Economics of Transportation 40 (2024) 100380

Contents lists available at ScienceDirect

Economics of Transportation

journal homepage: www.elsevier.com/locate/ecotra

Free rides to cleaner air? Examining the impact of massive public transport fare discounts on air quality

Daniel Albalate [a,c], Mattia Borsati [a,c,*], Albert Gragera [b,c,d]

[a] Department of Econometrics, Statistics and Applied Economics, University of Barcelona (UB), Barcelona, Spain
[b] Department of Applied Economics, Autonomous University of Barcelona (UAB), Barcelona, Spain
[c] Observatori d'anàlisi i Avaluació de Polítiques Públiques (OAP), University of Barcelona, Barcelona, Spain
[d] Institut d'Economia de Barcelona (IEB), Barcelona, Spain[1]

ARTICLE INFO

JEL classification:
L92
Q53
R41
R48

Keywords:
Public transportation
Air quality
Externalities
Pollutants
Modal shift

ABSTRACT

We quantify the effect of public transportation fare subsidies on air quality by exploiting the sharp discontinuity in the cost of ridership introduced by policy intervention. We identify this effect by taking advantage of four months of massive discounts for transit services introduced in Spain on September 1, 2022, as part of the national plan to tackle the global energy crisis. Across pollutants and specifications, we find no evidence that low-cost or free-of-charge public transportation financing schemes have improved air quality. Our results reveal that measures aimed at reducing transit prices may fail to achieve the claimed environmental benefits through a modal shift from private to collective modes of transport, which suggests that massive fare discounts may not represent an efficient allocation of public funds.

1. Introduction

Air pollution is a major environmental issue that poses significant negative effects on human health, including cardiovascular and respiratory diseases. It has a profound impact on society, as 99% of the global population is exposed to harmful air pollution levels, leading to approximately 4.2 million premature deaths per year worldwide. In Europe alone, this figure accounts for approximately 400,000 premature deaths per year (WHO, 2019; EEA, 2020). To tackle this issue, the World Health Organization (WHO) has proposed air pollutant concentration thresholds to eliminate such burdens, and many countries have established their own (less strict) thresholds by passing air quality legislation and establishing monitoring networks.[2] Policy-makers are implementing management plans to improve air quality and reduce long-term exposure levels, with a particular focus on urban areas where automobiles are a significant source of pollution. This process involves implementing regulations on urban vehicle access and promoting more sustainable transport modes, which have become priorities on the agenda of many cities in developed countries (especially on the European continent) following the increased social awareness about the negative impacts of private vehicle mobility such as — among others — air pollution.[3]

By focusing on air quality improvement, the effect of transport policies such as driving restrictions (Davis, 2008, 2017), road pricing schemes (Percoco, 2013), and gasoline regulations (Auffhammer and Kellogg, 2011) have been widely discussed. Likewise, the effect of new public transportation infrastructure supply on air quality has been extensively investigated. This is the case for new urban public transportation openings (Chen and Whalley, 2012; Gendron-Carrier et al., 2022; Lu et al., 2018; Sun et al., 2019; Zheng et al., 2019) and expansions (Goel and Gupta, 2017; Li et al., 2019), as well as

* Corresponding author at: Department of Econometrics, Statistics and Applied Economics, University of Barcelona (UB), Barcelona, Spain.
E-mail addresses: albalate@ub.edu (D. Albalate), mattia.borsati@ub.edu (M. Borsati), albert.gragera@uab.cat (A. Gragera).
[1] *Institution addresses:* Avinguda Diagonal, Edifici 690, 08034-Barcelona, Spain (UB). Avinguda Eix Central, Edifici B3, 08193-Cerdanyola del Vallès, Spain (UAB).

[2] Examples of this are the European Union (EU) 2008/50/EC Directive on Ambient Air Quality and Cleaner Air for Europe (EEA, 2021), the United States (US) Clean Air Act and their National Ambient Air Quality Standards (NAAQS) (EPA, 2022), and China's Atmospheric Pollution Prevention and Control Law (Huang et al., 2017).

[3] There is a broad and interdisciplinary literature that proves the importance of limiting private vehicle mobility to reduce various negative externalities such as public health impacts (Chay and Greenstone, 2003; Knittel et al., 2016; Zhang and Batterman, 2013), traffic accidents (Albalate and Fageda, 2021; Parry et al., 2007), greenhouse gas emissions (Chapman, 2007; Proost and Van Dender, 2012; Zhang et al., 2019), and noise (Kaddoura and Nagel, 2018).

https://doi.org/10.1016/j.ecotra.2024.100380
Received 8 January 2024; Received in revised form 28 October 2024; Accepted 29 October 2024
Available online 12 November 2024

related improvements in terms of quality (Beaudoin et al., 2015), service (Lalive et al., 2018), speed (Bel and Holst, 2018), and routing (Gallego et al., 2013). However, little is known about the effects of low-cost or free-of-charge public transportation financing schemes on air quality. Hence, the aim of this paper and its main contribution is to further investigate whether increased transit accessibility through massive public transport discounts improves air quality.

Currently, both political and academic interest in the effects of these public transportation financing schemes is growing worldwide, especially after their introduction in large EU countries such as Germany and Spain. This represents a qualitative leap in the scale of the adoption of such measures, as they were previously mainly implemented in isolated cities of different sizes. Free public transport has been periodically discussed within the sustainable mobility policy agenda, and it is often suggested as a tool with which to foster cleaner air, together with low emission zone policies and other pollution-reducing transport measures (such as road pricing schemes) that policy-makers are reluctant to implement due to political economy considerations[4] (De Borger and Proost, 2015).

