Assessing the impact of loading-unloading zones in emerging markets: Evidence from Mexico

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Abstract

We investigate the impact of dedicated loading-unloading zones (LUZs) in emerging markets, focusing on their effects on air quality and noise pollution. We conduct a field experiment in downtown area of Zapopan, Mexico. We use a quasi-experimental difference-in-difference approach to analyze changes in air quality and noise pollution before and after implementing the dedicated LUZs. The results indicate a significant reduction of up to 3.55% in CO_2 levels in the mornings and a 14% decrease in noise following the establishment of LUZs. Moreover, insights into the composition of companies involved in last-mile distribution reveals a predominant reliance on micro and small businesses, often utilizing personal vehicles for cargo transport, with a significant portion of freight vehicles being over a decade old. We contribute to the existing literature by providing evidence of the impact of LUZs on mitigating negative externalities associated with last-mile operations, particularly in a developing city.

Keywords Field experiment, loading-unloading zones, last-mile logistics, emerging markets

Paper type Research paper

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1. Introduction

Last-mile logistics in developing cities are hindered by a lack of parking space for freight vehicles, reducing the efficiency and effectiveness of distribution. When drivers do not find a parking space close to their destinations and do not want to miss their delivery, they tend to cruise around the block looking for a parking spot (Dalla Chiara and Goodchild, 2020; Kim et al., 2021, Shoup, 2006). This causes a greater total distance and leads to additional fuel consumption, thereby increasing costs and carbon emissions. Most freight vehicles in emerging markets are powered by fossil fuels, which emit greenhouse gases such as carbon monoxide (CO) and carbon dioxide (CO_2). Also, diesel-powered freight vehicles are significant sources of particulate matter 2.5 (PM2.5) and particulate matter 10 (PM10). High concentrations of these pollutants in urban areas degrades air quality, causing respiratory issues and other health problems among residents.

Another observed practice from freight drivers to reduce travel time is double parking (i.e. illegally parking next to another vehicle that is properly parked in a stall or on the street). Double parking blocks streets and contributes to traffic congestion and noise pollution, among other externalities (Dalla Chiara et al., 2021; Simoni & Claudel, 2018; Jaller et al., 2013). Noise pollution, frequently caused by frustrated drivers stuck in traffic, can cause stress, sleep disturbances, and cognitive impairment. It can also cause hearing loss and impact well-being (Singh et al., 2018). Consequently, the absence of parking space for freight vehicles implies logistics inefficiencies for companies with negative environmental and societal impact.

These issues currently affect millions worldwide and may affect many more as transportation activities are projected to grow (International Transport Forum, 2017b). According to the United Nations, approximately 4.4 billion people live in cities, or 56% of the world's population. By 2050, nearly 7 out of 10 people will live in cities, with the urban population expected to more than double from its current level. The situation is even more challenging in emerging markets, where urbanization is accompanied by market fragmentation. In Mexico City, for example, micro and small retailers (e.g., nanostores (Fransoo et al., 2017)) dominate the grocery retail landscape (Mora-Quiñones et al., 2021). Due to financial and space constraints, nanostores depend on frequent visits from suppliers to replenish their shelves (Escamilla et al., 2021; Boulaksil et al.,2019; Fransoo et al., 2017). This phenomenon implies an increase in last-mile distribution activities across cities, underscoring the necessity for feasible solutions to alleviate these adverse effects on citizens.

Loading-unloading zones (LUZs) have emerged as increasingly deployed interventions to improve last-mile logistics performance (Alho et al., 2022; Wilson et al., 2022; Fransoo et al., 2020). These areas are also commonly referred to as loading-unloading areas or loading-unloading bays. LUZs are urban parking spaces where vehicles can temporarily park to load or unload goods. These zones are typically delineated in the pavement, sometimes with vertical signage indicating their intended use. Most of the extent literature studying LUZs is prescriptive and model-based, either deploying discrete optimization techniques, microsimulation, or integrating these approaches using simulation-optimization. Recently, some empirical studies have appeared, with Dalla Chiara and Goodchild (2020) documenting cruising behavior based on field work in Seattle, and Fransoo et al. (2020) estimating the routing time benefits of creating LUZs based on fieldwork in Mexico.

While previous studies have established a wider understanding of the time impact of LUZs and their potential configurations (such as location, size, and operating hours), it is still unclear what is the impact of LUZs on air quality and noise pollution. These are particularly relevant in cities in developing countries and other emerging markets, where air quality is oftentimes very bad. Developing cities present logistical challenges due to market fragmentation, urbanization, limited curb space, narrow streets, and informality. For instance, one layer of complexity that has not been considered in previous studies is the informal freight transportation sector. By informal, we mean vehicles whose primary purpose is not cargo transportation. In emerging cities, it is common to observe family cars transporting raw materials and finished goods. Accordingly, this article aims to address the following research question: *What are the effects of LUZs on air and noise pollution in an emerging city?* In addition to our core research question, our data collection also provides insights into the usage of LUZs and the types of businesses and vehicles that use them.

In order to investigate this, we conducted a field experiment in downtown Zapopan, Mexico, during August and September 2021. This area has a dense population of about 15,000 people per square kilometer. The diverse mix of residential, administrative, and commercial activities of this urban area puts a strain on downtown Zapopan's narrow streets and limited parking. These factors contribute to a challenging logistical landscape in which efficient movement and delivery are hampered by traffic and infrastructure constraints. The mix of residential and commercial activities, as well as a retail landscape dominated by small businesses and nanostores, reflects the logistical challenges encountered in many other developing urban areas, making it an ideal location to assess the impact of LUZs. We used a quasi-experimental approach that allows us to establish a causal relationship between LUZs and the effects on noise and air pollution in an emerging market environment. We selected comparable treatment and control areas based on key urban characteristics. After defining the treatment area, we chose the control area with a primary focus on store density, as the intervention would affect last-mile deliveries to nanostores and other retail outlets. Additional criteria included area size (km^2), street types, and that both were on the same neighborhood to control for external variables that could bias our results. By selecting areas with similar characteristics, we aimed to have two areas that would be as comparable as possible (one serving as a suitable counterfactual and the other one exposed to treatment) to ensure the internal validity of the field experiment.

The results of our experiment show a sizeable reduction in CO_2 in the air of up to 3.55% in the morning hours and a reduction of 14% in noise. In our study, we go beyond these results to consider additional findings that might help policymakers create permanent programs to benefit the stakeholders interacting in emerging cities. Our results show evidence that 60% of companies that distribute goods are micro and small enterprises (MSEs) that typically transport their goods using personal vehicles. These vehicles are not intended to transport cargo. This finding suggests that a large portion of the freight transport sector may be considered informal. According to our findings, automobiles and pickup trucks account for more than 62% of all cargo transport vehicles. In addition, we discovered that roughly 47% of the vehicles used for freight purposes are more than ten years old, which typically pollutes more than more recent models (Dill 2004). Also, we captured the driver's time driving and walking in the area of intervention, revealing that more than 90% of the time, the drivers cover the area on foot to serve customers.

The contributions of this study are three-fold. To begin, to the best of our knowledge, we are the first to provide quantitative evidence on the effect of creating dedicated LUZs on noise and air quality in a real-world setting in an emerging city. Second, we provide insights into the fleet composition of freight vehicles, which is critical for designing the size of LUZs and for public policy development. Lastly, we shed light on drivers' behavior, revealing that they typically walk rather than drive during last-mile operations.

