The spatial-temporal distribution of exposure to traffic-related PM emissions and the role of SAEVs: A case study of Vienna[⋆]

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Abstract

Traffic-related particle matter (PM) emissions are mostly driven by road transport. Traffic volume is determined by the time of the day, road networks, and route choices, and therefore can result in considerable variations in exposure levels. Using a micro-simulation MATSim model for the city of Vienna, we explore hourly spatial variations of PM emissions using calibrated mobility behavior, traffic flows, facility locations, and dispersion patterns. We show that PM exposures vary by location types, especially at home, workplaces, and educational institutions, at different times of the day. We also show that different socioeconomic groups, for example, women, single, urban, or those living near the city center, face higher than average exposure to (traffic-related) PM emissions. Finally, we explore the distributive effects of Shared, Autonomous, Electric Vehicles (SAEVs) in reducing emissions. We discuss how such a simulation framework can be utilized for developing targeted emissions-related policies.

Keywords: MATSim model, Vienna, traffic simulation, shared autonomous vehicles, emissions, socioeconomic impacts, inequality

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1. Introduction

Exposure to traffic-related emissions, especially particulate matter (PM), has been a major concern for many cities (Zuurbier et al., 2010). There is sufficient evidence that shows that extended exposure to PM has detrimental health effects including loss of life expectancy, and premature deaths (Lelieveld et al., 2020) with a high chance of causing asthma, lung diseases, and increasing risk of cancer (WHO, 2016).

In order to combat urban pollutants, several cities around the world have adopted strategies to reduce emissions in line with various climate targets and Sustainable Development Goals (SDGs). For example, SDG3 deals with "health and well-being" while SDG11 specifically focuses on "sustainable cities" with key goals like green transportation (SDG11.2), particulate matter reduction (SDG11.6), and inclusive adaptation and mitigation of climate change (SDG11B). These goals also align with "reducing inequalities" (SDG10) and "climate action" (SDG13).

In large cities in several high-income countries, these targets has also spurred innovations in low-emissions electric transportation. Recent advances in e-mobility also include shared autonomous electric vehicles (SAEVs), which are expected to see commercial use in the coming decades (Bauer et al., 2020; Rafael et al., 2020). Such technologies may have overall societal benefits, that could potentially reduce congestion and localized emissions especially PM (Kopelias et al., 2020). For example, the city of Vienna, that is also our case study region, has launched a "Smart city initiative" that aims to address several of the SDG goals by 2030 with a major focus on sustainable transportation.[1]

While considerable advancements have been made in understand the role of traffic and emissions, several gaps in the literature still persist. First there is little data on the spatial and temporal affects of existing traffic patterns on different socioeconomic groups. Within the transport literature, it is common to measure exposure to emissions at fixed locations on a road network. Other studies try and measure traffic-related emissions in specific facilities, mostly home or work locations. While such studies are highly relevant, they do not provide a complete picture for several reasons. For example, an individual might be living in a high-income neighborhood with low exposure to emissions, but might spend the productive working hours in a high emissions neighborhood.

[1] https://www.wien.gv.at/english/politics/international/sdgs.html

Second, road traffic is not homogeneously distributed during the day. There are peak hours in the morning when schools and workplaces open up, and in the evenings when people return home or swap to errands, leisure and other activities. Hence it matters for the overall exposure for a person, where he/she spends these peak hours. Furthermore, several factors can determine exposure to emissions. These include location of the facility in relation to nearest roads, traffic on those roads, dispersion factor of the emissions, time of the day, and protection level within those facilities to road emissions. Third, the socioeconomic status of the population also varies considerably over space and thus different demographic groups like females, working age populations, households with kids, urban dwellers, etc., might have different level of exposure.

In this paper we construct a MATSim model for the city of Vienna, to replicate existing mobility patterns using a mix of mobility survey data, demographic data, and the spatial layout of the city. The baseline model is layered with an emissions module which accurately determines the emissions from car traffic based on speed, acceleration levels, and the extent of the use of the car using benchmark data. From this baseline model, we determine particulate matter (PM) for each road link at an hourly interval. Therefore for each agent in the model, we can very accurately determine the exposure level to PM for both locations or facilities and transport modes. Additionally the socioeconomic data of the population allows us to explore differential exposure intensities by different socioeconomic groups. Within the model, we introduce 2500 SAEVs as an extension of the public transport (PT) infrastructure (the best-case zero cost scenario) and changes in emissions exposures are tracked. While it is well established in literature that SAEVs reduce overall emissions like CO2, that still can cause some PM emissions. As a result the net gains from new technologies might not be evenly distributed across different socioeconomic groups.

Results show that exposure to emissions is the highest at work places, homes, and schools during the peak travel time and working hours. Outside these hours, other activities like errands and leisure activities see an increase in exposure levels. We also show that car owners that cause the PM emissions are also not the most exposed. Additionally different groups have different exposure levels at different facilities. For example women see the highest exposure at work locations, while the younger population and those living near the city center see elevated exposure at educational institutions. The introduction of SAEVs alleviates exposure across the board but not everyone sees an equal reduction in emissions. Those living near the city center, car owners, and high-income groups benefit the most from new technologies. The framework presented in this paper can be utilized for a host of nuanced policies targeting specific exposure levels.

The remaining paper is organized as follows. Section 2 provides a review of empirical literature dealing with measuring exposure in cities, and recent advances in models that simulate these exposures. Section 3 describes the model and section 4 presents the simulation results. Section 5 concludes and discusses potentials for future work.

2. Literature review

The first part of this section discusses evidence from empirical literature while the second part presents various simulation studies that explore exposure to emissions.

2.1. Empirical evidence

In recent years, empirical work on measuring emissions and their impact on the cities has gained significant traction. With the availability of high-frequency satellite data, and high quality censors for on the ground readings, papers have started exploring more nuanced evidence of road-level emissions.

For example, Pratt et al. (2014) uses satellite imagery to show exposure for the city of Minneapolis in the USA at a finer neighborhood level. Using micro data from the city of London from 2003–2010, Fecht et al. (2016) show that there emissions tend to be higher near the city center and tend to stay stable across the time periods. Barnes et al. (2019) use regional census and emissions data from the UK and Wales and show that there is high inequality in exposure where the poorer household face higher health-related risks while causing the least amount of emissions.