As widely recognised, public transportation systems play a key role in mitigating negative externalities (e.g., Basso et al., 2021; Adler and van Ommeren, 2016; Anderson, 2014; Bauernschuster et al., 2017). Hence, several policy mechanisms or incidence pathways exist to reduce private vehicle use. For instance, governments can influence the relative attractiveness of private and public transportation by affecting the components of the generalised transportation cost function. On the one hand, they can reduce the monetary cost of public transport or increase the cost of private transport through — for instance — road pricing schemes (Parry and Bento, 2001; Parry and Small, 2005). On the other hand, they can provide public transportation improvements in terms of time savings through higher frequencies, new routes, or increased speeds.

By focusing on measures aimed at subsidising public transportation, there is enough consensus in the economic literature to support the role of subsidies due to both the economies of scale of transit and the negative externalities generated by private modes (Basso et al., 2011; Hörcher and Tirachini, 2021; Parry and Small, 2009). Indeed, some scholars and policy-makers advocate extending budgetary or third-party funding down to free-of-charge financing schemes to promote not only a modal shift but also fairer, more sustainable outcomes.[5]

In a similar direction, some authors have estimated the social welfare gains produced by free-of-charge measures. Among others, Davis (2021) calculated that free public transportation in Mexico City would imply an increase of 400 million riders per year (equal to approximately 25% growth), which would translate into additional operating costs equal to 183 US$ million and a revenue loss equal to 350 US$ million. In return, and beyond the enormous growth of consumer surplus due to tariff cancellations, the welfare gains due to the reduction of negative externalities would amount to 303 US$ million annually. Similarly, other assessments question the efficiency of these schemes in achieving sustainable goals from both financial and environmental perspectives. On the one hand, if other anti-congestion policies are applied, there is evidence showing that the marginal contribution of increased transit subsidies diminishes rapidly due to substitution effects between policies (Basso and Silva, 2014). On the other hand, some empirical papers and reviews of case studies have questioned the effectiveness of this policy in its ability to attract sizable proportions of private vehicle users (Bull et al., 2021; Cats et al., 2017; UITP, 2020).

To further investigate the consequences of the aforementioned measures, this paper takes advantage of a four-month period of massive discounts (starting on September 1, 2022) that were applied to public transportation fares in Spain to empirically evaluate how public transportation low-cost or free-of-charge financing schemes affect air quality.[6] This massive reduction in monetary costs for both intra- and intercity railway services, as well as for urban public transportation, was expected to affect the relative generalised cost of public transport vs. private modes, making transit relatively more attractive. As shown by the recent work of Gagnepain et al. (2024), public transport pricing schemes might have a significant impact on commuters' habits. Thus, such a measure was expected to incentivise a modal shift from the most polluting modes (e.g., private vehicles) to collective or massive ones (e.g., trains, trams, buses, and subways).

The key empirical challenge in estimating the effect of this policy is one of identification. Indeed, variations in mobility patterns that are not confounded by other factors that affect air pollution are rare. In this paper, we address this identification issue by exploiting the sharp threshold in time produced by the implementation of the policy. By collecting air pollution data for a range of pollutants for 23 Spanish cities from January 1, 2019, to December 31, 2022, we rely on a regression discontinuity in time (RDiT) approach to identify the effect of massive public transport fare discounts on air quality.[7] Overall, our findings reveal that the investigated policy had no statistically significant effect on air quality, therefore suggesting that such massive fare discounts may not represent an efficient allocation of public funds.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature on the topic. Section 3 summarises the public transport fare policy discounts implemented in Spain. Section 4 describes the data used for the analysis. Section 5 presents the empirical strategy, the main results, and some robustness checks. Section 6 discusses the mechanisms driving our results. Section 7 concludes the paper.

2. Low-cost or free-of-charge experiences

The policy examined in this paper has some historical precedents, and it cyclically pops up in the policy debates the occur among urban planners and policy-makers. However, the evidence collected from the literature is not clearly encouraging about its ability to induce a modal shift from private to collective modes of transport; at the very least, it seems less favourable than what might be assumed.

Indeed, Cats et al. (2017) evaluated the effects of free public transportation in Tallinn, which was the first European capital to provide free public transportation starting in January 2013. The authors found an increase in its use of 14% — especially in the case of low-income families — but not a significant reduction in the use of private vehicles. Indeed, the congestion relief provided by the relative attractiveness of public transport decreased the generalised cost of transportation

[4] This research question is very relevant in the EU context due to the proposed revision of the *Ambient Air Quality Directives*, which will enforce the creation of air quality plans for municipalities to ensure that they comply with the pollution level standards. For further details, see the publications online at the following: https://environment.ec.europa.eu/publications/revision-eu-ambient-air-quality-legislation_en.

[5] For instance, several cities in the US are considering fare-free public transportation schemes for at least low-income users. A bill — known as the *Freedom to Move Act* — has even been introduced in the US Senate to grant federal funds to allow both state and local governments, as well as transit agencies, to implement fare-free travel. For further details, see the articles by Abigail Johnson Hess on *CNBC.com* (available online at the following: https://www.cnbc.com/2020/03/02/free-public-transportation-is-a-reality-in-100-citieshere-why.html) and Bruce Gellerman on *Boston's mayoral race* (available online at the following: https://www.wbur.org/news/2021/07/21/massachusetts-fare-free-public-transit-debates).

