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Abstract

Congestion pricing, also referred to as road pricing, is a form of Pigouvian taxation designed to limit or reduce vehicular traffic within a specific area. These systems aim to encourage changes in driving behavior and the choice of transportation mode. An example of a congestion pricing system is the Milan Area C charging zone, which operates on a fixed-rate basis. In recent years, two modifications to the restrictions have been introduced: i) limitations on vehicle types allowed to enter the zone, and ii) a 50 percent increase in congestion charges. By using open data from Area C vehicle access and mobile phone data on overall presence in the area, this study seeks to evaluate the effectiveness of these two restriction policies within the AREA C congestion policy. The findings indicate that both restrictions influenced the choice of transportation mode, with vehicle type limitations having a greater impact than price increases. This evidence showing the effectiveness of vehicle type restrictions and increased charges could support the enhancement of pricing policies and vehicle limitations in Milan and similar cities. Moreover, demographic factors, including the proportion of women and elderly people in the area, significantly influence transportation choices, underscoring the importance of equitable policy implementation to enhance acceptance and effectiveness among more vulnerable groups.

Keywords: congestion charge; road pricing; mobile phone data; traffic congestion.

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1 Introduction

In the last decade, from 2012 to 2022, the European Union witnessed a significant increase in the average number of passenger cars per 1,000 inhabitants, climbing to 560 by 2022— an increase of 14.3%.¹ In the Milan area, this figure climbs even higher to 622 cars per 1,000 inhabitants, as reported by the Milan Mobility Agency. Although this rate may be lower than in other Italian cities, it still stands relatively high when compared to European counterparts. Despite vehicular traffic has become synonymous with urban development in major cities, the rise in car ownership has not come without challenges. Particularly in densely populated areas, the increasing traffic has given rise to several issues, with pollution and congestion emerging as significant challenges.

To address these challenges, several cities across the globe have turned to innovative solutions with road pricing systems emerging as a promising solution. These systems, aimed at managing the demand for private car transportation modes, seek to reduce congestion and mitigate environmental impacts by ensuring that the costs associated with vehicle usage are internalized by the users themselves.

Cities like Singapore, London (Givoni, 2012), and Stockholm (Börjesson et al., 2012; Börjesson and Kristoffersson, 2018) implemented such systems demonstrating their efficacy in reducing traffic congestion and emissions. Following suit, Milan, one of Europe’s most congested and polluted cities,² embarked on its experimentation with a congestion pricing schema. In January 2008, the Municipality of Milan introduced the Ecopass scheme—a pioneering effort aimed at improving air quality within the city center.

This initial intervention, modeled after London’s congestion charge, encompassed an area-wide charge for vehicles entering the 8 km² city center zone during peak hours on weekdays. Building on the success and lessons learned from the Ecopass initiative, Milan expanded its efforts with the implementation of the Area C charging zone in January 2012. This expansion aimed to address the shortcomings of Ecopass while leveraging its public acceptance and popularity. Recently, Milan’s road pricing scheme underwent a series of policy adjustments aimed at further optimizing its effectiveness. In 2022 and 2023, these adjustments included restrictions on more

¹Eurostat. (2024, January 17). Passenger cars per 1 000 inhabitants reached 560 in 2022 [News article]. Retrieved from the link <https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20240117-1> on 05/14/2024

²EU Urban Mobility Observatory. (2024, March 8). Milan to see temporary vehicle bans from high levels of air pollution [News article]. retrieved from https://urban-mobility-observatory.transport.ec.europa.eu/news-events/news/milan-see-temporary-vehicle-bans-high-levels-air-pollution-2024-03-08_enon14/05/2024.

polluting vehicle types and an increase in toll fees respectively.

The Milan road charge scheme has been studied in academic literature from various points of view, including direct effects on travel behavior (Beria, 2016; Lehe, 2019), as well as economic and environmental impacts (Beria, 2016; Gibson and Carnovale, 2015; Percoco, 2013, 2014; Croci, 2016). While empirical studies have underscored the efficacy of Milan’s road pricing scheme in reducing vehicular traffic in terms of absolute number of cars accessing the area, these studies do not consider changes in the overall mobility flows in the area. Hence, these studies provide limited insights into overall shifts in transportation mode shares among individuals within the area. This study seeks to fill this gap by evaluating the recent regulatory changes’ effectiveness in terms of the percentage of vehicles on the Area C’s overall mobility flows. Leveraging vehicle access data sourced from the municipality’s open data portal and mobile phone data to gather information on the overall mobility flows in the area, this study aims to evaluate the effectiveness of two different congestion policy changes on car usage.

This paper is structured as follows. Section 2 provides a theoretical background on congestion pricing systems, along with a description of Milan’s Area C and previous efficacy evaluations. In Section 3, we outline the data sources, the methodology used, and we present some descriptive statistics. In Section 4, we present our results and discuss them. Finally, Section 5 concludes the study, addressing its limitations and suggesting avenues for future research.

2 Theoretical Background

2.1 Congestion Pricing Systems

Congestion pricing, also referred to as road pricing, functions as a Pigouvian tax aimed at constraining or reducing vehicular flow within a specific area, thereby enabling individual travelers to internalize the adverse externalities generated by their transportation behavior (Pigou, 1920). The Pigouvian designation stems from the work of Pigou (1920), where he advocated for a tax on congestion, launching the academic debate on congestion pricing (Pigou, 1920). While the majority of researchers advocate for the introduction of congestion pricing systems, some concerns regarding the design and practical implementation have been raised (Lindsey, 2006). This taxation model aims at dissuading drivers from automobile usage by mandating a fee for using private cars for transportation purposes (Ecola and Light, 2009). The final goal is therefore to drive changes in mobility behavior across various aspects

including trip frequency, destinations, modes of transportation, timing, routes, and even long-term decisions such as residential and occupational choices.