The remainder of our paper is organized as follows. Section 2 provides a review of the literature. Section 3 describes the methodology. Section 4 presents the main results of the study. Section 5 contains a discussion as well as implications. Finally, section 6 presents the conclusions and future research.

2. Literature review

Parking is a regular task that drivers of freight vehicles must perform when distributing freight in urban areas. Lack of parking frequently causes ineffective last-mile logistics, neglected customers, traffic congestion, and infractions. Jaller et al. (2013) illustrate the severity of the freight parking problem in New York by estimating the supply and demand for parking based on the frequency of vehicle arrivals and the amount of available curbside space. The parking problem in emerging cities is exacerbated by rapid urbanization, limited infrastructure, and increased economic activity. These cities frequently lack designated spaces for freight vehicles, resulting in last-mile inefficiencies, traffic congestion, air and noise pollution, and other externalities like accidents.

Over the last decade, academics have studied the design and construction of LUZs as a solution to parking problems. Scholars advanced the literature by developing optimization models to determine the optimal number, size, and location of loading-unloading areas (Muñuzuri et al., 2012; Tamayo et al., 2017; Lopez et al., 2021; Puente-Mejia et al. 2020). These models usually seek to minimize the weighted distance between the candidate locations of the LUZs and the customers. Recent contributions include models that consider time-differentiated policies for managing LUZs so that they are accessible during peak hours (Wilson et al., 2022).

Moreover, simulation models evaluate the economic and environmental impacts of establishing LUZs. These methods include agent-based simulations of freight parking demand management strategies (Alho et al. 2022), the study of the performance of stochastic systems with dedicated delivery bays and general on-street parking

(Abhishek et al. 2021), and works that have focused on the location, sizing, and number of LUZs to understand the impact on traffic congestion (Alho et al., 2018; Simoni & Claudel, 2018; Roca-Riu et al., 2017).

Furthermore, simulation-optimization has been explored to build lab-based scenarios and provide insights into how to design LUZs based on varying factors like demand, traffic, and the capacity of the LUZs, among other parameters. For example, a heuristic routing strategy for reducing emissions and delivery times using a mixed-integer linear model and an agent-based simulation model considering LUZs (Trott et al., 2021). Others in the field suggested a two-step strategy that combines simulation and optimization. They first determine the number and location of the LUZs using a set covering model, considering the maximum distance a delivery operator is willing to walk between the delivery bay and the delivery location. They then refine the solution using a simulation method to assess how stochastic variables and time variability will affect it (Pinto et al., 2019). To balance the objectives of different stakeholders in urban freight transport, researchers developed a simulation-optimization tool that considers road users' decision-making processes, interaction, and stochastic parameters (Muriel et al., 2022). Interestingly, their findings suggest that illegal parking yields better results than legal parking to balance the objectives of different stakeholders in urban freight transport. However, they recommend further research to validate the results and, if possible, in a more realistic scenario by incorporating detailed empirical data and taking into account a broader range of real-world variables.

In addition to model-based research, empirical research has also been conducted in the field to estimate the advantages of creating LUZs under real-life conditions. In a field experiment conducted in Queretaro, Mexico, Fransoo et al. (2020) found that LUZs may reduce the travel time of freight vehicles by 39% as well as reduce the total time parked by 17%. A study conducted in Seattle found that commercial vehicles spent on average, 28% of their total trip time cruising for parking, with an estimated parking search time of 2.3 minutes per trip (Dalla Chiara & Goodchild, 2020). These findings underscore the potential of available parking infrastructure to significantly decrease not only travel times but also the inefficiencies associated with parking in urban areas.

Although the contributions of the already-existing literature have aided in understanding how LUZs can alleviate the issues caused by the lack of parking for freight vehicles, it is still unclear what are the effects on noise pollution and air quality under the conditions of a developing city. Even though a number of scholars have remarked that noise pollution is an externality linked to the parking issue (Alho et al., 2022; Muriel et al. 2022; Muñuzuri et al. 2012; Dalla Chiara et al. 2021), no studies have been conducted on this topic to quantify the impact in a real-world setting as far as we are aware. Similarly, several researchers have indicated that urban freight parking problems affect air quality. However, no studies have been conducted to determine the effects of LUZs on air pollutants in emerging cities. In terms of air quality, we are referring to fine particles PM2.5 (i.e., particles with a diameter of 2.5 micrometers or less), coarse dust particles PM10 (i.e., particles with a diameter between 2.5 and 10 micrometers), carbon monoxide (CO), and carbon dioxide (CO_2) suspended in the environment. Particulate matter emitted mainly by diesel-powered freight vehicles can degrade air quality in urban areas, causing respiratory and cardiovascular health problems in residents, particularly those who live near busy areas. Furthermore, high CO and CO_2 concentrations in urban areas can worsen air quality, causing respiratory issues and other health problems among citizens (Jacobson et al., 2019). Previous research has reported that these pollutants are linked to increased traffic, which is affected when parking is scarce (Alho et al. 2022; Muriel et al. 2022; Simoni & Claudel, 2018, Jaller et al., 2013, Muñuzuri et al. 2012).

3. Methodology

This section describes the methodology, which includes the research design, the location of the LUZs, and the sampling points used to collect air quality and noise data. We provide information about the treatment, unit of analysis, and other additional information about how we conducted the field experiment (See Figure 1).