Khomenko et al. (2020) do a detailed analysis for the city of Vienna using official zoning data and socioeconomic data to assess the impact of public transport on emissions other mortality rates. They show that in most of the sub-district of Vienna, the PM concentration levels exceed the required WHO levels significantly. They also highlight that populations in car-heavy districts and around the inner city face the highest traffic-related environmental burden. As a result around 8% of total premature deaths can be attributed to traffic-related emissions. Using official socioeconomic status (SES) layers, they show that low SES groups have a higher exposure with little deviation, while the highest SES class, has a comparable exposure level to the lowest SES but see a much large deviation.

Wang et al. (2020) use monitoring sites to measure PM exposure on specific roads in the city of Beijing, China. They show how emission concentrations vary by time of the day along selected locations. Kumar et al. (2021) explore the exposure to emissions especially PM while driving in different scenarios. The measure PM concentration during peak and off-peak hours, and also track whether windows were open or the air conditioner was in use. Using a sample from 10 cities, they show that during peak hours, indoor air of cars can have five to ten times more PM as compared to off-peak hours. Chen et al. (2021) conduct a global analysis by collecting data from over 300 cities in 18 countries and show that a marginal increase in exposure to carbon monoxide concentrations. These are also highly correlated with an increase in mortality rates.

2.2. Simulations

Several simulation and modeling studies connect traffic, especially congestion to emissions and health outcomes. These models are relatively new, and focus on selected locations which have availability of transport data that allows for model calibration. Thus, they tend to mostly focus on cities or regions in high-income countries.

Levy et al. (2010) model 83 urban regions in the USA and show that traffic congestion can result in a high exposure to PM emissions. Additionally in the absence of significant infrastructure investments, and with rising populations, the health impacts are likely to worsen over time.

Zhang & Batterman (2013) highlight that populations living near roads show poorer health outcomes as compared to those father away. Using simulation models, they approximate hourly exposure to emissions and highlight that health-related risks tend to multiple for population living near major roads. And this risk is exacerbated during congestion. This study also highlights the need for better data for a more accurate analysis at finer time and spatial resolutions and for different socioeconomic groups. Tayarani & Rowangould (2020) is one of the first modeling studies to explore spatial exposure to emissions by facility type for the city of Atlanta in the USA. They also split the day into different time zones to show spatial-temporal variations. They highlight that most of the exposure to emissions comes from home and work locations especially those in the city center and highlight the need to better understand these spatial pattern for targeted policy responses. This paper is also the closest to our study design. Tikoudis et al. (2021) conduct a large scale simulation exercise across more than 240 cities to assess the ride sharing on emissions. They show that if ride sharing services gain traction with the public and policy makers, they can reduce emissions by over 6% in the coming decades.

Kopelias et al. (2020) conduct a comprehensive review of literature the connects the roll-out of SAEVs on the environment. They summarize over 20 studies which show that there are SAEVs can reduce emissions between 7 and 90% depending on the various conditions, and technological advancements.

2.3. Gaps in literature

The above literature, while being highly relevant, tend to summarize results at a daily or even at an annual level. Most of the studies also acknowledge the role of the timing and location of exposure but usually suffer from lack of data to generate meaningful results. Furthermore the distribution of emissions is not homogeneous. The road network and traffic intensity at different times of the day implies huge variations. Additionally, the spatial distribution of socioeconomic status (SES) also plays a role in who is exposed. It is well-established in literature that location decisions for both homes and work are endogenous and depend on various factors like education, income level, distance and travel time to work, and other factors like being single or having kids (Moriarty, 1974; Sermons & Koppelman, 2001). Significant research exists on understanding the role of emission on groups that live in low-income housings near major roads. But a broad spectrum of exposure by different socioeconomic classes and where it happens is still missing in literature.

In this paper, we aim to address the above two points and then link the change in exposure variations through the introduction of SAEVs.

3. The MATSim model

3.1. The core model

The model is programmed in MATSim to simulate traffic flow for the city of Vienna up to a radius of 30 kilometer from the city center. The simulated area covers approximately 4,100 square kilometers and contains a population of around 2.3 million. Out of these around 1.7 million inhabitants reside inside the official city boundaries (Eurostat, 2011). The road network data is extracted from OpenStreetMaps (OSM). Similarly, data on potential activity locations, referred to as facilities in the paper, are also derived from OSM. The facilities are categorized in six types - Home, Work, Education, Shopping, Leisure, and Errands. This data is combined with official population density rasters from the Eurostat (Eurostat, 2019) and employment density indicators from the Chamber of Commerce in Austria Wirtschaftskammer Österreichs 2019. Figure 3.1 shows a map of the simulated zone and the location patterns of the facilities:

Figure 3.1: MATSim simulation area

Note: Facilities are marked as colored dots. Background map: ©OpenStreetMap.

3.2. SAEVs

SAEVs are introduced in the model as Demand-Responsive Transport (*DRT*) (Maciejewski & Nagel, 2013). SAEVs are essentially cars, that drive around like taxis and respond to call from users. SAEVs are also shared allowing up to four passengers that is also plays a major role in SAEV routes. The DRT module of MATSim allows for relocation and rerouting of vehicles based on the demand patterns.

For this paper, 2500 SAEVs are introduced in the baseline model at zero cost. The value of 2500 closely represents the existing Taxi fleet in the city with the assumption that a similar magnitude of SAEVs will be permitted to operate in the future as well. SAEVs are assumed to be an extension of the public transport (PT), and thus represent the "best-case" scenario. Therefore other smaller fleet sizes and higher priced SAEV trips will yield lower outcomes (Peer et al., 2022).

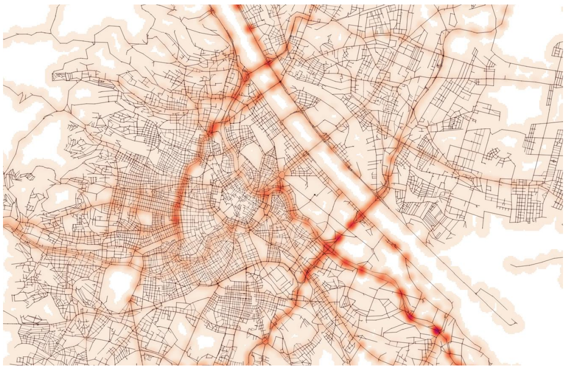
3.3. The emissions module

Emissions in the model come only from cars. The model also captures various types of emissions, of which we only focus on Particular Matter (PM) in this paper. This is to avoid adding additional layers of complexity. Various other traffic-related emissions are correlated with PM as well. The model runs various iterations to derive the optimal routes for all agents. In the last iteration, the Emissions Module (Hülsmann et al., 2011; Kickhöfer et al., 2013) is enabled. The Module distinguishes between cold and warm emissions. Cold emissions take place during the warm-up of the car engine, and are derived from distance previously traveled, parking time, and vehicle type. Warm emissions occur during the driving phase and factor in driving speed, acceleration, stop duration, and vehicle type (André & Rapone, 2009; Weilenmann et al., 2009). The vehicle characteristics are derived from the Handbook Emission Factors for Road Transport version 4.1 (HBEFA 4.1) (Notter et al., 2019)), a proprietary database that forms the benchmark for transport-specific emissions in several European countries. Since the emissions are defined at the car level, they can be assigned very accurately to specific road links, agents, trips, and locations. In order to condense the data generated from the simulations the data is condensed to hourly intervals.