De Palma and Lindsey (2011) in their overview paper on traffic congestion pricing methodologies defined four dimensions along which congestion pricing schemes can be classified, including the type of scheme, the variability of tolls over time, other dimensions of toll differentiation, and the technology. Given the subordinate nature of technology to choices in the other three dimensions, this section focuses on the first three dimensions of classification. Among the classification dimensions, the most prominent involves three types of congestion pricing systems: facility-based, area-based, and distance-based.

Facility-based systems, the most common pricing schemes, is a congestion charge applied to facilities such as roads, bridges, and tunnels, levying tolls either on the entire facility, a single lane, or the vehicle at specific points based on distance traveled (De Palma and Lindsey, 2011). An example of facility-based is the adoption of high-occupancy toll lanes (HOT lanes) in the United States. Conversely, area-based systems entail charging vehicles upon entering and/or exiting a designated area, and using checkpoints and video surveillance technology to regulate traffic. These systems can be designed as cordon or zonal systems, with cordon systems delineating man-made boundaries, such as concentric circles in the city center, and charging tolls upon entering or exiting. Examples of these systems are the Stockholm cordon zone and the Milan Area C. Conversely, zonal schemes are designed to charge fees for entering, exiting, or traveling within the zone without crossing its perimeter, with boundaries defined by natural features or elements of the built environment (De Palma and Lindsey, 2011). Examples of Zonal schemes include the Paris and London low-emission zones. Lastly, distance-based schemes entail charges varying with distance traveled, either linearly or non-linearly. While pure distance-based systems for managing private vehicle congestion have not been implemented, existing systems often overlap with facilities-based schemes (Veitch and Rhodes, 2024).

Moving to the toll variability dimension, the terminology delineated by authors distinguishes between "static pricing" and "dynamic charging" (Cottingham and Greenwood, 2007). The former refers to fixed schedules of charges announced well in advance of travel decisions, while the latter entails charges contingent upon real-time congestion levels. Expanding upon this classification, De Palma and Lindsey (2011) classify tolls as flat, time-of-day variant, or dynamic, the latter also known as responsive tolls. Flat tolls remain constant over time. These systems are historically prevalent due to technological constraints and public acceptance due to the simplicity of the scheme (Selmoune et al., 2020; Gu et al., 2018). Time-of-day tolls are still

static pricing strategies but introduce variations based on the time of the day, the day of the week, and the seasons. Conversely, dynamic pricing strategies, are designed to adapt to near-real-time traffic conditions (De Palma and Lindsey, 2011). Compared to static charges, dynamic pricing proves to be more effective at managing traffic demand by aligning tolls with congestion levels. The real-time optimization of traffic emerges as a pivotal strategy in congestion management and enhancing urban traffic conditions, as highlighted by recent studies (Lee et al., 2019).

Additional dimensions of differentiation can be employed in the designing and implementation of congestion pricing systems. These encompass distinctions based on vehicle attributes like type, axle count, and weight, variations according to speed and other indicators of hazardous driving conduct, and categorization of vehicles and drivers (De Palma and Lindsey, 2011). An example of the latter tolls differentiation involves the exemptions implemented by London, such as a 90% discount for residents and a 12.5% discount for fleets, alongside reductions for monthly and annual payments.

2.2 Milano Area C

The Area C charging zone was implemented in Milan on January 16, 2012, with the aim of revising and re-branding the Ecopass system, introduced in 2008, in response to identified shortcomings and to leverage its existing public support (Hensher and Li, 2013). Prior to the implementation of Area C, a public consultation was held in 2011 indicated strong approval for continuing the system, with a 79% voter endorsement for the congestion pricing program (Percoco, 2013). Area C retained the same geographical boundaries and entry points as its predecessor, along with the technological infrastructure, while introducing modifications to the fee structure (Hensher and Li, 2013). Employing a fixed-rate system, Area C simplified the fee mechanism compared to Ecopass, which utilized variable rates based on vehicle engine and fuel type (Rotaris et al., 2010; Beria, 2016). Vehicles entering the cordon on weekdays are subject to a flat fee, categorized as general, resident, or commercial rates, thereby reducing the complexity of the payment system (Hensher and Li, 2013; Lehe, 2019). The introduction of exemptions for specific vehicle types, including motorcycles, and restrictions on certain vehicles further enhanced perceived fairness, contributing to public acceptance (Veitch and Rhodes, 2024). Area C charging zone consists of the Cerchia dei Bastioni (CB) area (see Fig. 1), covering an 8 km² area in central Milan inhabited by more than 99,000 residents as of the 12/31/2019.³

³The data is sourced from the report "Milano e i suoi quartieri 2020", retrieved from the link <https://www.comune.milano.it/documents/20126/2313917/MILANO+QUARTIERI+2020.pdf>

Figure 1: Milan Area C area and entrance points as blue and red dots; in red are those dedicated to public transport.



