0.848				
soc_renters						−0.423									0.336			
soc_renters × treated						0.468^{**}									0.179			
priv_renters							1.129^{**}									0.389		
priv_renters × treated							-1.142^{***}									0.276		
homeowners								-1.551^{***}									0.384	
homeowners × treated								0.025									0.136	
carowner_hh									−0.545									0.459
carowner_hh × treated									0.853^{**}									0.317
Num.Obs.	38673	38673	38673	38673	38673	38673	38673	38673	38673									
R2	0.669	0.669	0.669	0.670	0.670	0.669	0.670	0.669	0.669									
R2 Adj.	0.628	0.628	0.628	0.629	0.629	0.628	0.628	0.628	0.628									
AIC	193368.5	193347.6	193345.4	193256.8	193253.4	193357.0	193315.9	193359.9	193342.2									
BIC	230231.8	230210.9	230208.7	230120.1	230116.7	230220.3	230179.2	230223.2	230205.5									
RMSE	2.64	2.64	2.64	2.63	2.63	2.64	2.64	2.64	2.64									
Std.Errors	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode	by: postalcode									

$+ p < 0.1$, $^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$.

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