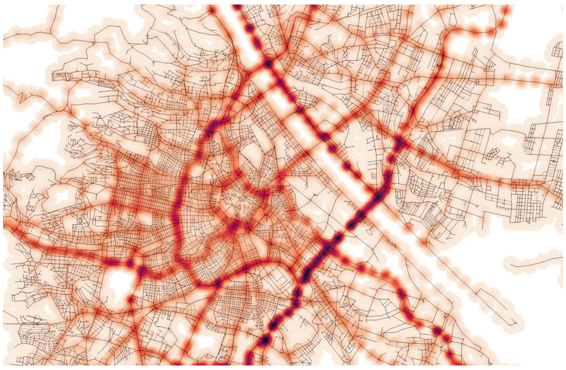
3.3.1. Calculating exposure

The model stores emissions information at the car and the road link level. Since facility locations are at different distances from different road types, and surrounded by different road densities, their exposure to emissions also varies over the course of the day. In line with transport literature, we assume that emissions disperse strongly in the 200-250 meter range and decay exponentially beyond this range (Fecht et al., 2016; Batterman et al., 2014; Li & Managi, 2021). Therefore, for each hour, we calculate diffusion rasters of PM emissions from road level emissions. Figure 3.2 showcases these rasters for selected hours.

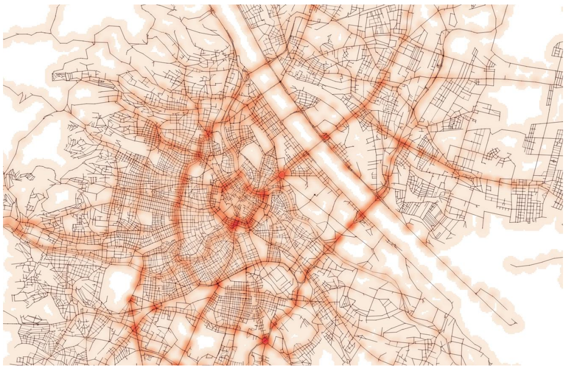
Figure 3.2: Diffusion of PM emissions at different hourly intervals



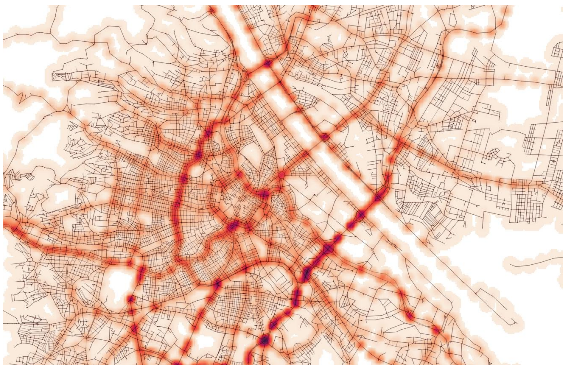
(a) 0500 - 0600



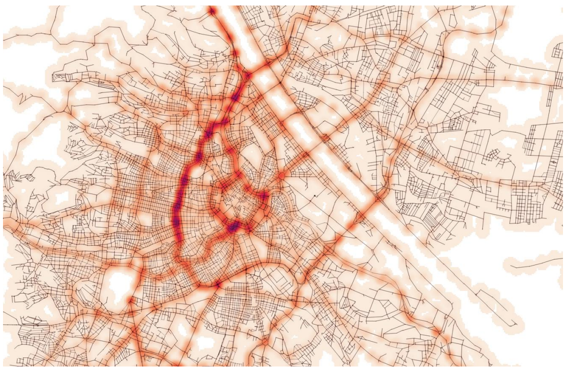
(b) 0700 - 0800



(c) 1100 - 1200



(d) 1500 - 1600



(e) 1900 - 2000

(f) 2200 - 2300

Note: Diffusion of emissions is calculated in QGIS using a normal decay function.

In the next step, the values of the raster grids are extracted for each facility and road link. This ensures that the diffusion of emissions are also correctly captured for travel modes. Otherwise individual road level link emissions are a very small fraction of overall dispersed emissions. Figure 3.3 shows how diffusion levels can vary for various location types. As shown in the figure, locations near several roads and intersections have a much higher exposure.

Figure 3.3: Facilities exposure near the Vienna city center

Note: Yellow dots represent home locations, while blue dots show work locations.

The individual level data contains detailed information for each trip. Trips are split into legs which include starting and ending times, locations, and transport modes used. This information is converted into hourly blocks for both facilities and transport modes. For each mode and location type, the share of time spent for each hourly interval is extracted.

The hourly exposure is merged with the extracted raster data shown in Figure 3.3. From these two databases, the hourly exposure for each agent is calculated as follows:

$$Exp_{it} = \sum_{m} \beta_m \gamma_{im} m_{it} + \sum_{k} \beta_k \gamma_{ik} k_{it} \tag{1}$$