The cordon includes 43 access points equipped with cameras to capture vehicle number plates upon entry, with charges remaining constant throughout the day and requiring only one payment per day. Charging hours are from 7:30 AM to 7:30 PM on weekdays. Policy adjustments were enacted in 2022 and 2023, including restrictions on more polluting vehicle types and an increase in toll fees. On October 1, 2022, access to Area C was restricted for certain categories of vehicles,⁴ while on October 30, 2023, the entry fee for transportation of people within Area C was increased from €5 to €7.5, with service vehicle fees increasing from €3 to €4.50, representing a total increase of 50%.

2.3 The Effectiveness Of The Area C Policy

The effectiveness of the Area C policy was investigated in previous studies across various impact dimensions, including direct effects on travel behavior, as well as economic and environmental impacts.

Examining the direct impact, Beria (2016) analysed the distribution of entries per vehicle category, revealing an overall 31.1% reduction in traffic within the area compared to the previous 2011 period when Ecopass pricing scheme was in place. Another comparison between EcoPass and Area C, as reported by Lehe (2019) citing data from the Report published by Agenzia Mobilità Ambiente Territorio in 2018, underscored the latter's increased effectiveness in reducing entries and charging a greater number of vehicles, with the charged share surging to 56%. A more recent estimation published by Agenzia Mobilità Ambiente Territorio in 2022⁵ revealed a reduction of entries from 90,000 recorded in 2012 to 81,000 in 2021, marking a reduction of 38.5%. The figure for 2020 (-46.8%), naturally reflects the effects on mobility caused by the Covid-19 pandemic. The impact of the outbreak propagated also to 2021 with an increase in private transportation due to the fear of using public transport.

Concerning the pollution reduction effect, (Beria, 2016) showed that the traffic decline in 2012 led to an 18% reduction in particulate matter and a 35% decrease in CO₂ emissions within the Area. Moreover, a two-month suspension of charging in 2012 prompted by protests from parking garage owners served as a natural experi-

on 05/01/2024.

⁴Euro 2 gasoline passenger transport vehicles, Euro 3 and 4 diesel with factory-installed particulate filters (FAP), Euro 0, 1, 2, 3, and 4 diesel with aftermarket-installed FAP by December 2018 and with compliance class (reported on the registration document) for particulate mass of at least Euro 4, and Euro 5 diesel

⁵Data retrieved from the link <https://www.comune.milano.it/-/mobilita.-area-c-compie-10-anni-l-analisi-dell-andamento-del-provvedimento-nei-dati-di-amat> accessed on 05/01/2024.

ment for assessing the policy’s pollution effects, with differing conclusions drawn by various studies (Gibson and Carnovale, 2015; Percoco, 2013, 2014). While Gibson and Carnovale (2015) found that the policy reduces traffic and pollution significantly, Percoco (2013) found that the charges significantly decreased the concentration of certain pollutants, particularly carbon monoxide, and particulates, but only in the short term. The authors noted that pollution levels returned to pre-treatment levels one week after implementation. Additionally, they suggest that the policy’s under-performance may be attributed to motorbikes not being subject to charges.

From a revenue standpoint, Beria (2016) estimated that the policy yielded a net annual revenue of approximately €13 million after accounting for operating costs, with funds reinvested in enhancing public transport and expanding bicycle-sharing initiatives. The revenue recycling of Area C fosters a positive rapport between the public and government, enhancing the acceptability of congestion pricing systems Veitch and Rhodes (2024). Additionally, fines contribute to revenues, with penalties from 2012–2014 totaling roughly €20-25 million per year.⁶ More recent studies indicated that the system consistently generates gross revenue double to triple the cost of operation, further highlighting its financial viability (Croci, 2016; Lehe, 2019).

3 Data, methodology and descriptive statistics

3.1 Data collection

Two primary data sources were used to gather information on the percentage of cars relative to the overall mobility flows in Area C. For the number of cars, data were collected from open data provided on the Open data platform of the Metropolitan City of Milan. This dataset includes the daily number of accesses to Area C from January 2019 to December 2023. The overall flow of mobility in the area was computed by using data provided by a telecommunications provider. These data provide an estimation of the daily presence based on collected mobile phone data. The reference period for these data spans from January 2022 to December 2023. Consequently, the dataset built on these two sources contains the percentage of cars out of the total number of presences in the area for the period January 2022 to December 2023. This percentage represents our dependent variable.

To estimate the influence of two policy changes on the percentage of vehicles within overall mobility flows in Area C, additional information was collected on the

⁶Data retrieved from https://milano.repubblica.it/cronaca/2015/09/25/news/area_c_bottino_d_oro_2_3_milioni_di_verbali_magenta_varco_killer-123613594/ on 05/01/2024.

occurrence of strikes and holidays, the prices of diesel and gasoline, the cost of public transportation, and weather conditions in terms of rainfall precipitation. Furthermore, to control for the type of population present in the area (as transportation mode preferences may vary among individuals), the dataset also includes the percentage of women and the percentage of elderly individuals (over 66 years) within the total mobility flow in the area. These two pieces of information are available within the phone data used to calculate the total number of mobility flows in the area. Sources and data descriptions for these datasets are provided in the subsequent paragraph.