[6] The measure was later extended for the entire 2023 year.

[7] As highlighted by Hausman and Rapson (2018), such a methodological framework particularly suits applications where policy implementation affects all observed subjects (i.e., all 23 Spanish cities considered in our sample) on the same day so that the lack of cross-sectional variation in treatment exposure makes the difference-in-differences approach not suitable.

for private car users, particularly for those with higher income who usually value time savings the most. Nevertheless, the results seemed to highlight an increase in public transport demand, pushing the Estonian government to improve transit capacity and quality. Other cities have opted for pilot experiments, such as the one documented by Bull et al. (2021) in Santiago de Chile, which also reported poor results. Although travellers with free-of-charge vouchers increased their use of public transport, they did so only during off-peak hours, indicating that the increase in use was mainly explained by leisure activities, while private car use was not reduced. In Monterrey, the subway was offered free of charge for two months in 2009 (shortly before the general elections) to alleviate the economic crisis among the population. Similarly, Slovakia and the Czech Republic have introduced massive fare discounts (equal to 100 and 75%, respectively) for children, students, and pensioners on their long-distance railway and bus services since November 2014 and September 2018, respectively. As reported by Davis (2021) and Tomeš et al. (2022), ridership increased by 61% in the Mexican city and significantly for the targeted groups in both central European countries; however, those articles do not reveal what the impact has been on private transport.

Such evidence is coherent with the findings of a review elaborated by the International Association of Public Transport (UITP), which is mainly formed by operators of public transportation services and public transport authorities. Indeed, the (UITP, 2020) report concluded that there is no clear evidence that a free-of-charge financing scheme alone is enough to bring about a modal shift, social inclusion, and economic development in a city. According to the analysis discussed in the report, "*public transport is already cheaper than car use and a small further improvement in the price is unlikely to lead to a significant shift. It should not be a surprise that studies suggest a shift instead from other low-cost modes such as walking and cycling*". Therefore, the report does not consider free public transport to be the main priority over improving its capacity, frequency, and overall quality. Consistent with this argument, the French city of Lyon rejected the implementation of such a measure after concluding that even if transit demand increases by between 15 and 30% (according to their estimates), few private transport users would be transferred to the collective transportation system (approximately 2%).

Other low-cost or free-of-charge public transportation experiences can be found worldwide, but research articles providing quasiexperimental or high-quality quantitative analysis are not available. In Luxembourg, the gratuity of all modes of public transport has been implemented since 2020, which means that this small, high-income country was the first to consolidate universal free transit. Malta followed suit in October 2022. In the USA, Kansas City became the first major city to adopt free transit fares in 2019. In Europe, free public transportation supply is offered in the municipalities of Cascais (Portugal), Torrevieja (Spain), and Livigno (Italy), as well as in the 34 municipalities of the Attica region in Greece. In France, the municipalities of Calais, Dunkirk, Nantes, and Strasbourg — as well as some suburbs of Marseille and Toulouse — apply some sort of free public transport mobility for specific subsets of users, services, routes, and days of the week. In Paris, transit has also been free for those under 18 years of age since 2020. Since 2022, a similar policy has also been operating in Scotland for youth under 22 years old who are travelling by bus across the country.[8]

[8] To provide a comprehensive review, more cities offering illustrative examples of free public transport services should be mentioned. In North America, other free transit systems are the *Metromover* in Miami (Florida), the *Silver Line* in Boston (Massachusetts), the *Downtown Circulator* in Columbus (Ohio), rail services in Tacoma (Washington), and the *CTrain* in Calgary (Canada). In Europe, the *Metroshuttle* in Manchester (England) should be mentioned. In Asia, the free buses in Chengdu and Changning (China), the free *BMTA* buses in Bangkok (Thailand) and the *GoKL* city bus in Kuala Lumpur (Malaysia) represent other examples. In Australia, other cases are the free city loop of Brisbane and the free transit zones of Adelaide and Perth.

Contrary to the previously mentioned cases, the massive discounts applied to public transportation fares in Spain seem to be inspired by the flat fare applied to transit services in Germany between June and August 2022, which was aimed at alleviating the cost of living and combating the 2021–2022 global energy crisis exacerbated by the recent escalation of the *Russo-Ukrainian War*,[9] as well as improving air quality by increasing the attractiveness of public transport compared to private transport. More specifically, the *9-Euro-Ticket* was a German scheme through which passengers could travel for 9 euros per month on local and regional transport nationwide.

The environmental goals of such policy interventions have gained the attention of researchers, and the first recently available empirical studies provide mixed evidence on the relationship between transit fares and air quality. In particular, fare discounts have been found to reduce pollutant concentration levels in Germany, which appears to be at odds with the findings reported earlier in this section; therefore, these works may face some methodological concerns. For example, the paper of Gohl and Schrauth (2024) solely exploits time variation for a daily aggregate air pollution index for the month before (May) and after (June) the implementation of the policy, using the months of May 2018 and May 2019 as pretreatment periods. Hence, it does not fully control for seasonal patterns and other potential confounding factors. In contrast, the yet unpublished paper of Aydin and Kürschner Rauck (2023) proposes an alternative identification based on a difference-in-differences strategy where the treated monitoring stations are those located in core traffic areas and the control monitoring stations are those located in background areas; therefore, the study measures the differential treatment across stations instead of the average treatment effect, which opens the door to potential biases. Conversely, the paper of Yang and Tang (2018) assess the impact of a transit fare hike occurred in Beijing in December 2014 on an aggregate air quality index by combining synthetic control and difference-in-differences strategies. They found an increase in air pollution in the short run but no effect in the long run. Finally Webster (2024) evaluated the impact of free public transit in the state of Colorado (which was implemented in August 2022) by using the same methodological tools. The author found no evidence of a decrease in local air pollution.