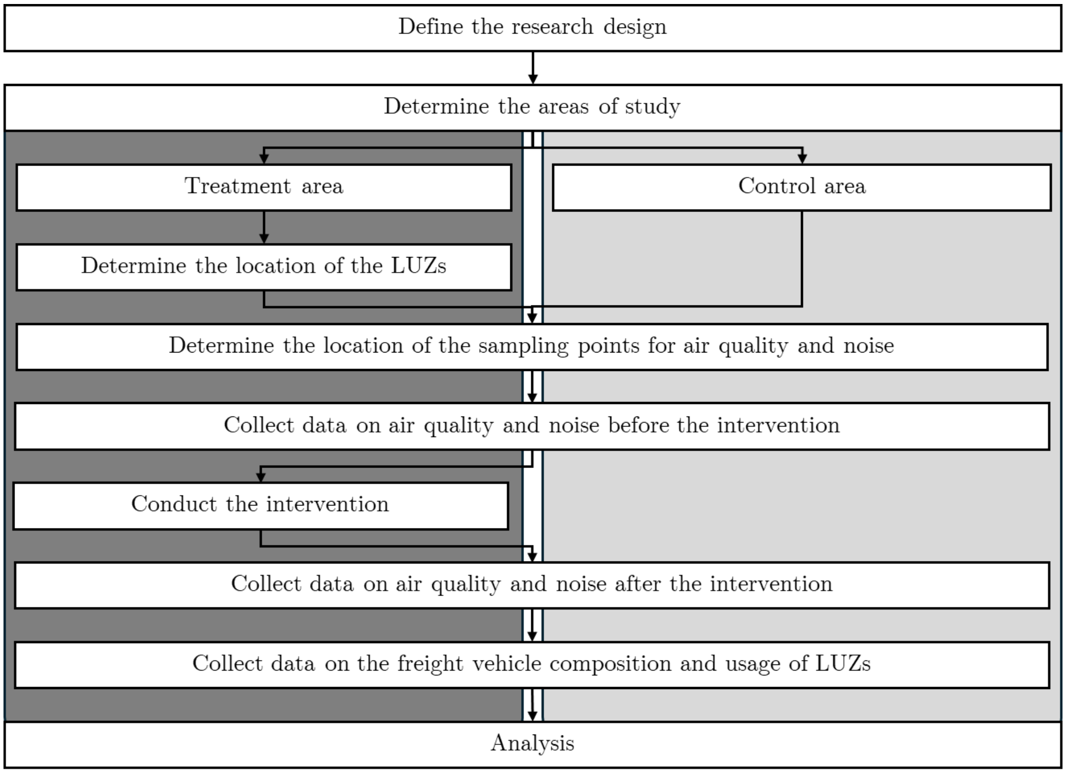

Figure 1. Methodology for the field experiment

3.1. Research design and setup for the field experiment

We followed a quasi-experimental approach to investigate the causal relationship between the LUZs and the effects on noise and air pollution in an emerging market environment. Given the complexities of the real-world conditions, we thoroughly planned the field experiments before carrying them out to ensure valid and reliable results. The planning phase included various tasks. Initially, the areas of study were defined. We chose a downtown zone with a mix of residential and commercial activity for the treatment area. Downtown Zapopan has a population density of approximately 15,000 inhabitants per square kilometer. To ensure the experiment's internal validity, we defined a comparable control area based on similar characteristics such as area size (km^2), the number of nanostores, and other retail stores frequently visited by suppliers, and street types. Further, the control area is located in the same neighborhood, which ensures similarities across a range of important dimensions (local culture and architecture, overall atmospheric conditions, etc.). Table 1 provides a detailed comparison of the retail landscape between the control and treatment areas, including the distribution and density of various retail establishments. This comparison is crucial to ensure that the study areas are sufficiently similar, thereby allowing us to assess the effects of the intervention with a suitable counterfactual.

Table 1. Composition of the retail landscape of the areas of study in Zapopan

	Control	Treatment
Area (Km2)	1.40	1.43
Nanostores	103	71
Fresh produce (fruits and vegetables)	17	19
Butcher shops	17	11
Pharmacies	13	16
Grains and seeds stores	6	14
Ice cream shop	7	12
Hardware store	12	6
Poultry shops	10	4
Dairy stores	8	6
Total establishments of fast-moving consumer goods	193	159

We used a p-median facility location model (See Appendix A) to determine the location of the LUZs by minimizing the total weighted distance between the candidate facilities (in this case, we considered every street crossing as a candidate facility) and the stores in the region. For the distance, we used walking distance and obtained the data from Google Maps. For store weight, we used the number of employees per store as a proxy for demand. This model was limited by the number of bays that could be built, which was 21 LUZs. We used secondary data from the Mexican National Institute of Statistics and Geography INEGI to obtain the location (i.e. latitude and longitude) and size (i.e. number of employees) of the stores in the areas of study.

After determining the optimal location of the LUZs, we validated the results by conducting field inspections with the authorities to verify the viability of creating the bays in the points determined by the model. In some cases, we had to relocate a LUZ because the optimal location blocked a garage or was a reserved parking space for neighbors or cab companies. Then, the LUZ was relocated to the nearest feasible location, which was always less than 30 meters away.

During our field trips before the intervention, we observed that the curb was not strictly managed. While some sections had basic infrastructure for parking, these areas were not designated for specific uses and were available to anyone on a first-come, first-served basis. This led to a variety of uses, including food trucks and pushcarts frequently occupying the curb.

3.2. Building infrastructure and technology

The LUZs were marked with yellow paint, and vertical signage was installed to clearly indicate that the space was for loading and unloading goods. A plate beneath each sign displayed a QR code for drivers to scan to register for the project. They filled out a form with their contact information, license plate, and company details. We prepared a group of promoters to facilitate this process and discourage potential non-freight drivers from parking there. Following that, we shared tutorial videos with the drivers on installing and using the EZ Parking App[1] to assist them in adopting the technology and using the LUZs.

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[1] The EZ Parking App was developed to manage loading and unloading zones, gather data, and make the intervention as realistic as possible.

The EZ Parking mobile application was conceived with two primary goals in mind. First, it displayed available LUZs, allowing freight drivers to park legally and serve customers. Second, it was one of our study's standardized primary data collection tools. We collected data on the users' arrival and departure times at each LUZ. We also tracked the users' movements in the area under study with the App. Because we were registering their speed and geolocation, we could determine whether the drivers were walking or driving. We assumed they were walking if they traveled slower than 4.5 km/h (average walking speed) for more than 1 minute (to avoid capturing stops at traffic lights as if they were walking.)

After the intervention was implemented, participants used the EZ Parking app to manage and record their activities in the LUZs. When drivers arrived at a zone, they scanned a QR code with the app, which automatically recorded their arrival and tracked their movements using geolocation and speed monitoring, ensuring accurate data collection. This process improved data accuracy by reducing the reliance on manual input. Figure 2 depicts the more than 100,000 records collected from both the control and treatment areas. Each record contained detailed information, including the user's identity, the exact time of entry, speed, and location data. The green dots on the figure represent movement patterns and activities in the control area, where no LUZs were installed, whereas the orange dots represent similar patterns in the treatment area, where LUZs were created. The blue circles indicate the locations of the EZ Parking zones within a 50-meter radius, displaying the activities within each LUZ.

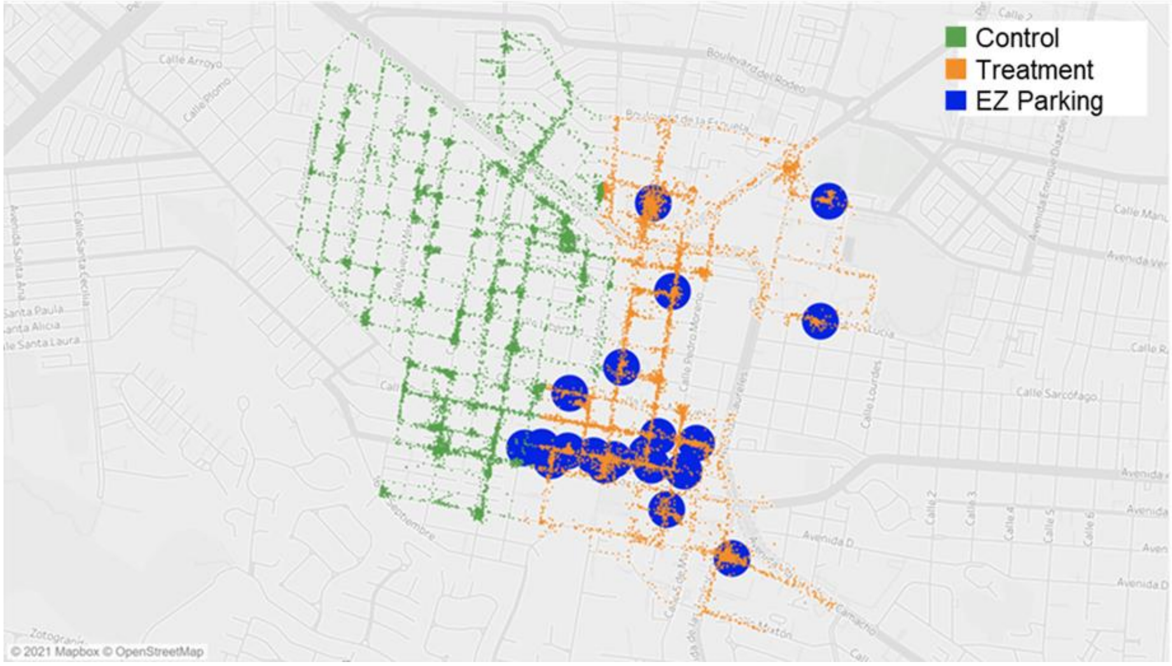

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Figure 2. User activities in Control and Treatment areas with EZ Parking LUZs