The independent variables are summarized in Table 1. The FEST variable (festive day) and STRIKE variable (strike day) are boolean variables equal to 1 if the day is a holiday or festivity or if the day is marked by a public transport strike, and 0 otherwise. These two variables are collected manually. The DIES (diesel price) and GAS (gasoline price) variables represent the average quarterly prices of diesel and gasoline, calculated based on daily values and obtained from the Ministero delle Imprese e del Made in Italy, respectively. The RAIN variable refers to daily precipitation measured in millimeters for the area of Milan (city center, sensor in Brera area), and the data is sourced from ARPA Lombardia - Agenzia regionale per la protezione dell'ambiente della Lombardia. The PUB variable (public transportation price) indicates the price of a single-ride ticket for public transportation usage, collected manually. Finally, the WOM (women percentage) and ELD (elderly percentage) variables correspond to the daily percentages of women and elderly people (66+) present in the area each day, respectively, with these data provided by a telecommunications provider. Each of these variables allows for the assessment of the impact of various socio-economic and contextual factors on the effectiveness of the charge increase and the car limitation in Area C.

3.2 Methodology

The goal of this study is to assess the effectiveness of two different restriction policies within the Area C congestion policy based on traffic data from the city of Milan and mobility data of individuals from a telecommunications operator. We estimate the effects of these two policies by adopting a regression discontinuity design (Percoco, 2013) and using fixed effects regressions. Our dependent variable corresponds to a ratio between the number of cars entering Area C compared to a sample of the population present in the same area on the same day, which we capture through mobile mobility data. We apply a logarithmic transformation to this dependent variable. The equation to be estimated is of the form:

Table 1: Definition of independent variables

Name	Description	Source
Festive day	Boolean variable equals 1 if the day is a holiday/festivity, and 0 otherwise	Manual collection
Strike day	Boolean variable equals 1 if the day is a public transport strike day, and 0 otherwise	Manual collection
Diesel price	Average price of diesel per trimester	Ministero delle Imprese e del Made in Italy
Gasoline price	Average price of gasoline per trimester	Ministero delle Imprese e del Made in Italy
Rainfall precipitation	Daily rainfall precipitation in millimeters	ARPA Lombardia
Public transportation price	One-ride ticket price for public transportation usage	Manual collection
Women percentage	Daily percentage of women present in the area	Telecommunication provider
Elderly percentage	Daily percentage of elderly people (66+) present in the area	Telecommunication provider

$$\ln Y_t = \alpha + \beta_1 R1_t + \beta_2 R2_t + \mathbf{X}_t' \gamma + \mathbf{Z}_t' \delta + \kappa_t + \lambda_t + \mu_t + \nu_t + \epsilon_t \quad (1)$$

where Y_t is the outcome of interest, i.e. the vehicle share of mobility flows in Area C in day t . $R1_t$ and $R2_t$ are the variables of interest, respectively for restriction 1, i.e. the car limitation, and for restriction 2, the charge increase. $\mathbf{X}_t'$ includes a set of covariates, including a binary variable to indicate whether it is a day of festivities or holidays, a binary variable for strike days, diesel, gasoline and public transport prices and the level of precipitation. We also include a set of socio-demographic variables, $\mathbf{Z}_t'$ which encompass the proportion of women and people aged over 66. We include fixed-effects for the year (κ_t), the month (λ_t), the week (μ_t) and the day (ν_t). $\epsilon_{i,t}$ is an unobserved error term.

3.3 Descriptive statistics

In this section, we present the descriptive statistics of the variables used in the study to analyze the impact of congestion pricing policy restrictions in Area C in Milan on overall mobility flows and specific population groups. Descriptive statistics relating to the socio-demographic characteristics of our study population are presented in Table 2. These statistics are taken from mobile phone data on overall presence in the area over the period 2022-2023.

The average proportion of females in the area is 0.38 with a standard deviation of 0.04, ranging from 0.22 to 0.44. Males constitute an average of 0.45 of the population with a standard deviation of 0.05, ranging from 0.27 to 0.51. The data shows a slightly higher average proportion of males compared to females in the area. It is worth mentioning that the total does not sum to 100% due to the inclusion of masked gender and undefined gender categories. Despite masked gender representing negligible proportions of the population, the high proportion of undefined gender cases indicates a significant portion of the population whose gender was not identified, which could impact the accuracy of gender-related analyses.

For nationality, Italians make up an average of 0.83 of the population, with a standard deviation of 0.08, while foreigners represent 0.17 of the population with the same standard deviation. Masked nationalities are negligible. The overwhelming majority of the population in the Area C zone is Italian, with a consistent proportion of foreigners. This highlights that the congestion pricing policy implemented in 2012 primarily affects national residents, commuters, and visitors rather than foreign visitors.

Classes of travelers distribution show that commuters represent an average of

0.74 of the population with a standard deviation of 0.04, while inhabitants represent 0.26 with the same standard deviation. The higher proportion of commuters and visitors indicates that Area C is a significant transit zone for people who do not reside there. This can be interpreted as the congestion pricing policy mainly targeting daily commuters rather than the local inhabitants. This is further demonstrated by the exceptions in place for residents who enjoy 50 free entries per year and reduced rates after exceeding this threshold (Rotaris et al., 2010). To cope with the sudden protests of residents and shops, two new tolls were introduced: 3€/day for vehicles associated with commercial activities and 2€/day for residents after a package of 40 free entries per year (Boggio and Beria, 2019), which has been increased to 50 free entries.

Regarding age, the groups are distributed as follows: under 18 years (0.04 on average), 19-30 years (0.14 on average), 31-45 years (0.17 on average), 46-65 years (0.29 on average), and 66+ years (0.19 on average). Undefined ages represent an average of 0.17 of the population. The substantial proportion of undefined ages may reflect data identification challenges for the telecommunication provider. The two age groups that are most prevalent, 31-45 and 46-65, are those that correspond to working people, again arguing for policies that aims to reduce commuter and visitor traffic by private cars in Milan’s city center.