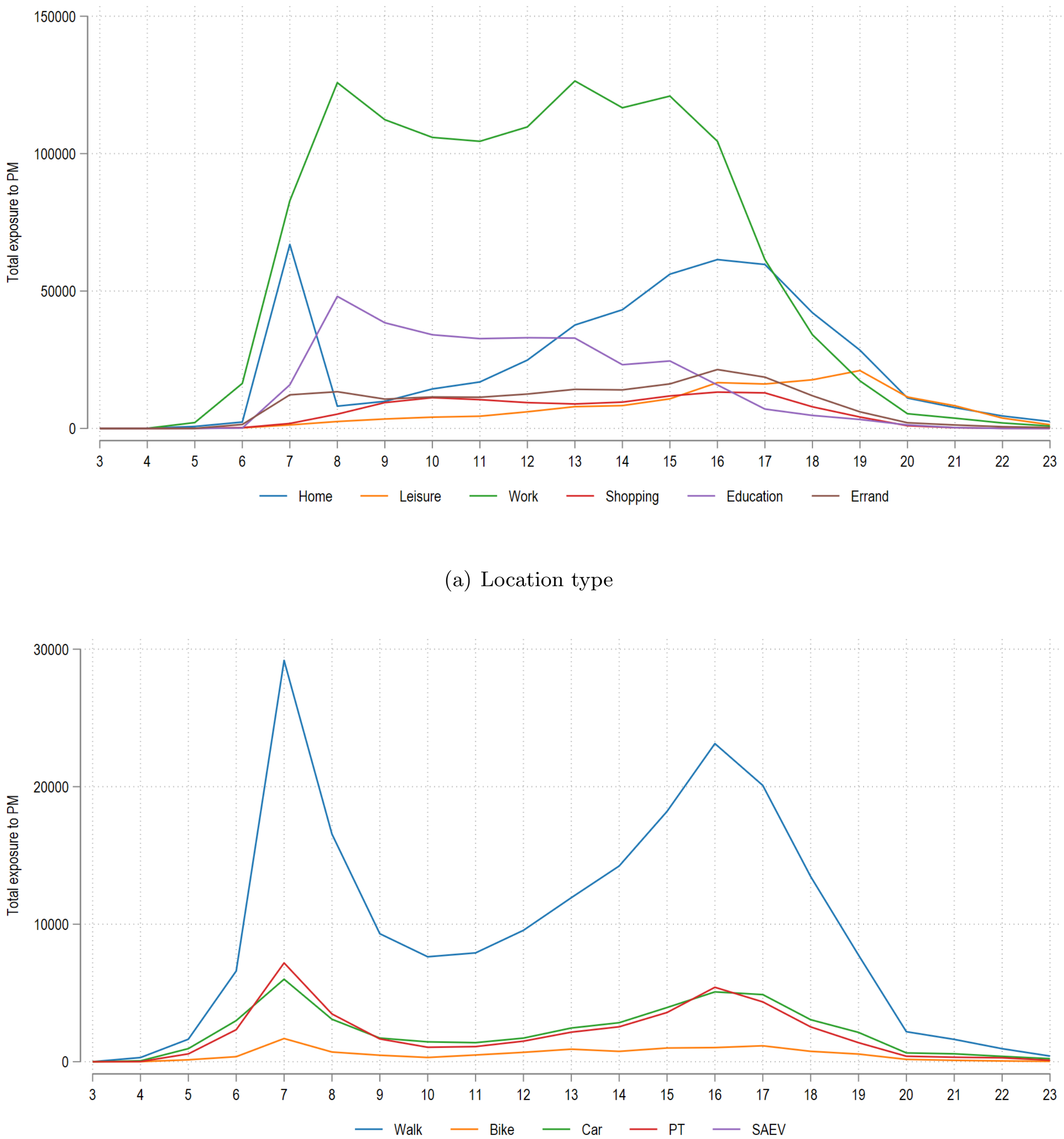
where $t = \{0, 1, 2, \ldots, 23\}$ is the hourly time interval, m is the transport mode where m=walk, bike, car, PT, SAEV. The parameter β_m is the dampening factor of each mode. This factor tells the reduction in emissions as a result of using a specific model. For example, walking or biking will cause a full exposure to emissions such that $\beta_{walk} = \beta_{bike} = 1$, while cars and PT reduce emissions by half $\beta_{car} = \beta_{PT} = \beta_{SAEV} = 0.5$ (EPA, 2011; Matz et al., 2018; Rafael et al., 2020; Tikoudis et al., 2021). The parameter γ_m is the share of the hour spent in that particular transport more. The second half of equation 1 gives us the exposure at facility k where k={home, leisure, work, shopping, education, errand}. The dampening factor for each facility is set at a constant $\alpha_k = 0.5$, which means that the exposure to emissions is halved within each location type. While this can be varied by building and material type, we assume this to be constant since Vienna has properly followed building codes and standards, including those dealing with ventilation. Moreover, we do not have data on the building type the agents spend time in. Similarly γ_k is the share of hour spent at a facility.

4. Results

Figure 4.1 shows the distribution of cumulative hourly exposure by facility types and transport modes. In Figure 4.1a, we can observe that emissions start rising after 0600 with the highest exposure at home and work places. Workplace exposure stays constant till 1700 before declining. This reduction in traded-off with an increase in home, leisure, and errands related emissions. Exposure at schools is also significantly higher around 08:00 and slowly declines till 13:00 before dropping further.

Similarly in Figure 4.1b, we can track the transport mode related emissions in the baseline scenario. As expected, the highest cumulative exposure to emissions comes from walking. Cars and PT have the second highest exposure level simply because they have a larger volume share in total travel time. Bikes have the lowest share of cumulative exposure as they tend to avoid major roads, especially in Vienna, which has access to several green spaces with dedicated bike paths