However, a few challenges arose during implementation. IT restrictions prevented some drivers from installing the app on company-issued cell phones, forcing them to use personal devices instead. Furthermore, one limitation of the technology was that the EZ Parking app was developed exclusively for Android devices. Before development, we consulted with several companies, all of whom confirmed that their fleets used only Android phones, leading us to prioritize Android compatibility to serve most users. However, this decision did result in at least one instance where a driver using an iPhone was unable to access the app. Participation in using the app was voluntary, with more than 90 freight drivers signing up. This adoption indicates a perceived value among participants. While we did not collect data on the specific compliance rate between the use of LUZs and the EZ Parking app, the significant utilization of the zones points to a likely strong level of compliance.

3.3. Determining the sampling points to measure noise and air pollution

We used a p-median facility location model to determine the sampling points for collecting noise and air pollution data. Given that these externalities affect the population, the objective function of our model minimized the weighted distance between candidate facilities (i.e. street corners) and block centroids, using the number of residents per block as a weight. The data was obtained from INEGI's population census. Our budget was limited to six sampling points in each area (i.e. treatment and control). Therefore, we defined the constraint of the number of facilities to six for each area.

3.4. Primary data collection and collaborating with authorities to carry out the intervention

We trained two groups of samplers to collect noise and air pollution data at the study areas' collection points during the pretest and posttest periods. We held training sessions to thoroughly explain the data collection process and how to use high-precision equipment. We measured noise with an ST9604 digital sound level meter (aka. sonometer) and air pollution with a multi-functional air quality monitor Temtop M2000C. The samplers were given the calibrated equipment and told to record the results in an online form using their mobile devices every two hours between 7:00 a.m. and 5:00 p.m. every day. The time frame corresponds to the period when freight vehicles are most active in the region. The data collected included the sample's location (i.e. latitude, longitude), time of day, noise in decibels (dB), fine particles PM2.5, coarse dust particles PM10, carbon monoxide (CO), carbon dioxide (CO_2), temperature in Celsius, and humidity in percentages.

To deploy our intervention, we worked closely with the local authorities of Zapopan. Several meetings were held with Mobility and Transportation department officials.

The pilot project was announced to the traffic police. Officers were notified when vehicles other than freight vehicles were parked in LUZs. We integrated a reporting feature into the EZ Parking App, enabling freight drivers to report any misuse of the LUZs. These reports were automatically forwarded to local mobility authorities, who then responded by visiting the LUZ to ensure compliance. Only three cases of misuse were reported throughout the intervention period. In addition, the authorities communicated with the neighbors about the creation of the LUZs and the promoters' presence to alleviate any potential discontent from the citizens, particularly those who live in areas where the LUZs were located directly in front of their homes.

Furthermore, coordination with authorities was critical for building the LUZs and installing vertical signage. The LUZs were put up simultaneously on a Sunday, when there are typically fewer last-mile operations, allowing the intervention to begin the following Monday morning.

3.5. Analysis and unit of analysis

For the analysis, we employed the difference-in-differences method to compare the changes in outcomes over time between the treatment and control areas. We defined the treatment and control areas as the unit of analysis (See Figure 3). In each area, we measured noise in decibels (dB) and air quality (i.e. PM2.5, PM10, CO, and CO_2) before and after the intervention.

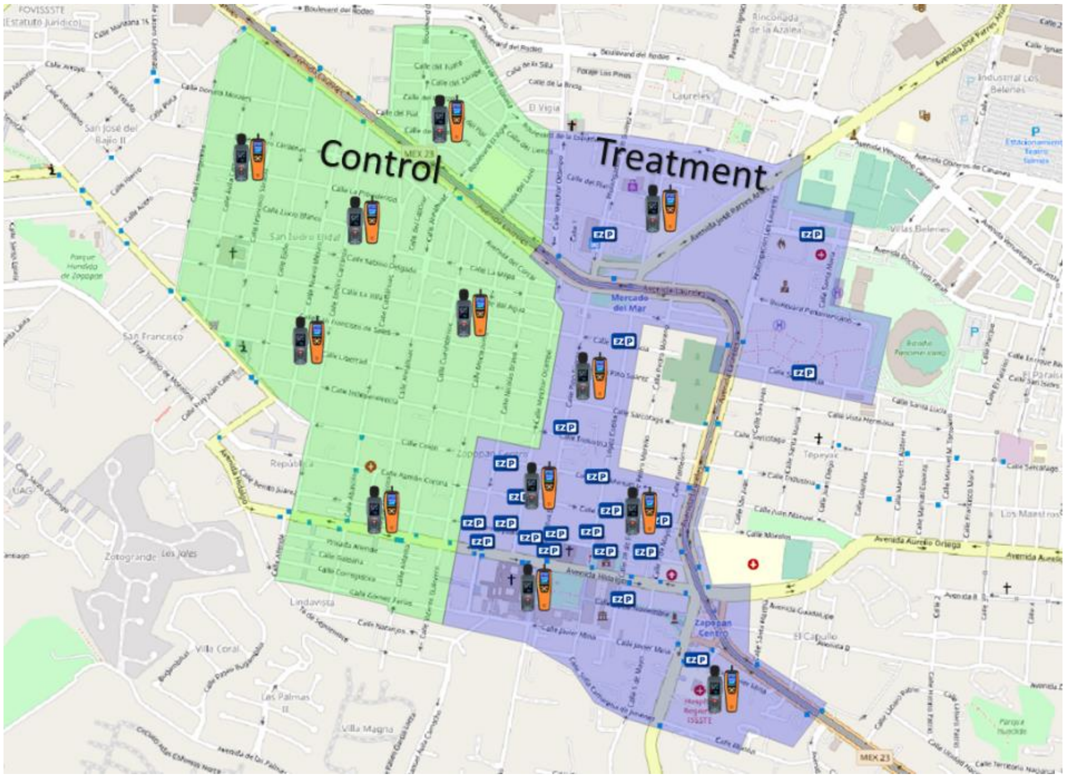

Figure 3. Overview of the experimental area in Zapopan, Mexico. The equipment icons indicate the location of the sampling points, and the blue EZP markers indicate the location of the LUZs.

This pre-test and post-test control group design allowed us to measure the change in the noise and air quality (i.e. dependent variables) over time for both the treatment and control groups. By comparing the change in the dependent variables between the two groups, we were able to determine whether the intervention caused the change in the experimental area. To reduce the limitations of the experiment in terms of internal validity, we included time and weather conditions as covariates in our analysis. These variables were incorporated into the regression model as control variables. We included temperature in Celsius and humidity in percentages (both measured by our samplers directly in the field), and time of day (which was operationalized using three dummy variables: morning (7:00 to 10:00), noon (11:00 to 14:00), and afternoon (15:00 to 17:00).)