The small proportion of masked information in terms of gender, nationalities, and age implies the data collection process is quite transparent and reliable.

Figures 2 and 3 display respectively monthly variations in overall mobility flows in Area C and monthly variations in vehicle flows in Area C in the years 2022 and 2023. The combined view of these two pieces of information allows for a first descriptive overview of how different restrictions, such as vehicle type limitations and congestion charge increases, influence the choice to use a private car to access the study area.

Thus, we can see that if the average monthly number of people accessing Area C between September 2022 and October 2022 increases, this is not the case for the number of vehicles, seemingly indicating some effectiveness of the vehicle limitation policy implemented on 1st October 2022. This observation repeats throughout the year 2023, with the increase in the number of average monthly vehicles occurring in proportions lower than those of the number of people accessing Area C. If each month, more people access Area C than in 2022, the number of vehicles is on average lower each month than the values of 2022. Furthermore, the policy of charge increasing on October 30, 2023, seems to follow a similar pattern, with in November and December 2023, an average number of people accessing Area C higher than the values of the same months in 2022, but a number of vehicles accessing Area C in November and December 2023 almost equal than the values of the same months in 2022.

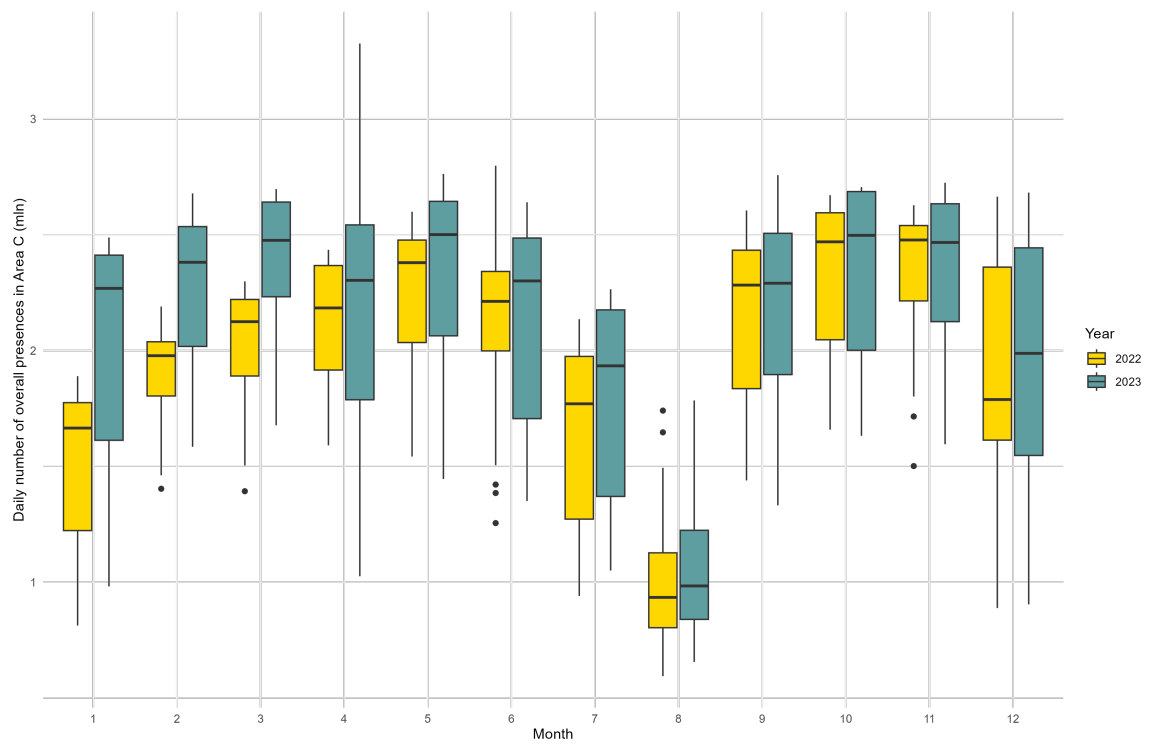
Table 2: Socio-demographic characteristics of the population in Area C

Variable	Statistic	Mean	St. Dev.	Min	Max
Gender	Female	0.38	0.04	0.22	0.44
	Male	0.45	0.05	0.27	0.51
	Masked gender	0.001	0.001	0.00	0.01
	Undefined gender	0.17	0.08	0.07	0.51
Nationality	Italian	0.83	0.08	0.49	0.93
	Foreigner	0.17	0.08	0.07	0.51
	Masked nationality	0.00	0.00	0.00	0.001
Class	Commuters and visitors	0.74	0.04	0.53	0.82
	Inhabitants	0.26	0.04	0.18	0.47
	Masked class	0.00	0.00	0.00	0.001
Age	Under 18 years	0.04	0.01	0.01	0.07
	19-30	0.14	0.02	0.07	0.17
	31-45	0.17	0.02	0.10	0.21
	46-65	0.29	0.03	0.17	0.34
	Over 66 years	0.19	0.02	0.14	0.24
	Undefined age	0.17	0.08	0.07	0.51

Notes: The Table shows Area C presence data according to the socio-demographic characteristics of the people present in 2022 and 2023. We indicate the average, standard deviation, minimum and maximum values over the observed period.

Source: Telecommunication provider.