Figure 4.1: Exposure by activity

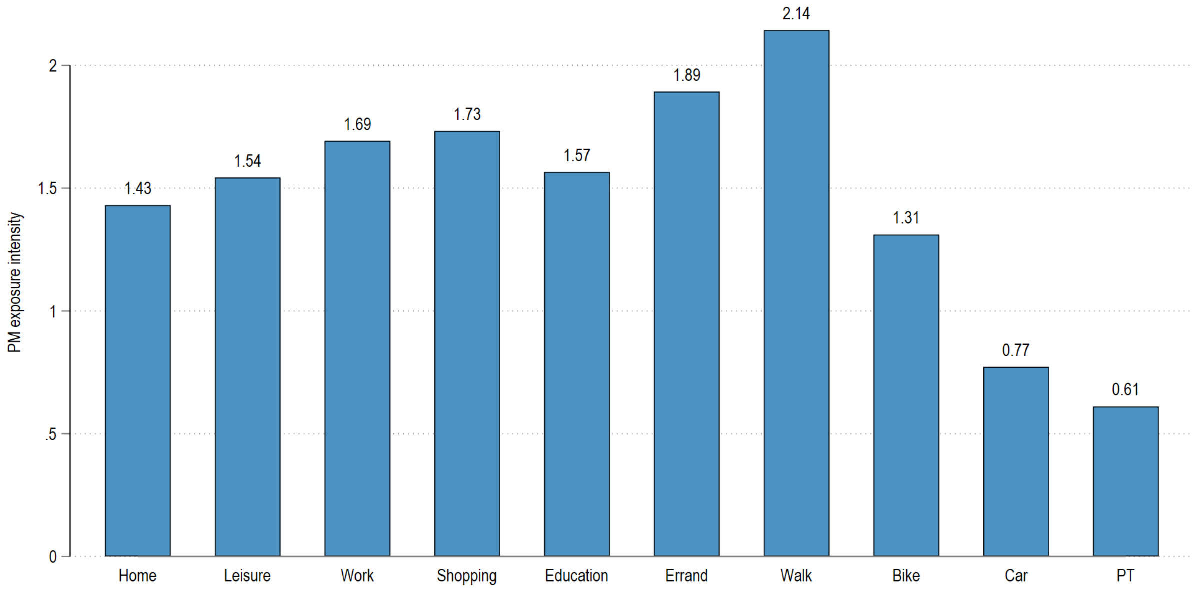


(a) Location type

(b) Transport mode

Since travel times and time spent in different locations vary, it is important to normalize the comparisons. This is done by comparing the exposure intensity, i.e. the average exposure per hour per activity type. This is summarized in Figure 4.2.

Figure 4.2: Exposure intensity by activity type



The PM exposure intensity is the highest for walking, followed by errands and shopping. This is due to the fact that most of these activities take place in time slots where emissions are peaking. Therefore, even though the overall time spent is a small fraction of all activities, they have a higher impact. The activities where a large share of the time is spent, like home, workplaces, educational institutions, and leisure activities, still see high intensity levels. In contrast, cars, which cause the PM emissions, themselves have very low intensities. This also underscores the fact that while road-level emissions are hazardous for human health, the exposure is mostly in locations that are affected by PM emissions dispersing from road traffic.

Figure 4.3 shows the difference in the emissions caused by agents versus how much of the emissions they are exposed to for all activities. First, there is a large set of agents that do not themselves cause any emissions but their exposure to PM is very high. These are represented by the thick vertical column at zero on the x-axis. These agents are dealing with a pure negative externality caused by other agents. Second, we can see that emissions caused by the agents are a small fraction of exposure of the agents. This can be observed by the difference in magnitude of the axes values. The y-axis is ten times the magnitude of the x-axis. This is not surprising since traveling, especially by cars, is a small fraction of the daily activity. This is especially true for the city of Vienna which has a very good road and PT infrastructure. As a result, travel times are usually less than an hour across the city.

Figure 4.3: Emissions versus exposure

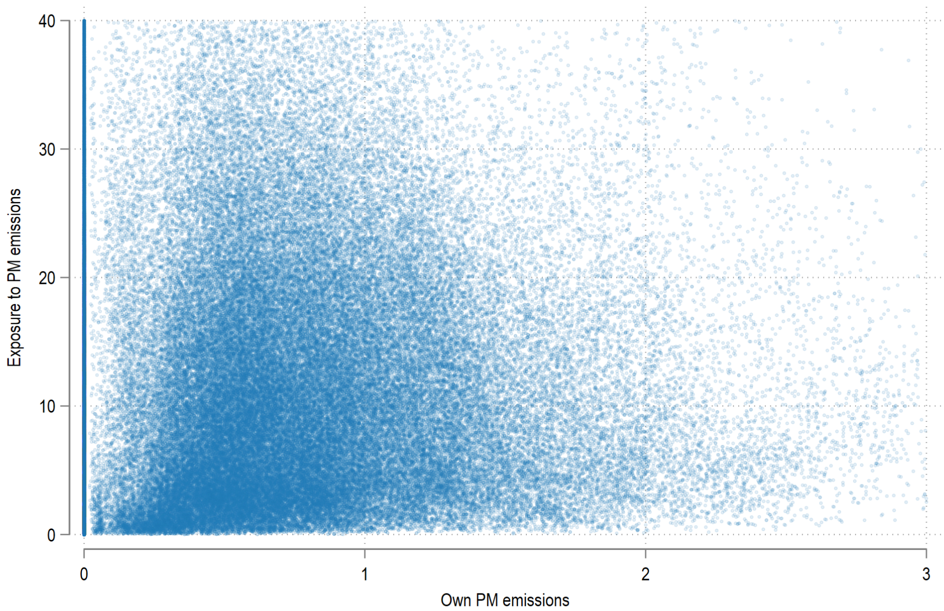
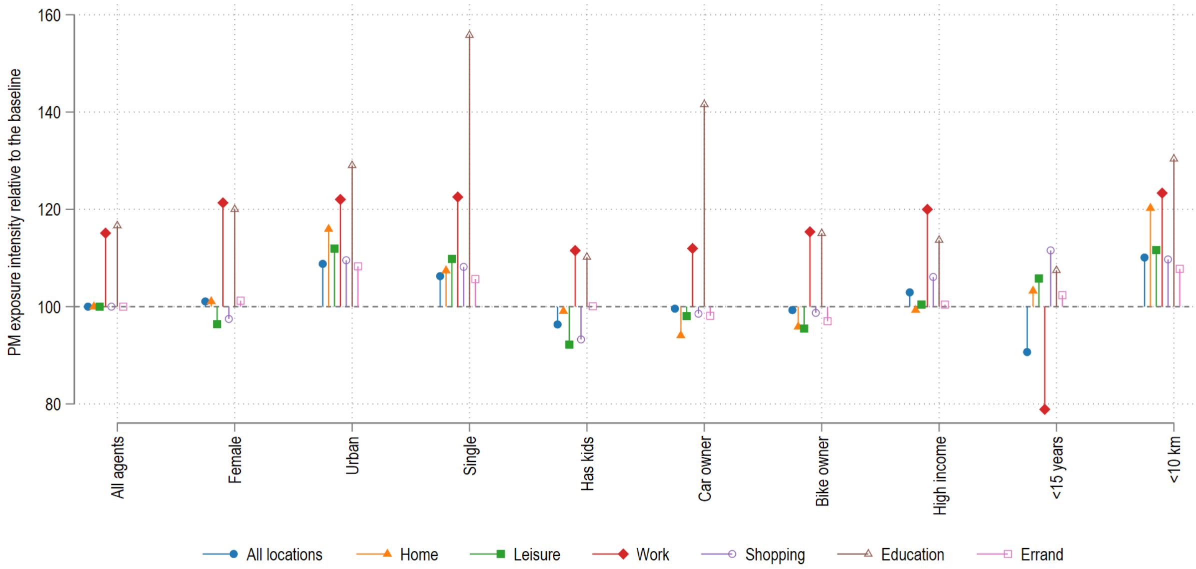


Figure 4.4 shows the variation in exposure by different socioeconomic groups and at different facility locations. The overall exposure for all agents is used as the benchmark to compare all the other groups. This is shown as the blue dot in the left most category that is indexed to 100. If the average for a group is higher than the baseline value, then it implies that the reverse category has the opposite sign to allow us to arrive at the mean value of a 100. For example, we can see that females, have a 20% higher exposure at work compared to the global average implying that males have a lower than average exposure.