3.6. Treatment and timeline of the intervention

The treatment consisted of the LUZs, the EZ Parking App, and the promoters on the field (See Figure 4). The program was designed to cater to freight drivers with free dedicated parking spaces and technology to provide real-time information about their location and usage.

Figure 4. EZ Parking LUZ in Zapopan

The field experiment was conducted between August 10 and September 11, 2021, with the intervention going live on August 29 (See Figure 5). Promoters invited freight drivers to learn about and participate in the pilot project.

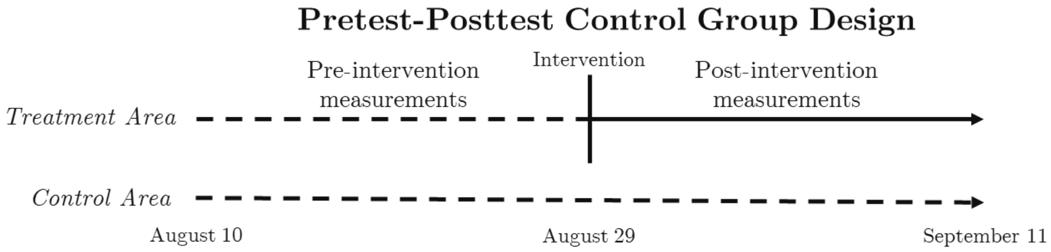

Figure 5. Timeline of the Field Experiment conducted in Zapopan, Mexico in 2021

4. Results

4.1. Data

We collected data from both the treatment and control groups 19 days before and 14 days after treatment. We obtained 346 observations with almost 4,000 data points regarding noise and air quality, including CO and CO_2 concentration, fine particles (PM2.5), coarse dust particles (PM10), temperature, and humidity. We approached data collection with a high level of rigor, using specialized and calibrated equipment to ensure the accuracy of the readings. To address potential outliers, we compared the maximum values to the 95th percentile of each of our dependent variables and found no extreme values. Given this meticulous process, we did not remove any data points for our analysis. Table 2 depicts the environmental conditions of the studied region, providing a baseline understanding of the conditions and allowing for comparison with other studies or datasets.

Table 2. Descriptive statistics of noise and air quality data

	dB	CO_2	PM 2.5	PM 10	Celsius	Humidity
mean	54.82	407.34	13.44	20.16	27.74	56.67
standard deviation	8.57	25.79	6.88	10.48	3.85	14.82

4.2. Model specification

We seek to estimate the impact of LUZs on air quality and noise pollution. With the primary data collected, we constructed a panel data set that included several units of analysis. One of each of the parameters of air quality and noise pollution, that is, noise measured in decibels (dB), and the following variables for air quality: PM2.5, PM10, CO, and CO_2 in Parts Per Million (PPM) during week t. We use the difference in difference estimator, which is defined as the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the control group before and after treatment. The following regression equations estimate the impact of LUZs on air quality and noise pollution (See Table 3).

Table 3. Regression equations

Model	Equation
1	$(\text{PM2.5})_{iht} = \beta_0 + \beta_1 Area_i + \beta_2 Period_t + \beta_3(Area_i * Period_t) + Controls + \varepsilon_{iht} \quad (1)$
2	$(\text{PM10})_{iht} = \beta_0 + \beta_1 Area_i + \beta_2 Period_t + \beta_3(Area_i * Period_t) + Controls + \varepsilon_{iht} \quad (2)$
3	$(\text{CO})_{iht} = \beta_0 + \beta_1 Area_i + \beta_2 Period_t + \beta_3(Area_i * Period_t) + Controls + \varepsilon_{iht} \quad (3)$
4	$(\text{CO}_2)_{iht} = \beta_0 + \beta_1 Area_i + \beta_2 Period_t + \beta_3(Area_i * Period_t) + Controls + \varepsilon_{iht} \quad (4)$
5	$(\text{dB})_{iht} = \beta_0 + \beta_1 Area_i + \beta_2 Period_t + \beta_3(Area_i * Period_t) + Controls + \varepsilon_{iht} \quad (5)$

In the equations, $Area$ is a dummy binary variable, that is, 0 for the control area and 1 for the treatment area, $Period$ is a binary indicator for the after-treatment period (i.e., 0 for before and 1 for after), and $Area * Period$ is the interaction term. Regarding the coefficients, β_0 is the intercept (i.e. level) of the regression, β_1 captures the difference between the average outcome of the control group before and after the treatment, β_2 captures the difference between the control and treatment group before the treatment, and β_3 captures the effect of the treatment on the treated (i.e. estimate of interest). Lastly, ε_{iht} is the error term that represents factors that affect the unobservable dependent variables in the data.

Equations (1) to (5) include several control variables. We include the dummy variable $Time$ to control for different effects depending on the hour of the day. We categorized $Time$ as morning (i.e. 7:00 to 10:00), noon (i.e. 11:00 to 14:00), and afternoon (i.e. 15:00 to 17:00). In addition, the regressions include covariates capturing the local weather, that is, the temperature measured in Celsius, and humidity measured in percentages at each area to control for the effect of local weather on air quality and noise pollution. In the models, i represents each observation at the sampling points, h the hour of observation, and t the day of observation.

4.3. Noise pollution

The effects of the regression analysis reported in Table 4 reveal that the creation of LUZs can significantly reduce the levels of noise at an p = 0.05 level of significance. The drop of 4.61 dB represents a 14% reduction in noise in dB compared to the baseline.

Table 4. Results of the regression analysis for noise

	dB
Intercept	32.82
	(25.44)
Area	3.45*
	(2.06)
Period	2.89
	(2.30)
Area*Period	-4.61**

	(1.86)
Dummy for Time	Yes
Weather	Yes
Observations	30
R-squared	0.72
R-squared Adj.	0.59

Robust standard errors in parentheses.
* $p < .1$,** $p < .05$,*** $p < .01$

4.4. Air quality

With respect to air quality, our field experiment shows that the LUZs reduce CO_2 in the air by 2.79% (See Table 5). When controlling for time of day, the results show that LUZs have a greater effect on CO_2 in the mornings (i.e. 7:00 to 10:00), lowering it by 3.55%. Our findings also show a CO, PM2.5, and PM10 reduction, but not statistically significant.

Table 5. Results of the regression analysis for air quality

	PM2.5	PM10	CO	CO_2
Intercept	13.08	6.00	0.93***	402.48***
	(12.32)	(28.97)	(0.32)	(0.38)
Area	5.16***	4.82	0.50	22.06***
	(1.38)	(4.58)	(0.58)	(3.92)
Period	-0.33	0.94	-0.25	-0.45
	(0.81)	(2.39)	(0.49)	(0.47)
Area*Period	-2.10	-3.99	-0.30	-11.24***
	(1.85)	(3.09)	(0.59)	(4.22)
Dummy for Time	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes
Observations	30	30	30	30
R-squared	0.57	0.54	0.31	0.68
R-squared Adj.	0.48	0.33	0.09	0.58

Robust standard errors in parentheses.
* $p < .1$,** $p < .05$,*** $p < .01$

4.5. Parallel trends

We analyzed the parallel trends for the dependent variables affected by the LUZs, noise (dB), and CO_2. First, we visually inspect the pre-treatment trends of noise in dB for both the treatment and control groups over time. The trends appear parallel before the treatment, administered in week 34, supporting the parallel trends assumption (See Figure 6). The observed slow decline in noise levels following the intervention could indicate a period of adjustment in which drivers began to consistently use the LUZs, resulting in a cumulative reduction in noise over time rather than an abrupt change.