Overall, the large amount of public funds devoted to these types of financing schemes and the mixed evidence provided by the literature clearly motivate the need to carry out additional robust causal estimates of the effect of public transportation fare subsidies on air quality.

3. The policy: massive fare discounts in Spain's public transportation systems

In the following section, we provide a detailed description of the policy implemented in Spain and evaluated in this paper.

In July 2022, the President of Spain, Pedro Sánchez announced a four-month period of massive discounts on fares for public transportation services managed by the central government to mitigate inflationary pressures (particularly related to energy and fuel prices) resulting from the economic consequences of the *Russo-Ukrainian War*. In addition, the other stated motivations of the policy were to promote public transport and reduce the use of private vehicles, which would contribute to reducing Spain's energy dependence and carbon footprint. Such environmental goals where crucial for the approval of the measure. On August 1st, 2022, a royal decree[10] was approved

[9] This is an ongoing international conflict between Russia (alongside Russian-backed political groups) and Ukraine, which began in February 2014. In February 2022, the conflict saw a major escalation as Russia launched a full-scale invasion of Ukraine.

[10] For further details, see the royal-decree law (RDL 14/2022) available online at the following: https://www.boe.es/buscar/act.php?id=BOE-A-2022-12925.

by the government to execute the PTD policy[11] based on the gratuity of multitrip tickets for short- and medium-distance railway services[12] operated by the national railway company, *Renfe*.

The policy was implemented as a specific transit subscription through a voucher (available starting on August 24, 2022) that was valid for unlimited intra- and intercity trips in each metropolitan or regional area of the country between September 1 and December 31, 2022. To target commuters and frequent travellers, the voucher would be free for all users who made a minimum of 16 trips between the same origin–destination city pair during the four months in which the voucher was valid. To acquire a voucher for short-distance railway services, customers had to pay a deposit of 10 euros. To acquire a voucher for medium-distance conventional railway services, customers had to pay a deposit of 20 euros. In both cases, the deposits was returned at the end of the period, subject to compliance with the minimum requirement of 16 trips. Furthermore, other 50% fare discounts were also granted to medium-distance high-speed railway services and bus lines concessioned by the state, most of which covered public service obligations.

Additionally, the royal decree also allowed public transport authorities to cut fares for multimodal tickets in metropolitan areas by 30% thanks to funding provided by the Ministry of Transport. Hence, regional and local governments could simultaneously contribute their funds to decreasing prices further on local train, bus, subway, and tram services operated by their owned transportation companies, typically bringing discounts up to 50% or even more. This specific discount setup is heterogeneous across metropolitan areas and depends on how discounts are applied to transit subscriptions and multipass tickets within the variety of fare schemes available. For example, cities such as Madrid and Barcelona have applied a 50% discount to subscriptions and a 30% discount to multipass tickets, while cities such as Bilbao and Vitoria have applied a 50% discount to both. Other cities, such as Valencia, Sevilla, Zaragoza and Granada, have generally used a 30% discount, while some others have gone as high as 75% (Oviedo) or even 100% (Palma de Mallorca).

These combined measures affecting both urban and intercity public transportation services were welcomed by hundreds of thousands of users. By the start of the four months, approximately half a million users had applied for *Renfe*'s discounts alone. According to the declarations made by the Minister of Transport (Raquel Sánchez) and *Renfe*, the number of users had reached 900 000 by mid-September and more than two million by the end of 2022.[13] However, monthly ridership figures for the railway services affected by the PTD policy gathered by the *Ministry of Transport* (and shown in Fig. 1) suggest that the increase in short-distance ridership in September 2022 (reaching 35 million trips) was approximately 33.5% when compared to September 2021 but only approximately 1.4% when compared to the same month of 2019, therefore revealing that the prepandemic level has only been matched. Regarding medium-distance railway services, the increase in September 2022 (reaching 3.5 million trips) was approximately 21.5% when compared to that in September 2019.

Such evidence has been confirmed by a recent press release (MITMA, 2023) that stated how short-distance ridership had not significantly increased from 2019 levels and that the major change had simply been a shift away from multipass tickets towards this transit subscription. However, the press release argued that the increase in medium-distance transit ridership, paired with a general decrease in mobility for trips above 50 km and a slight decrease in fuel consumption, is indicative of a shift away from car travel and of a positive environmental impact of the policy.[14] In short, such evidence suggests that the PTD policy may have concentrated its impact on medium-distance railway services only, which represent just approximately 10% of the trips affected by this financing scheme.