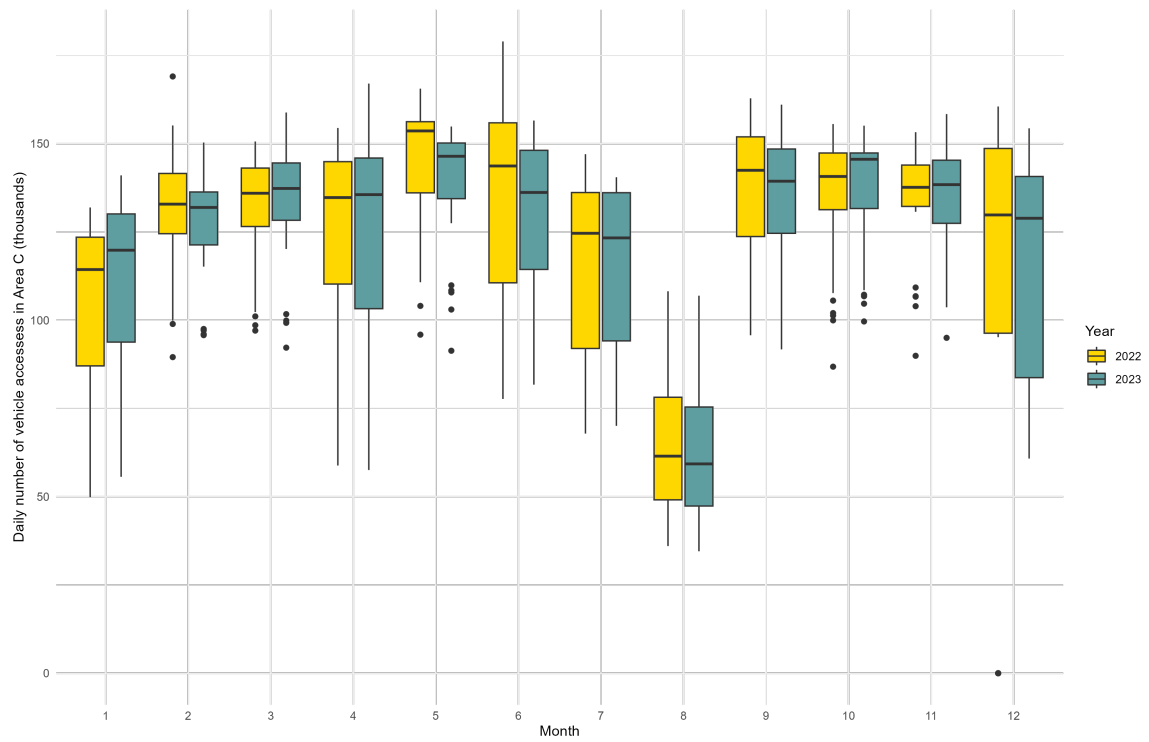
Figure 2: Monthly distribution of daily number of overall presences in Area C (mln)



Notes: The Figure shows the first quartile, the median, the third quartile and the minimum and maximum values for the number of people accessing Area C each day per month over the years 2022 and 2023.

Source: Telecommunication provider.

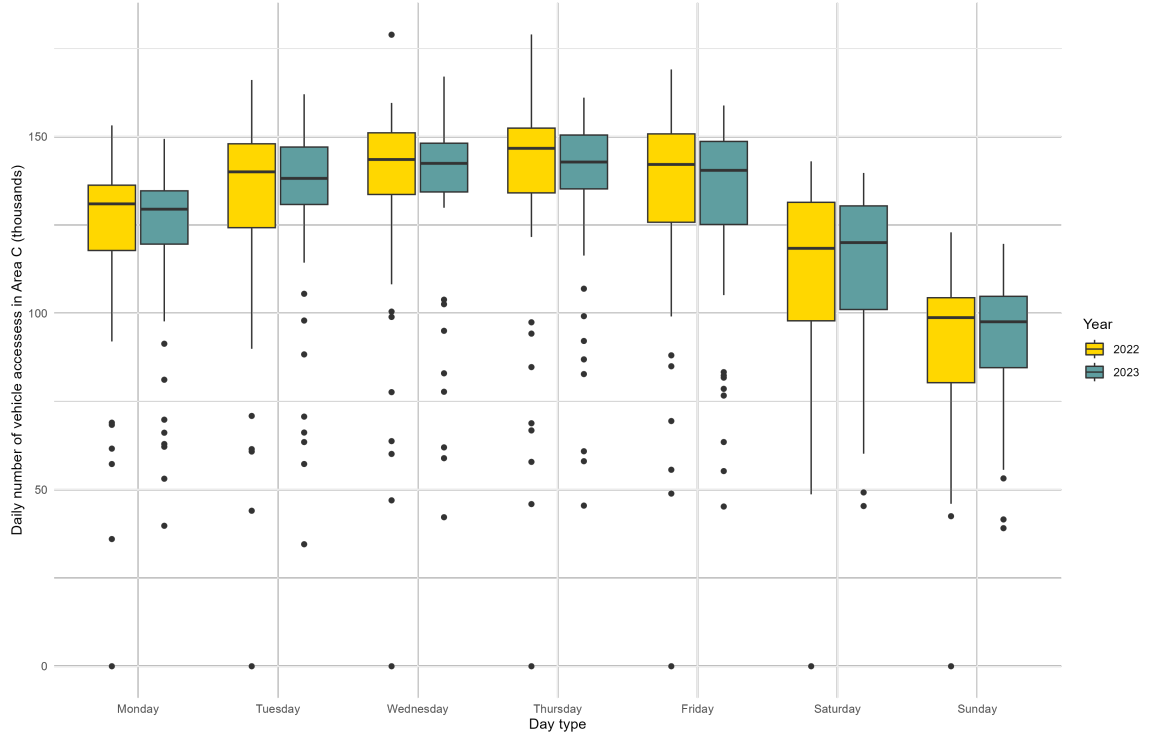
Figure 3: Monthly distribution of daily number of vehicle accesses in Area C (thousands)



Notes: The Figure shows the first quartile, the median, the third quartile and the minimum and maximum values for the number of vehicles accessing Area C each day per month over the years 2022 and 2023.