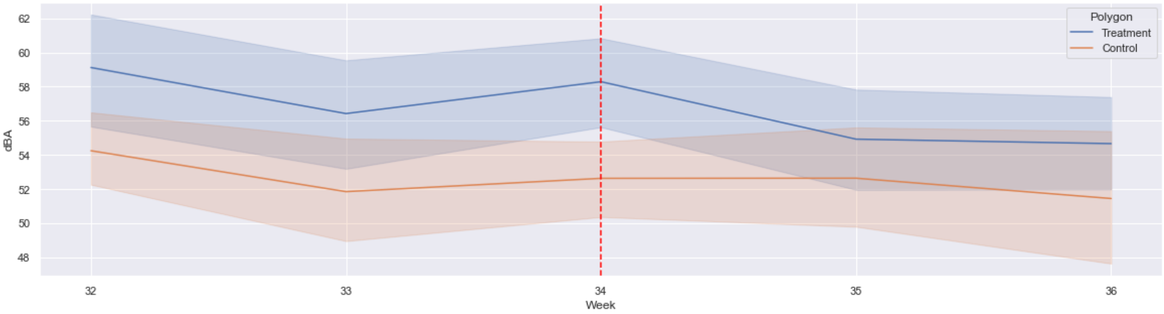

Figure 6. Descriptive evidence of no violation of the parallel trends for noise in dB

Likewise, in the case of CO_2 in the air, we can observe the parallel trends before the intervention in week 34 (See Figure 7). The shaded areas represent the 95% confidence interval of the estimates.

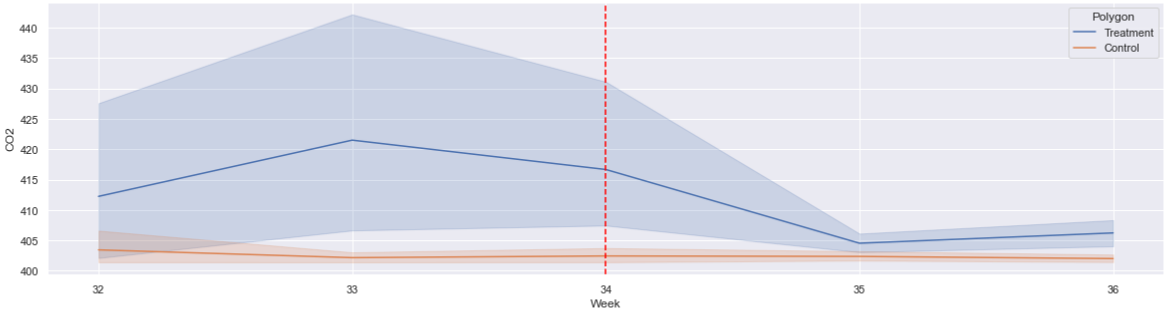

Figure 7. Descriptive evidence of no violation of the parallel trends

Furthermore, we incorporated time effects into the regression model as another approach to test for parallel trends. We used one dummy variable for each week to measure changes in the outcome variable over time, regardless of group or treatment. For our analysis, week 32 (w32) is the reference period. By including time effects, we can control for any common shocks or trends that affect both groups over time while isolating the effect of the treatment. To test for parallel trends, we interacted with the time effects with the group indicator (i.e., Area) and determined whether the coefficients were statistically significant. Given that they are not, the two groups exhibit comparable trends, and the parallel trends assumption is not violated (See Table 6).

Table 6. Analysis to test the parallel trends for dB and CO_2

Variable	dB	CO_2
Intercept	54.24***	403.43***
	(0.59)	(0.95)
Area	5.02	9.57
	(3.32)	(11.16)
Period	-0.23	-0.79
	(1.73)	(0.64)
w33	-2.33**	-1.28
	(1.08)	(1.18)
w34	-1.67	-0.93
	(1.92)	(1.00)
w35	-0.55	-0.28
	(2.52)	(0.36)
w36	0.32	-0.50
	(2.82)	(0.35)
w33*Area	-0.51	9.77
	(4.28)	(12.65)
w34*Area	0.70	4.59
	(4.18)	(13.01)
w35*Area	-3.56	-7.41
	(4.88)	(11.16)
w36*Area	-4.69	-5.49
	(5.37)	(11.24)
Observations	30	30
R-squared	0.31	0.52
R-squared Adj.	0.00	0.30

Robust standard errors in parentheses.

$* \ p < .1, ** \ p < .05, *** \ p < .01$

Given that treatment began in week 34, we expect to find no systematic difference between the treatment and control areas in the preceding week, relative to the baseline week 32 (omitted for identification purposes). Instead, we expect to see such differences emerge following treatment introduction. Aligned with this, the coefficient for Week 33 is statistically indistinct from zero for our two dependent variables. Then, we observe a substantial drop for our two dependent variables in weeks 35 and 36 (see Figure 8). Note that, although the treatment began in week 34, this period functioned as a warm-up phase where drivers registered, familiarized themselves with the EZ Parking App, and adapted to using the LUZs. This transition period reflected a natural learning curve, which resulted in minimal immediate effects. In short, according to the evidence, dB and CO_2 levels followed parallel trends before and shortly after treatment began, with a drop in weeks 35 and 36. While not individually significant in this dynamic estimate, such effects are significant in aggregate for weeks 34-36 (see Tables 4 and 5).