4. Measuring air quality in Spanish cities

To investigate the impact of the PTD policy on air quality, we rely on data provided by the *Air Quality Open Data Platform* (AQICN), which reports the daily median pollution levels based on multiple measurements recorded by several monitoring stations per city. Our sample includes data from across 23 Spanish cities (for the detailed list, see Table A.1). In particular, we focus on those harmful pollutants that are direct products of incomplete fuel combustion, such as particulate matter (PM_{10}), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and ground-level ozone (O_3). We collect data from January 1, 2019, to December 31, 2022; this four-year time window allows us to credibly control for seasonal variations.[15]

Figs. 2a–2d plot the daily median pollution levels in Spain during our period of analysis. Such national daily averages are constructed by weighting by the number of measurements recorded by the monitoring stations, which vary across cities, days, and pollutants. Given that the vertical lines indicate the implementation day of the PTD policy, as well as the same day of all previous years, we can notice how the levels of all pollutants vary widely across days and do not exhibit long-term decreasing trends significantly different from their seasonal patterns.

Table 1 reports the standard descriptive statistics of the pollution levels, as well as the temperature, atmospheric pressure, humidity, and wind speed recorded by the same stations used to monitor air quality. Accordingly, the table reports the descriptive statistics of the average number of measurements used to monitor all variables in Panels A–B. In addition, we take into account other natural events affecting the concentration levels of PM_{10}, such as *Calima* and biomass combustion events. More specifically, *Calima* events refer to Saharan air masses — usually carried by a sirocco wind — that bring high temperatures, dust, and sand and produce natural haze. Biomass combustion events refer to wildfires that occurred in different areas of the country during our period of analysis. Consistently, the table also reports the descriptive statistics of these natural events.

5. The effect of the PTD policy on air quality

5.1. Empirical strategy

In this section, we describe our empirical approach in terms of econometric specifications. to identify the causal impact of a shock in

[11] For the sake of simplicity, we refer to the policy implemented in Spain as the "PTD" (i.e., public transportation discounts) policy throughout the rest of the paper.

[12] Short-distance railway services operate within a metropolitan area and its suburbs within a radius of approximately 60 km. According to the Spanish rail transport system, these short-distance railway services are called *Cercanías* and *Rodalies* Medium-distance railway services provide intra- and interregional connections of between 60 and 300 km. They are called *Media Distancia* (for conventional railway services) and *Avant* (for high-speed railway services). For a detailed map of the aforementioned railway services, see Fig. B.1.

[13] For further details, see the publications available online at the following: https://www.renfe.com/es/es/grupo-renfe/comunicacion/renfe-al-dia/ultimas-publicaciones.

[14] For the sake of clarity, note that MITMA (2023) offers no further evidence supporting their claim about the positive PTD policy impact.

[15] For the sake of clarity, note that AQICN data are gathered from real-time open data provided by Environmental Protection Agencies running the official measurement stations. So, AQICN offers the fastest and most readily available data to conduct an impact assessment, yet the dataset might include measurement errors as data are not fully validated (in terms of instrument precision checks) at the time of publication. Our usage of median average daily concentration levels, however, limits the impact of potentially defective stations. Additionally, our identification methods are unbiased as long as potential measurement error is not correlated with the policy implementation.

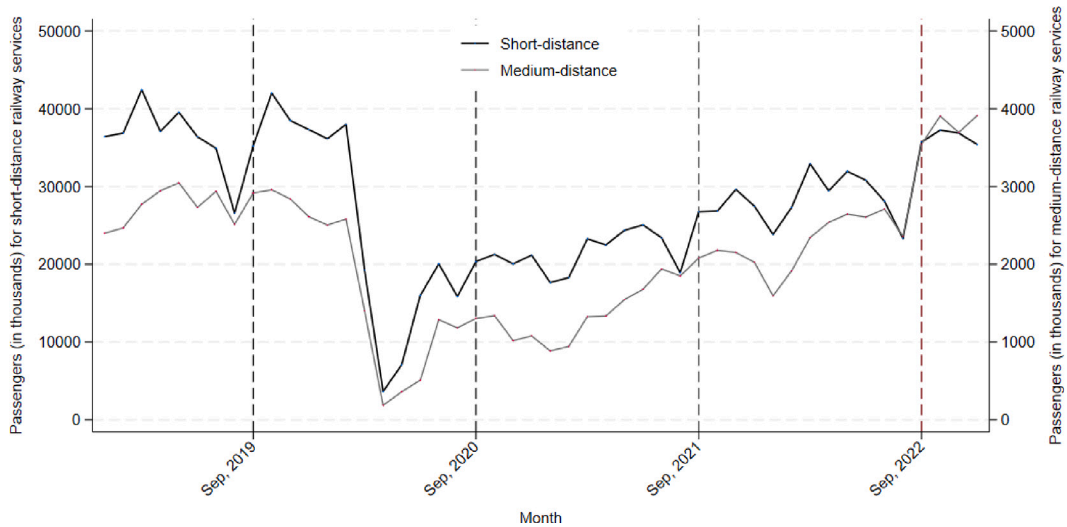


Fig. 1. Evolution of ridership for railway services affected by the PTD policy, 2019–2022. *Notes*: The unit of observation is the month. *Source:* Authors' own elaboration.