The figure shows interested patterns. For all agents, Work and education location have a higher than average exposure. This is not surprising since the time spent at these locations also results in high exposure to PM. These exposures are also not evenly distributed across various socioeconomic groups. For example, overlapping groups like urban and singles, and those living within ten

Figure 4.4: Exposure intensity by socioeconomic groups



kilometers of the city center have much higher exposures as compared to other groups. Agents with kids and car owners, two categories that also overlap, see much lower exposures as compared to other groups. Similarly high income groups, see very little exposures at home but face fairly high emissions at their work place. Kids under the age of 15 see high exposures at educational institutions, home, and during leisure activities.

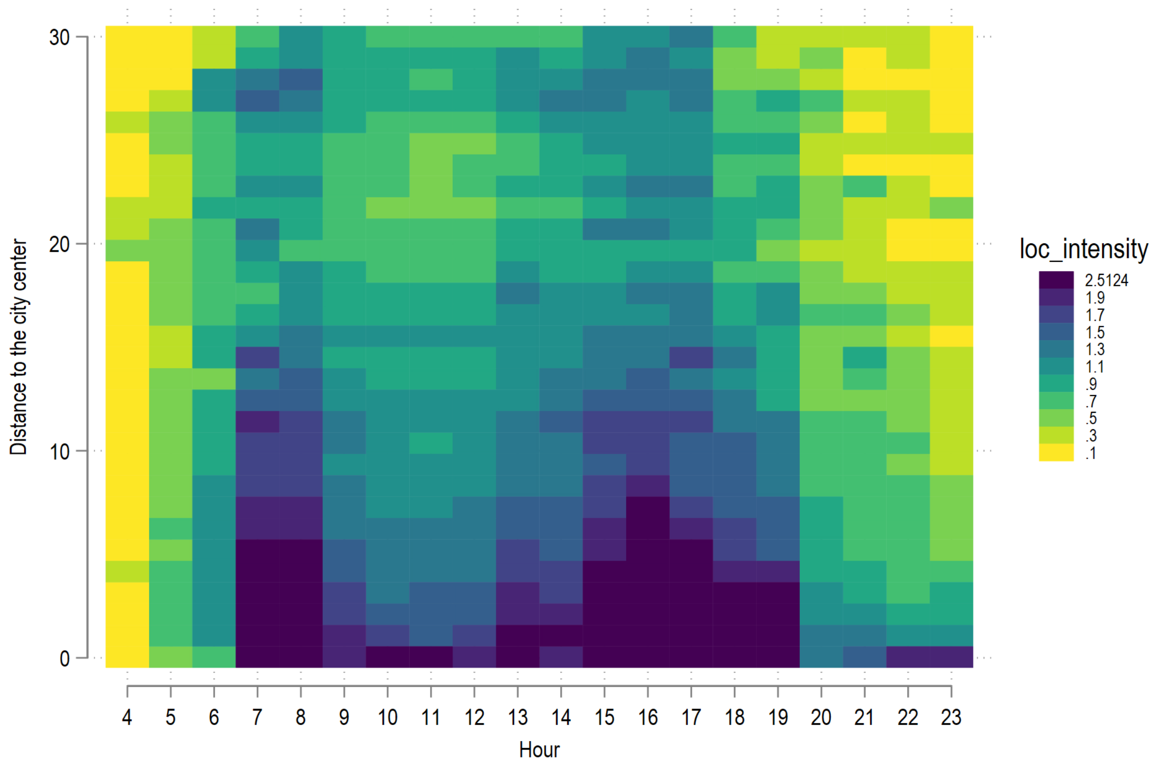
Figure 4.5 compares the emissions intensity at different hours to the distance to the city center.

Vienna has a circular layout, with two ring roads surrounding the inner city, that see major traffic volumes. Agents living within the 10 kilometer threshold since elevated exposure intensity that remains high between 07:00 and 19:00. This is a fairly long exposure time especially for the innermost districts that have a mix of income residents and workplaces. We can also observe that between 0700 and 1900 exposures stay high even for locations farther away from the city center.

4.1. SAEVs

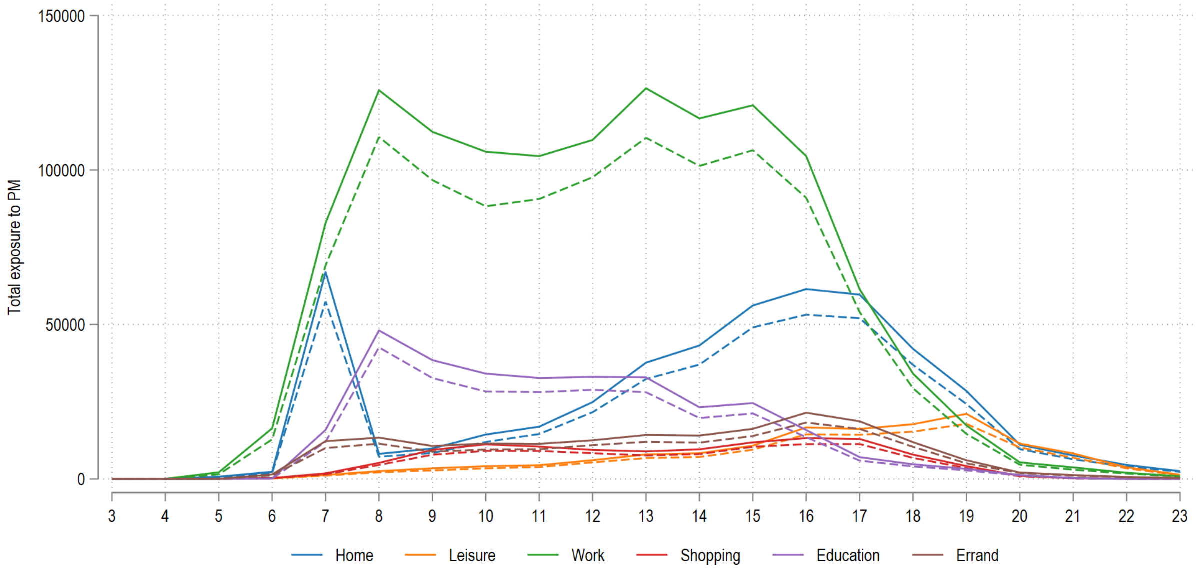
Several papers shows that SAEVs, on average reduce emissions (Peer et al., 2022). In this section we will explore how the reduction in emissions varies over time and by different socioeconomic status. Figure 4.6 shows average reductions in emissions by location type and transport mode at