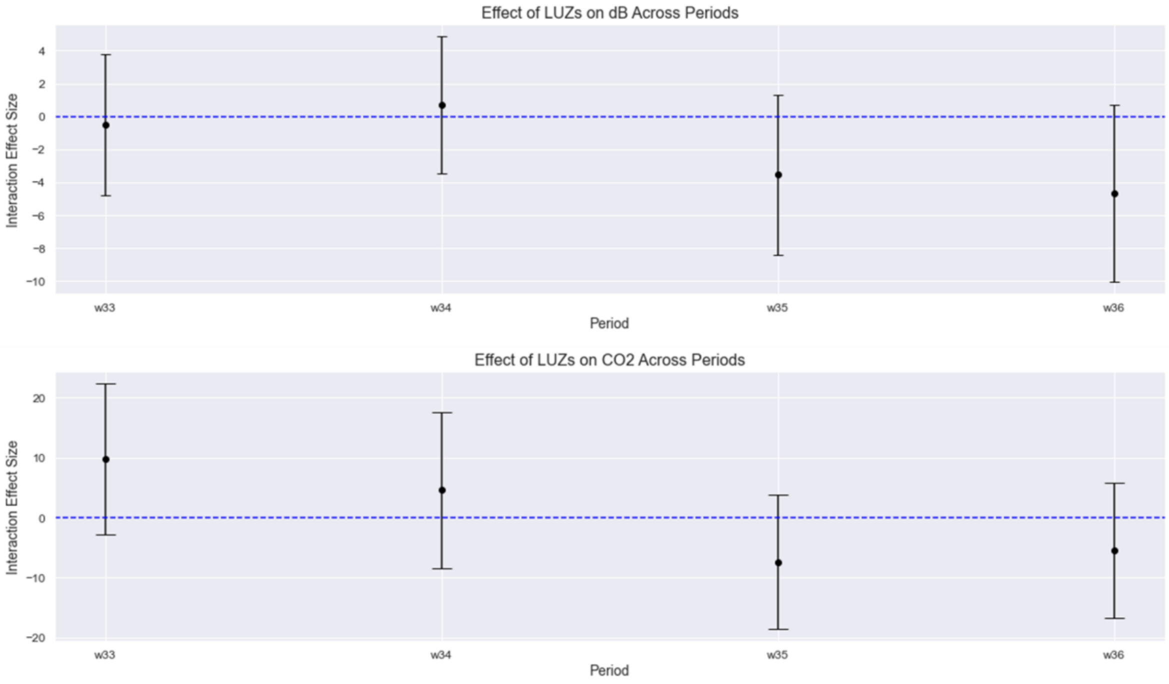

Figure 8. Effect of LUZs on dB and CO_2 across periods

4.6. Freight vehicle composition and usage of LUZs

More than 90 freight drivers registered to use the LUZs for free. Each user filled out a form, providing contact information, license plate, and company details. We retrieved the vehicles' information by consulting them in the Registry of Motor Vehicles of Mexico (REPUVE for its abbreviation in Spanish). The available data were used to construct a data set to learn about the participating companies and the types of vehicles employed for last-mile distribution in the area under study.

Table 7. Freight vehicle composition by company size and model

Model	Micro	Small	Medium	Large	Total
2001-2005	3%	0%	6%	3%	11%
2006-2010	9%	3%	0%	6%	17%
2011-2015	20%	9%	3%	11%	43%
2016-2020	9%	11%	6%	3%	29%
Total	40%	23%	14%	23%	100%

Our empirical evidence shows that 63% of enterprises conducting last-mile deliveries are MSEs (See Table 7). These firms primarily use personal vehicles to transport goods, indicating an informal mode prevalent in freight activities. A consequential aspect of this finding is the empirical evidence that 36% of cargo transport vehicles are represented by sedans, hatchbacks, and sport utility vehicles (SUVs). Another finding from our field study is that nearly 30% of the vehicles used for freight purposes have operated for over a decade (See Table 8).

Table 8. Freight vehicle composition by type and model

Type	2001-2005	2006-2010	2011-2015	2016-2020	Total
Pick Up	4%	8%	17%	12%	41%
Sedan	3%	6%	9%	3%	21%
Cargo Van	4%	3%	6%	9%	21%
Hatchback	0%	0%	6%	3%	9%
SUV	0%	0%	3%	3%	6%
Heavy Duty	0%	0%	3%	0%	3%
Total	11%	17%	43%	29%	100%

To record their use of the LUZs, drivers scanned a QR code using the EZ Parking application (See Appendix B). Then, the system recorded when the user left a LUZ based on geolocation and speed. The data indicates that freight drivers used the LUZs for an average of 20 minutes (SD=10).

5. Discussion and implications

This research draws on recent academic literature to present evidence about the causal relationship between LUZs and their impact on noise pollution and air quality. Our results reveal that LUZs can decrease CO_2 in the air in a developing city, particularly during the morning rush hour. This outcome suggests that if LUZs are available, double-parking and cruising are reduced. The former implies fewer roadblocks, leading to fewer vehicles emitting pollutants during traffic jams. The latter entails that vehicles save fuel and time by not having to circle around looking for a parking space. Therefore, companies that perform last-mile logistics can benefit from using LUZs to streamline their delivery operations. Companies can reduce carbon emissions associated with unnecessary mileage, save travel time, and potentially improve service levels, as drivers are less likely to miss deliveries.

Furthermore, the availability of LUZs means that cargo drivers are less likely to block the streets, resulting in less traffic congestion and, as a result, lower noise pollution. Since decibels are measured on a logarithmic scale to compare the intensity of different sounds, an increase of 10 dB represents a tenfold increase in noise intensity, meaning that a sound with an intensity of 60 dB is ten times more intense than a sound with an intensity of 50 dB. Thus, the drop of 4.61 dB reported in our study represents a reduction of 65% in the sound intensity in watts per square meter (W/m^2). This result indicates a more comfortable and stress-free environment for thousands of residents, pedestrians, and drivers. Given these positive results, Zapopan officials have expressed interest in transitioning from a pilot to a fully developed program, with plans to expand the use of LUZs to other parts of the city. While this study focuses on the short-term effects of LUZs, there may be a significant opportunity to collect longitudinal data to assess the long-term effects of LUZs.

Aside from the environmental benefits, LUZs can lead to significant cost savings for companies that service nanostores and other businesses. When vehicles spend less time idling in traffic or looking for parking, they save time and fuel, lowering operational costs (Fransoo et al., 2020). Faster delivery times allow vehicles to complete more deliveries in the same amount of time or reduce the total number of trips required, resulting in improved fleet utilization. This increased efficiency lowers fuel and labor costs while increasing overall productivity.

Moreover, our data reveals that 90% of drivers cover the area on foot rather than driving. This finding could be attributed to congested traffic or limited vehicular access, prompting drivers to choose on-foot navigation as a more efficient alternative to serving customers. This finding emphasizes the importance of having LUZs and illustrates the need to improve pedestrian infrastructure, such as sidewalks and crosswalks, that facilitate the transportation of heavy goods in trolleys.

Regarding the users of the LUZs, our findings show that most companies involved in last-mile distribution in the emerging city under study are MSEs. This outcome is reasonable, given that MSEs account for 99% of all businesses in Latin America and the Caribbean and contribute to 47% of total employment (CEPAL, 2020). Moreover, the fact that cars and pickups account for more than 62% of cargo transport is related to the previous finding. MSEs may lack the resources to invest in a cargo truck for their businesses, so they use personal vehicles instead. Cars, hatchbacks, and sport utility vehicles (SUVs) account for 36% of cargo transport vehicles. Shedding light on fleet composition used for last-mile distribution is important for planning infrastructure, including the dimensions of LUZs. The many drivers who registered for the intervention demonstrate that they are willing to use technology-supported LUZs primarily because they perceive added value to their operations at no cost (See Appendix C).

Furthermore, the study illustrates the age of cargo vehicles. Approximately 47% of freight vehicles are over ten years old, contributing more to pollution. Policymakers can use this information to make informed decisions about urban planning, such as the design and dimensions of LUZs tailored to these vehicles.

Given that this is a quasi-experiment, we cannot definitively state that the observed effects will apply to other cities, particularly those with different logistical challenges or economic conditions. However, based on the conditions of the study area, we can gain insights into the types of urban environments in which similar effects may occur. The downtown area of Zapopan, where this experiment was conducted, has a high population density, a fragmented market with a variety of commercial activities, narrow streets, and a high concentration of nanostores.

6. Conclusions and future research

Loading and Unloading Zones (LUZs) have received increasing attention in the transportation research literature and by transportation policy makers to resolve illegal parking movements by urban logistics actors. Earlier research has demonstrated that well-placed LUZs have the ability to substantially reduce cruising and route time, with both public and private benefit. In this paper, we have addressed another set of externalities, namely those related to air quality. Air quality is a challenge in many cities, especially in developing and other emerging markets.

To investigate this, we conducted a field experiment to investigate the effects of LUZs on noise pollution and air quality in the downtown area of an emerging city. Our results highlight the positive impact of these zones, revealing improvements in air quality, including a significant reduction of up to 3.55% in CO_2 and a 14% reduction in noise pollution. These findings are critical because they show the potential of LUZs to decarbonize urban logistics while ensuring the efficient and effective flow of goods to MSEs, benefiting millions of people in developing countries.