Table 1
Descriptive statistics.
Source: Data for all variables in Panels A–C are retrieved from *AQICN*. Data for all variables in Panel D are retrieved from the *Ministry of Environment*

	Mean	SD	Minimum	Maximum	Observations
Panel A: Pollutants					
Particulate matter (PM_{10})	17.84	12.93	1.00	828.00	32 758
Nitrogen dioxide (NO_2)	6.92	4.53	0.20	56.80	32 788
Sulfur dioxide (SO_2)	2.18	1.61	0.10	148.80	31 965
Ground-level ozone (O_3)	23.19	8.47	0.50	53.90	32 026
Panel B: Atmospheric conditions					
Temperature	16.43	6.68	−8.50	39.00	32 015
Atmospheric pressure	1016.66	12.06	599.90	1039.70	32 011
Humidity	66.20	17.76	1.00	100.00	32 017
Wind speed	3.57	3.39	0.10	33.00	31 703
Panel C: Measurements					
Measurements	143.76	101.06	14.63	448.13	30 263
Panel D: Natural events					
Calima	0.27	0.44	0.00	1.00	33 077
Biomass combustion	0.08	0.27	0.00	1.00	33 077

Notes: The unit of observation is the daily median for all variables in Panels A–C. The unit of observation is the day for all variables in Panel D. All variables in Panel A are expressed in micrograms per cubic meter (μg/m^3), temperature is expressed in degrees Celsius, atmospheric pressure is expressed in millibars, humidity is expressed in percentage terms, and wind speed is expressed in meters per second.

public transportation fares on the change in pollutant concentration levels. First, we estimate the following simple ordinary least squares (OLS) model:

$$y_{it} = \delta_0 + \delta_1 T_t + \delta_2 W_{it} + \delta_3 C_{it} + \delta_4 B_{it} + \delta_5 X_t + \alpha_i + \epsilon_{it} \tag{1}$$

where y_{it} is the log of the city-median concentration for a given pollutant — among those described in Section 4 — in city i on day t, while T_t is the running variable indicating the treatment period, taking a value of one for all days after the introduction of the PTD policy and a value of zero before its implementation. Given that atmospheric conditions have significant explanatory power for air pollution, we control for general weather conditions affecting pollutants' chemistry and dispersion with a vector of covariates, W_{it}, including current and 1-day lags of quartics in temperature, atmospheric pressure, humidity, and wind speed, as well as the average number of measurements recorded by the monitoring stations to control for the size of the samples used for calculating the daily median values.

In addition, we control for *Calima* and biomass combustion events affecting PM_{10} concentration levels by including two dummy variables, namely C_{it} and B_{it}, which take a value of one if these phenomena occurred in city i on day t and zero otherwise. We also control for seasonality with a vector of indicator variables, X_t, including day of the week, day of the month, week of the year, month of the year, quarter of the year, and year fixed effects, as well as the full set of interactions between (i) week of the year and year fixed effects (to control for COVID-19-related restrictions on mobility and fuel tax reductions applied by the Spanish government in 2022) and (ii) day of the week and month fixed effects (to control for potential changes in commuting patterns). Finally, α_i denotes a full set of city fixed effects, while ϵ_{it} denotes heteroskedasticity- and autocorrelation-consistent standard errors clustered at the city level.

Such simple prepost settings serve as a useful baseline to estimate the conditional correlation between the implementation of the PTD policy and air quality. However, potential unobserved factors changing over time and affecting air quality may cause ϵ to be correlated with time and thus with the PTD policy, producing biased estimates of our main coefficient of interest δ_1.

To address such endogeneity concerns, we take advantage of an exogenous source of variation in the accessibility to Spain's public transportation systems by exploiting the sharp discontinuity in time in the cost of ridership that occurred on the implementation day of the massive public transport fare discounts. By doing so, the unobserved