Source: Open data platform of the Metropolitan City of Milan.

Figure 4: Day type distribution of daily number of vehicle accesses in Area C



Notes: The Figure shows the first quartile, the median, the third quartile and the minimum and maximum values for the number of vehicles accessing Area C per day over the years 2022 and 2023.

Source: Open data platform of the Metropolitan City of Milan.

The variations in traffic on different days reported in Table 4 shows that on weekdays, traffic in the Area C in 2023 is lower than that observed in 2022. This may suggest that the two limitation policies of increased charges and vehicle restrictions primarily affect commuters.

In summary, our descriptive analysis provides a first understanding of mobility patterns and the potential impacts of congestion pricing policies on vehicle attendance in the Area C zone. The reliability of these initial insights must now be assessed using models for quantitatively estimating the effects of the two limitation policies.

4 Results and discussion

We estimate Equation 1 by running different types of models. First, we estimate the effects of the charge increase and car limitation with a simple OLS model, without fixed-effects (Model 1). In a second step, we include fixed-effects to our model (Model 2). Third, we also include covariates for transport conditions and costs (Model 3),

before including socio-demographic characteristics in a fourth step (Model 4). Table 3 shows the result of the estimation for the entire population of interest, whereas Table 4 is restricted to individuals identified as Italian (identified by using nationality variable) in the mobile phone mobility data.

Regardless of the specification used (from (1) to (4)), the two restrictions appear to have a significant negative effect on vehicle share of mobility flows in the Area C zone, with Restriction 1 (vehicle type limitation) having higher impact than Restriction 2 (charge increase). For the entire population, the intensity of the negative effect of the first restriction, i.e. the limitation of the type of cars, diminishes as more variables are added to the model, while that of the second restriction, the one concerning the car charge increase, increases as more variables are added. Whether for the entire population or Italians, the first restriction seems to have a slightly stronger effect than the second on charge increase in Milan center city. While limiting the type of cars logically has an effect on people’s access to Area C by car as it affects the number of cars that can enter the area, our results indicate also that increases in charges tend to discourage people from coming by car to the city center. Considering the results of Model 4, the increase in charges reduces vehicle share of mobility flows in the Area C zone by 5.3% (by 4.9% when only Italians are considered) and the restriction linked to the number of cars in the zone reduces vehicle proportion of mobility flows in Area C by 8% (by 10.3% for Italians). These findings corroborate what has been demonstrated by other studies, indicating that price increases do have an impact, albeit less pronounced than the implementation itself (Lehe, 2019). Indeed, the initial implementation of the Ecopass congestion policy did have an impact; the share of charged vehicles decreased from 22% in 2008 to 14% in 2011 (Lehe, 2019). In our study, we observed a mere 5% decrease in the vehicle proportion of mobility flows when the charge was increased.

Covariates for transport conditions and costs have similar effects for the whole sample and for Italians only. Festivities and holidays have a significant negative effect on vehicle share of mobility flows, suggesting that special events reduce the number of cars in the zone. Strikes seem to have a significant positive effect on vehicle proportion of mobility flows. This could indicate that when there are strikes in public transportation, people turn to their cars as an alternative. While diesel prices have a significant effect on vehicle share of mobility flows, the magnitude of this effect is almost negligible (0.002). On the other hand, gasoline prices show a significant negative effect (-0.549). This indicates that price variations can influence individuals’ transportation choices, which aligns with the findings of previous studies (Coria et al., 2015). Public transport prices and rainfall does not appear to have any

effect on vehicle share of mobility flows. Furthermore, we’re not only interested in the effect on traffic, but also in the demographic characteristics of people who come to the area by car after the policy. As demonstrated by Franklin (2012) demographic factors affect travel responses to congestion pricing. In our study, we demonstrated that the percentage of women have significant negative effects on vehicle proportion of mobility flows, suggesting that they are less likely to use cars. This result is consistent with the work of Franklin (2012), which shows that women are less likely to have access to a private car and more likely to have a public transport pass. On the opposite, the percentage of people over 66 years old have positive effects on vehicle share of mobility flows, suggesting they might be inclined to use their car.

The results suggest that traffic restrictions, especially car limitations, have a significant impact on vehicle share of mobility flows in the Area C zone in Milan. However, other factors such as fuel prices, public transport prices, and special events also play a role in individuals’ transportation choices. The effects of restrictions and covariates, such as the proportion of women, on people’s vehicle proportion of mobility flows in Milan’s Area C appear to have stronger and more significant effects on the subsample of Italian people.

5 Conclusion

The Milan road charge scheme has been extensively studied in academic literature, focusing on its direct effects on travel behavior (Beria, 2016; Lehe, 2019) as well as its economic and environmental impacts. While empirical studies have demonstrated the scheme’s effectiveness in reducing vehicular traffic accessing Area C, these studies have often overlooked shifts in transportation mode preferences compared to the overall mobility flows within the area.