Figure 4.5: Exposure intensity by distance to the city center

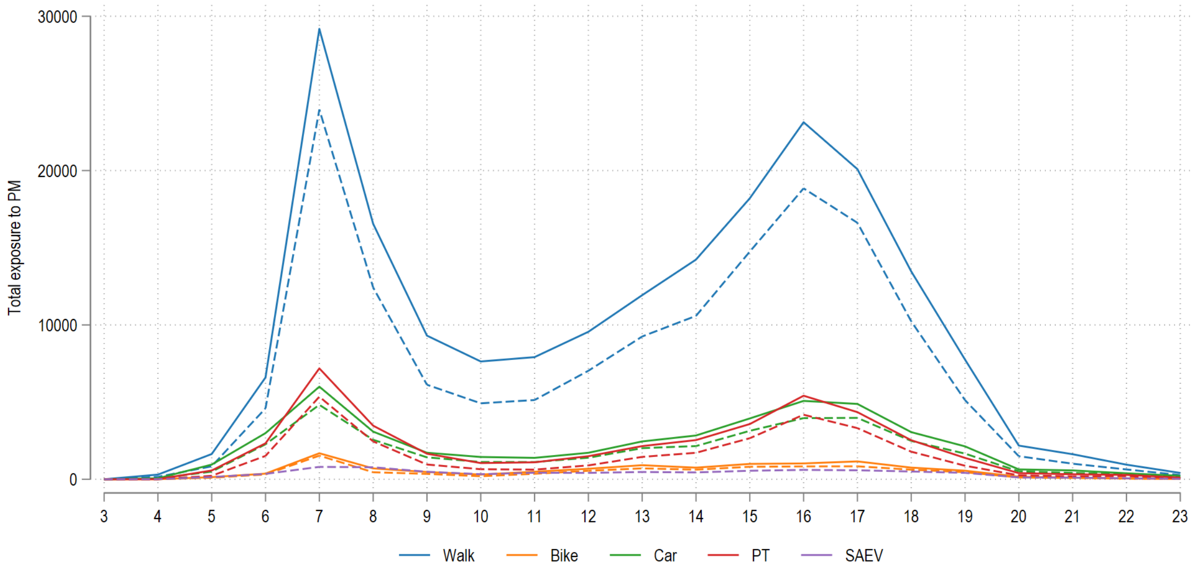


different times of the day.

Figure 4.6: Exposure by activity



(a) Location type



(b) Transport mode

In both the figures we can observe an overall reduction. Since the SAEVs are randomly distribution across the city and across time, they reduce overall emissions roughly equally across all the categories. Regardless, during the peak travel times between 0600 and 1700, the reductions in overall emissions are substantive.

Since emissions are endogenous to the system, Figure 4.7 shows the distributional changes across the agents both in terms of causing emissions and reduction in exposure to cumulative emissions. While we can observe the clustering in the negative third quadrant implying an overall decline in emissions caused and exposure levels, some other interest patterns can also be observed. For example, some agents also increase emissions. This is driven by the fact that SAEVs reduce car usage for some car owners and hence free up road space. For those agents who have a high value of time and own a car, are induced to drive more. Furthermore while these agents also show a reduction in direct emission exposure (second quadrant), other segments of the population see an increase in exposure (forth quadrant). This group is the most adversely impacted since it reduces the emissions that this group causes iteself. Thus introducing SAEVs on the road does not guarantee and overall reduction for all agent categories and distributional changes can be significant.

Figure 4.7: Change in emissions and PM exposure

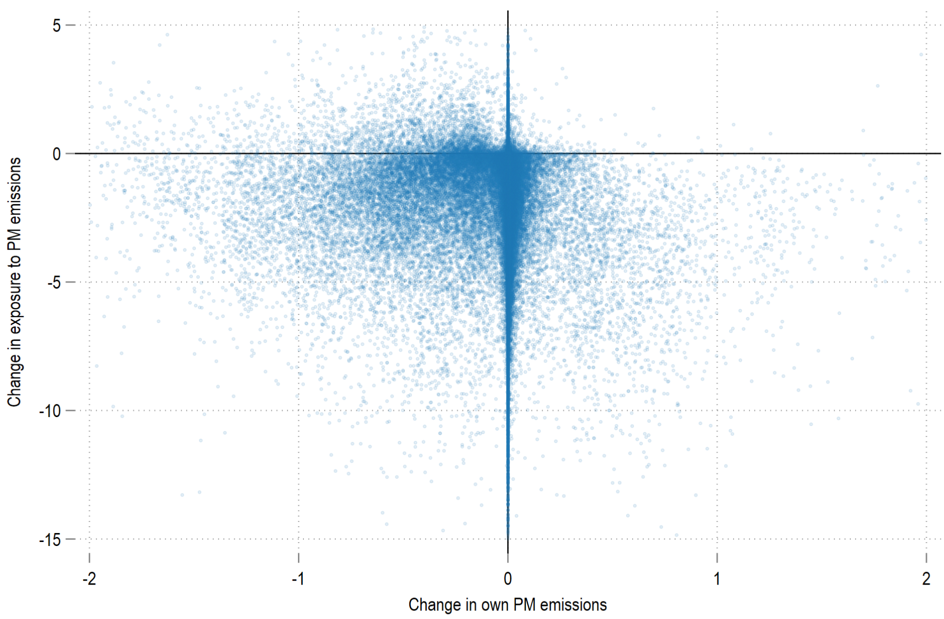
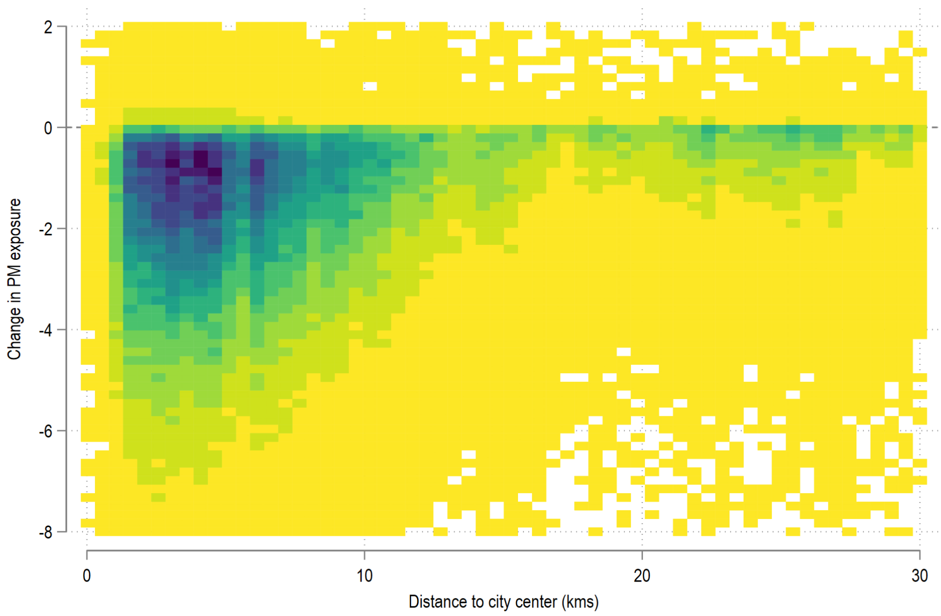