(a) PM_{10}

(b) NO_2

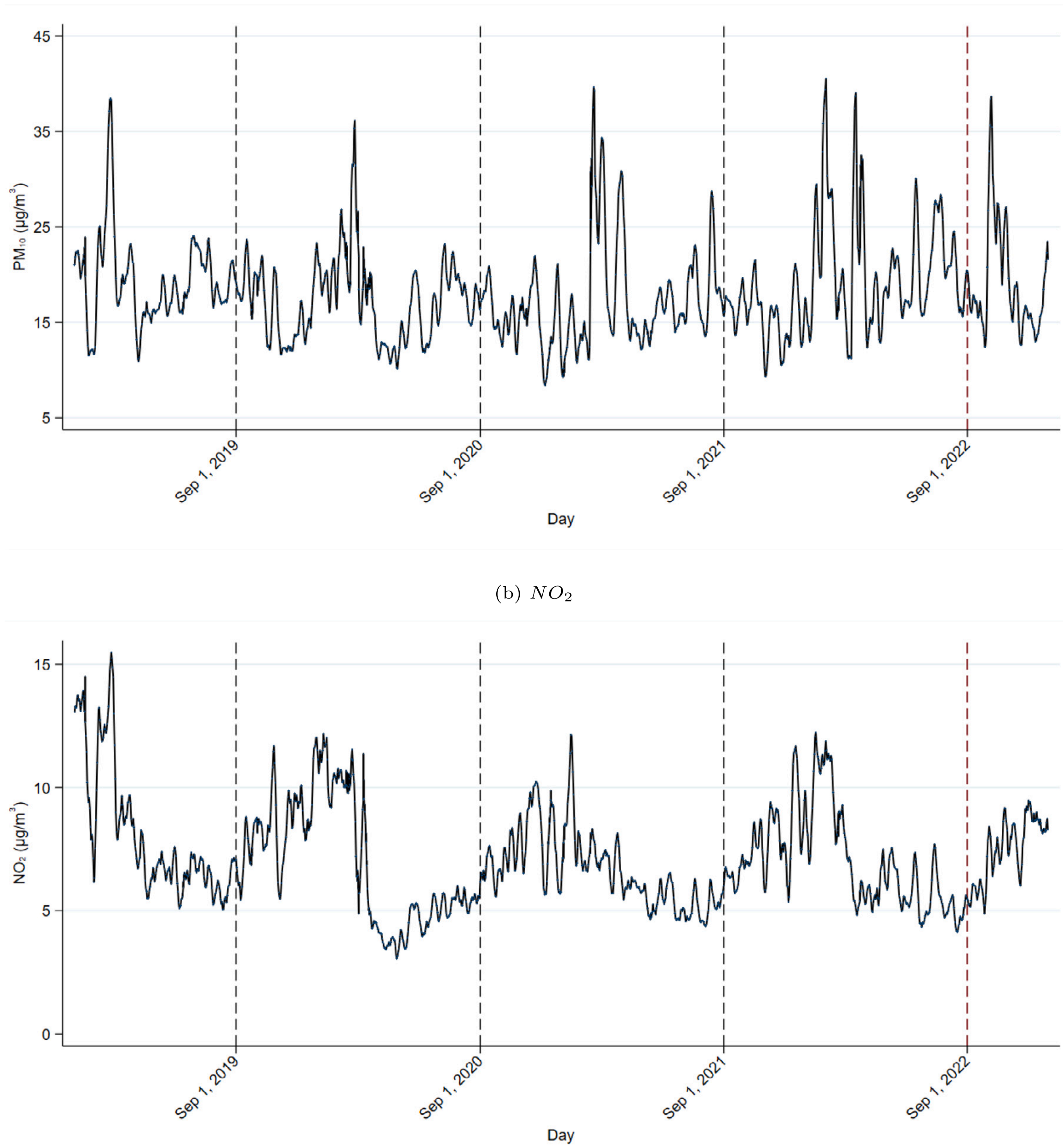


Fig. 2. Air quality in Spanish cities, 2019–2022. *Notes*: The time series represents a 7-day moving average weighted by the number of measurements recorded by the monitoring stations.
Source: Authors' own elaboration.

factors affecting air quality around the implementation of the PTD policy are likely to be similar so that pollutant concentration levels just before the implementation of the policy form a valid counterfactual group for pollutant concentration levels just after the implementation of the policy. Specifically, we use OLS to also estimate the following regression discontinuity in time (RDiT) model:

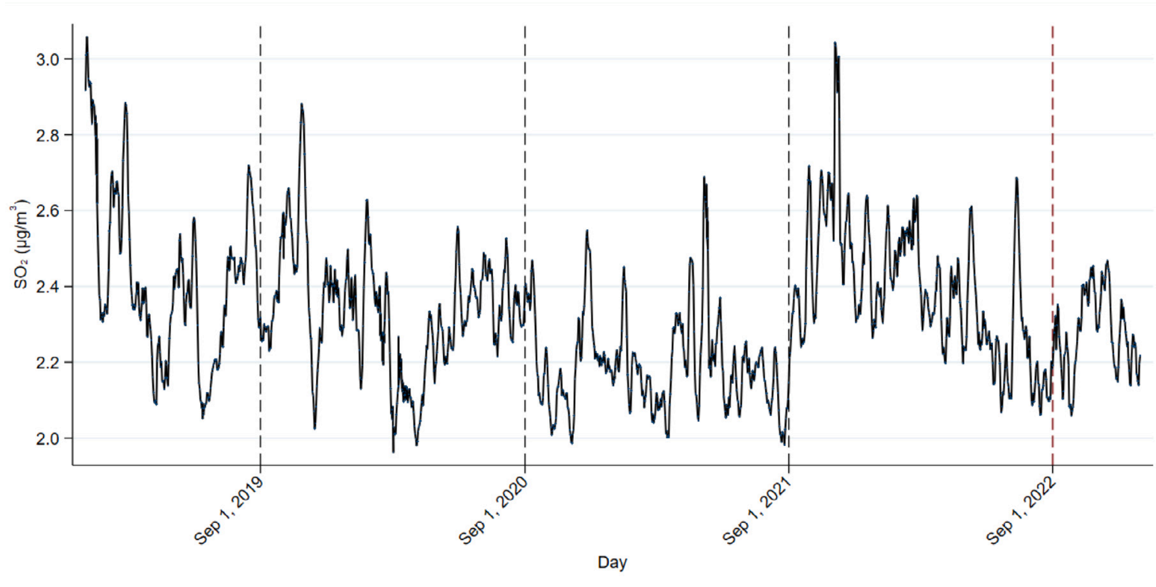
$$y_{it} = \delta_0 + \delta_1 T_t + f(\tilde{x}_t) + \delta_2 W_{it} + \delta_3 C_{it} + \delta_4 B_{it} + \delta_5 X_t + \alpha_i + \epsilon_{it} \tag{2}$$

where all terms are the same as those described for Eq. (1) except for the addition of a highly flexible pth-order polynomial time trend, $f(\tilde{x}_t)$, to control for the aforementioned potential smooth changes in the relationship between air pollution levels and time functional form, where $\tilde{x}_t$ is centred at x_0 (i.e., the day of the PTD policy implementation) so that $\tilde{x}_t = x_t - x_0$.

Our identification strategy relies on the key assumption of local randomisation around the implementation date. That is, the date of the introduction of the PTD policy is exogenous, as it was not driven by specific atmospheric conditions. In other words, there is no manipulation of the running variable depending on high pollution episodes, which would otherwise bias our main coefficient of interest. Thus, the identifying assumption is that in the absence of the PTD policy, air quality would not discontinuously change in Spanish cities on September 1, 2022.