This paper addresses this gap by evaluating recent regulatory changes’ impact on the percentage of vehicles in Area C’s overall mobility flows. Using vehicle access data from the municipality’s open data portal and mobile phone data to capture broader mobility flows, this study assesses the effect of congestion policy changes on the percentage of vehicles over the total mobility flows.

More specifically, recent adjustments to Milan’s road pricing scheme, implemented in 2022 and 2023, included restrictions on more polluting vehicle types and increases in toll charge. We estimate the effects of these policy changes using a regression discontinuity design.

Our findings indicate that both restrictions had a significant negative impact on vehicle attendance in Area C. Specifically, Restriction 1, targeting vehicle type limita-

Table 3: Results of fixed-effects regression for the two congestion limitation policies

	(1)	(2)	(3)	(4)
Restriction 1 (vehicle type limitation)	-0.104*** (0.008)	-0.118*** (0.010)	-0.091*** (0.011)	-0.080*** (0.014)
Restriction 2 (charge increase)	-0.014 (0.011)	-0.047*** (0.014)	-0.047*** (0.013)	-0.053*** (0.013)
Festivities and holidays			-0.075* (0.030)	-0.119*** (0.032)
Strikes			0.045*** (0.010)	0.037*** (0.011)
Diesel price			0.002*** (0.000)	0.002*** (0.000)
Gasoline price			-0.006 (0.081)	-0.549*** (0.128)
Public transport price			0.380* (0.174)	0.081 (0.166)
Rainfall			0.000 (0.000)	0.000 (0.000)
Women				-2.341*** (0.549)
People over 66 years old				6.207*** (0.980)
Constant	-2.729*** (0.007)	-2.713*** (0.021)	-3.388*** (0.334)	-2.203*** (0.367)
N	723	723	723	723
Year fixed effects	No	Yes	Yes	Yes
Month fixed effects	No	Yes	Yes	Yes
Week fixed effects	No	Yes	Yes	Yes
Day fixed effects	No	Yes	Yes	Yes
Robust standard errors	Yes	Yes	Yes	Yes

Notes: This table reports estimates the effects of the two Milan's congestion limitation policies, covariates for transport conditions and costs and socio-demographic covariates on vehicle attendance in the Area C zone. Column 1 presents the results of the OLS estimation without covariates. Column 2 includes fixed effects. Column 3 includes covariates for transport conditions and costs. Column 4 includes socio-demographic characteristics. Robust standard errors are in parentheses. Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.001, 0.01, 0.05, respectively).

Table 4: Results of fixed-effects regression for the two congestion limitation policies on Italians

	(1)	(2)	(3)	(4)
Restriction 1 (vehicle type limitation)	-0.072*** (0.012)	-0.082*** (0.011)	-0.072*** (0.012)	-0.103*** (0.014)
Restriction 2 (charge increase)	-0.050** (0.016)	-0.060*** (0.013)	-0.061*** (0.013)	-0.049*** (0.013)
Festivities and holidays			-0.019 (0.035)	-0.103** (0.034)
Strikes			0.045*** (0.011)	0.036** (0.011)
Diesel price			0.002*** (0.000)	0.002*** (0.000)
Gasoline price			-0.161 (0.095)	-0.353** (0.130)
Public transport price			0.334 (0.186)	-0.007 (0.178)
Rainfall			0.000 (0.000)	0.000 (0.000)
Women				-4.917*** (0.588)
People over 66 years old				6.407*** (1.047)
Constant	-2.556*** (0.009)	-2.465*** (0.022)	-2.810*** (0.370)	-1.197** (0.385)
N	723	723	723	723
Year fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes
Robust standard errors	Yes	Yes	Yes	Yes

Notes: This table reports estimates the effects of the two Milan's congestion limitation policies, covariates for transport conditions and costs and socio-demographic covariates on vehicle attendance in the Area C zone. Column 1 presents the results of the OLS estimation without covariates. Column 2 includes fixed effects. Column 3 includes covariates for transport conditions and costs. Column 4 includes socio-demographic characteristics. Robust standard errors are in parentheses. Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.001, 0.01, 0.05, respectively).

tions, appears to have a greater impact compared to Restriction 2, which involved an increase in charges. Nevertheless, other factors such as fuel prices, public transport costs, and special events also influence individual transportation choices. Additionally, demographic factors such as the proportion of women and the percentage of elderly people significantly affect vehicle usage in Milan’s Area C, particularly among Italian residents.

The findings of this study offer practical implications for policymakers in several areas. Firstly, the evidence supporting the effectiveness of vehicle type restrictions and increased charge level could justify the enhancement of pricing policies and vehicle limitations in Milan and similar cities experiencing congestion issues. Specifically, the study highlights the more pronounced impact of vehicle type restrictions compared to the charge increase. While this effect is immediate in the short term, further research is needed to understand the medium- to long-term impact of these policies on vehicle purchasing behavior.

Secondly, ensuring equity in the implementation of pricing policies, particularly for vulnerable demographic groups, is crucial. Monitoring the policy changes’ impacts on different segments of the population and implementing measures to mitigate any negative effects on those with specific mobility needs, such as women or elderly people, could enhance policy acceptance and effectiveness. While the study lacks individual-level data to directly assess these effects on different demographic groups, analyzing the impact on the percentage of these groups reveals initial evidence of varying attitudes toward the impact of policies on car usage.

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