Figure 4.8 shows how exposure to cumulative PM emissions changes with the introduction of

SAEVs relative to city center. Locations closest to the city center, that are also the most polluted, see the highest decline. Additionally the locations closer to the outer ring roads, that lie between the 20-30 km range, also see considerable reduction in PM exposure.

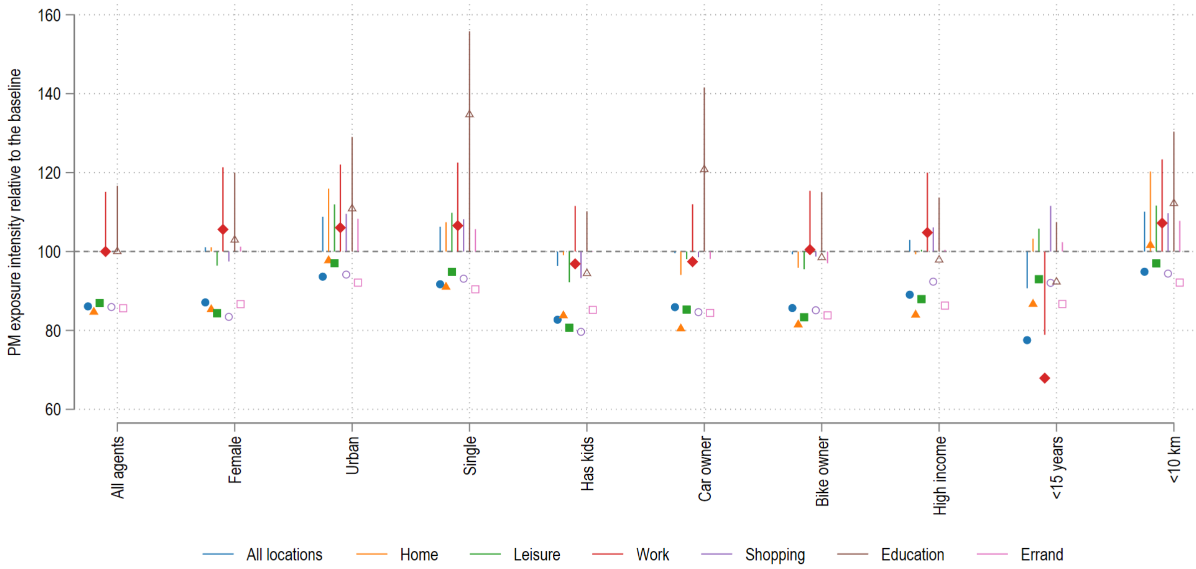
Figure 4.8: Exposure intensity by distance to the city center



Finally, Figure 4.9 summarizes how the emissions develop relative to the benchmark 100 for the all agents for allocations in the baseline scenario. The lines represent the extent of change in the baseline and are the same height as shown in Figure 4.4. The markers however show the values in the SAEV simulation.

The figure shows an overall decline in exposure across the board. But we can also observe that the exposure value and the level of reduction varies significantly. The urban and city center population see a decline but their values are still above the baseline average for workplace and educational institutions. This is also true for females, singles, and high income groups, and surprisingly car owners see considerable reduction in emissions at their workplace. Kids under the age of 15 see the highest decline in exposure. The remaining values for emission exposure at other locations relatively equalize in the SAEV scenario to show much less variation.

Figure 4.9: Changes in emissions by different socioeconomic groups



5. Conclusions and directions for future research

Rising urban emissions, especially particulate matter (PM), mostly step from road traffic especially cars. They are also a major cause of concern in cities, especially given their detrimental health impacts. Emissions in an urban setting are driven by several factors. This includes road network configuration, and choice of traffic routes at different times of the day. The combination of these imply that emissions are not homogeneously distributed. There are significant variations by the time of the day that also affect different location types like homes, work places, and educational institutions. Additionally, the population exposed can also vary significantly.

In this model, we use a micro-simulation MATSIM model for the city of Vienna to explore hourly spatial variations for PM exposure. This information is extracted using a combination of spatial road networks, geo-locations of different facility types, calibrated mobility behavior, and dispersion patterns of PM emissions. We show that exposure varies by location types, especially home, work, and education, and by different times of the day. We also show that different socioeconomic groups, like women, single, urban, or those living near the city center, face higher-than-average exposure levels.

The results presented in this paper highlight how calibrated mobility simulations can provide accurate assessment of emissions and exposure patterns. More important, they can help identify how different groups are exposed, at different times, and at different locations. Such a tool can have important implications for targeted traffic-related policies. For example, school locations with above average exposures can have nearby traffic reduced at certain times of the day. Neighborhoods with high emission levels can have restrictions put into place on traffic volumes. The city center can have a congestion tax like structure or limit movement in peak hours. Other policies can target investments in public transport infrastructure, distribution of electric vehicles, especially SAEVs in car-heavy zones.

In order to better improve the model results and understand socioeconomic conditions, more accurate socioeconomic layers can be added to the city, or more frequent travel diaries and mobility patterns can be collected for representative samples of groups at regular intervals. These mechanisms also allow for frequent updating of the model to allow for a more accurate calibration, especially with changes to road and PT infrastructure.

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