In addition, our findings provide insights into the composition and dynamics of freight vehicles in the context of last-mile distribution in developing cities. According to the data, 63% of companies distributing goods are MSEs, primarily using personal vehicles, such as sedans and SUVs. Such vehicles tend to be relatively old and poorly regulated, potentially explaining the relative large effect size that we found in our experiments. The high percentage of informal and private vehicles that play a role in urban logistics in developing countries warrants further research, as we believe we are one of the first to document this with an innovative app-based self-registration system.

Future research could expand on our findings by addressing some of its limitations. First, escalating the study to include a broader range of urban areas in different emerging markets could improve the generalizability of the results, allowing for a more comprehensive understanding of how different urban conditions affect the effectiveness of LUZs. Longer-term studies would also shed light on the sustained effects of LUZs on air quality and noise pollution. Also, future research could explore the gradual adoption of LUZs and the associated technology to better understand the diffusion process among freight drivers, particularly in relation to the stages outlined in the Diffusion of Innovation Theory. This would provide valuable insights into how new interventions are embraced over time. Finally, future research could investigate the impact of LUZs on traffic flow, as well as the influence of additional confounding variables such as construction activities and other concurrent urban dynamics. These areas of research would significantly contribute to a better understanding of LUZs in various urban contexts.

Our study contributes to an emerging comprehensive understanding of the potential effects of LUZs, especially in cities in developing markets. We hope this will trigger further work to collect such data, as our results show large effects sizes that warrants the attention of policy makers when deciding on interventions in the public space of these cities.

7. Acknowledgements

We would like to acknowledge the authorities of Zapopan and the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH for cooperating to deploy the EZ Parking project as part of the Sustainable Transport Program (PTS) funded by the German Federal Ministry for Economic Cooperation and Development (BMZ). Also, we acknowledge the work of all the collaborators who participated in developing EZ Parking.

8. Appendix A

We used the p-median facility location model (Daskin, M. 2008) to locate p facilities to minimize the demand-weighted total distance between demand points and the nearest EZ Parking candidate facility. To do so, we defined (6) the assignment variable Y_{ij}, which equals 1 if demand node i is assigned to a candidate j (i.e. LUZ), and 0 otherwise. Also, we defined the decision variable X_j, which equals 1 if the LUZ is located in j, and 0 otherwise (7). The objective function (8) minimizes the demand-weighted total distance. For the distance, we used walking distance and obtained the data from Google Maps. For store weight, we used the number of employees per store as a proxy for demand. In addition, constraints (9) indicate that is node is assigned, while constraints (10) limit assignments to open. Constraint (11) states that p facilities are to be located. Finally, constraints (12) and (13) are integrality constraints. The formulation is as follows:

$$Y_{ij} = \begin{cases} 1 & \text{if demand node } i \in I \text{ is assigned to a candidate } j \in J, \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$X_j = \begin{cases} 1 & \text{if the bay is located in } j \in J \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$Min \sum_{j \in J} \sum_{i \in I} h_i \, d_{ij} Y_{ij} \tag{8}$$

Subject to

$$\sum_{j \in J} Y_{ij} = 1 \forall i \in I \tag{9}$$

$$Y_{ij} - X_j \leq 0, \forall i \in I; \forall j \in J \tag{10}$$

$$\sum_{j \in J} \mathrm{X_j} = p \tag{11}$$

$$X_j \in \{0,1\}, \forall j \in J \tag{12}$$

$$Y_{ij} \in \{0,1\}, \forall i \in I; \forall j \in J \tag{13}$$

9. Appendix B

During the field experiment, we documented the use of the LUZs through photographic evidence. These images capture key moments in the process, from registration to the final delivery. Illustration 1 shows company representatives scanning the QR code to register for the pilot program, while Illustration 2 captures freight drivers scanning the QR code upon arrival to access the LUZs. Once registered, drivers began using the LUZs for their intended purpose, as seen in Illustration 3, where drivers are unloading and delivering goods. Illustration 4 highlights the use of trolleys for transporting goods after unloading in the LUZs. Illustration 5 depicts drivers preparing orders and moving goods, and Illustration 6 showcases informal sector users effectively utilizing the LUZs for their deliveries. These images provide a comprehensive visual overview of the implementation and use of the LUZs during the experiment.

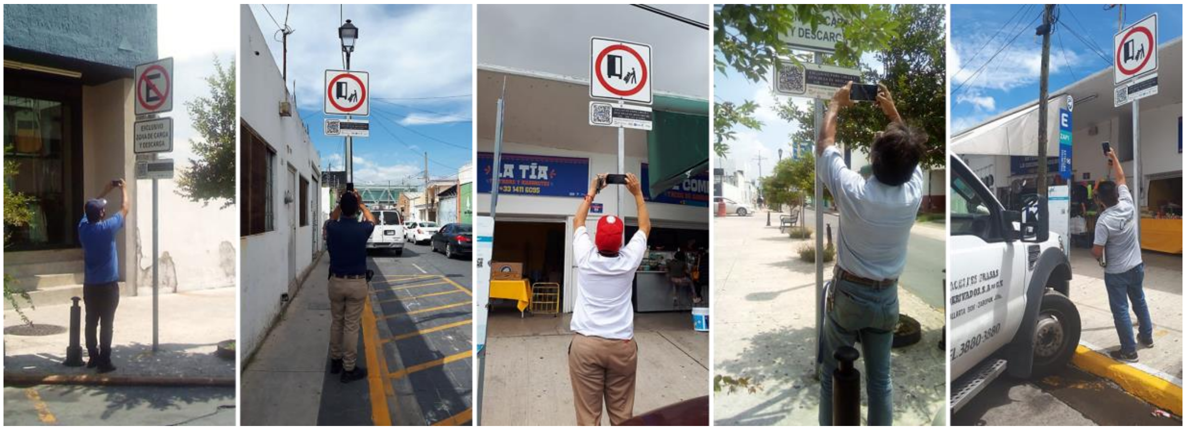

Illustration 1. Company representatives scanning the QR code to register for the pilot program

Illustration 2. Freight drivers scanning the QR code to start using the LUZs

Illustration 3. Using the LUZs for unloading and delivering goods

Illustration 4. Using the LUZs for unloading and using a trolley to carry the goods

Illustration 5. Preparing the order and transporting goods

Illustration 6. Users from the informal sector using the LUZs

10. Appendix C

The following quotes highlight the benefits of the LUZs from the perspectives of a local shopkeeper and a freight driver who participated in the intervention. These transcripts, taken from video footage, have been translated from Spanish to English to preserve the original meaning and context.

<u>Shopkeeper:</u>

"Suppliers were not able to reach my store…It was a problem. Sometimes they did not supply my store…Taking two or three days to deliver the products".

"It (the LUZs program) benefits me a lot because suppliers were not able to serve my store because on one day, the promoter came to take my order, and on another day, the freight drivers could not find a parking spot due to the traffic. We are located in Zapopan's downtown where it is complicated to park".

<u>Freight driver:</u>

"The loading and unloading bays will benefit us in terms of time...because we lose a lot of time finding a parking spot, and when we find one, it is usually far away from the store. Therefore, this will help us to facilitate the process (delivery)".

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