By flexibly controlling for nonlinearities in pollutant concentration levels from other confounding factors through the polynomial time trend, we can disentangle changes in air quality solely due to the PTD policy. Our coefficient of interest, δ_1, estimates the reduced form effect of the introduction of the massive public transport fare discounts on air

(c) SO_2



(d) O_3

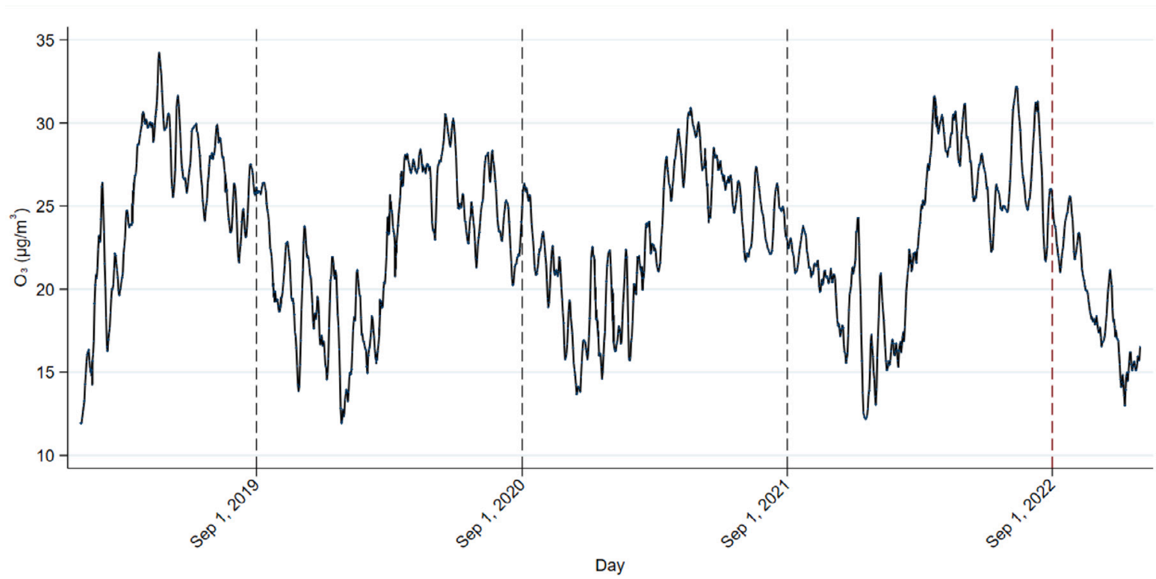


Fig. 2. (*continued*).

quality, measuring the local estimation of the treatment effect around the date of implementation. Our empirical approach, which is in line with that used by Davis (2008) and Chen and Whalley (2012), offers clear advantages when the evaluated policy affects all observed subjects simultaneously (i.e., all the monitoring stations of the 23 Spanish cities considered in our sample), leaving no appropriate counterfactual available.[16]

[16] As discussed in Section 2, our empirical strategy is a convenient complement to check the validity of the counterfactuals used by those papers adopting a difference-in-differences approach to measure the impact of transit discounts on air quality, as pollution spillovers carry over long distances and can affect the control groups.

5.2. Estimation results

Table 2 reports OLS estimates from fitting Eq. (1). Each column presents the results of a regression that estimates the correlation between the PTD policy and each of the pollutant concentration levels without including any polynomial time trend. Ranging from −0.09 to 0.09, none of the coefficients are statistically significant. Hence, the OLS estimates provide no evidence that the PTD policy has improved the air quality.

Table 3 reports RDiT-OLS estimates from fitting Eq. (2). Each column presents the results of a regression that estimates the effect of the PTD policy on each of the pollutant concentration levels, including a third-order polynomial time trend to flexibly control for potential omitted variables. The choice of the third-order polynomial for our baseline specification is because (i) higher-order polynomials do not increase the precision of our estimates and (ii) odd-order polynomials tend to be preferred from the econometric properties point of view,

Table 2
Effect of the PTD policy on pollutants' concentration levels: OLS.

Model:	PM_{10} OLS (1)	NO_2 OLS (2)	SO_2 OLS (3)	O_3 OLS (4)
PTD policy	0.019 (0.069)	−0.085 (0.080)	0.093 (0.077)	−0.074 (0.051)
Calima	Yes	No	No	No
Biomass combustion	Yes	No	No	No
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	30 121	30 121	30 121	30 121
R^2	0,48	0,57	0,07	0,56

Notes: The table reports estimates from 4 separate OLS regressions fitting Eq. (1). The unit of observation is the daily median, and the sample for all regressions extends from January 1, 2019, to December 31, 2022. The dependent variables are the pollutants' concentration levels in logs, where PM_{10} is particulate matter, NO_2 is nitrogen dioxide, SO_2 is sulfur dioxide, and O_3 is ground-level ozone. Specifications also include current and 1-day lags of quartics in temperature, atmospheric pressure, humidity, and wind speed, plus the average number of measurements recorded by the monitoring stations. Time fixed effects include indicator variables for day of the week, day of the month, week of the year, month of the year, quarter of the year, and year, as well as interactions between week of the year and years and day of the week and months. Standard errors clustered at the city level appear in parentheses. Significance values: ***p < 0.01, **p < 0.05, *p < 0.10.

Table 3
Effect of the PTD policy on pollutants' concentration levels: RDiT-OLS.

Model:	PM_{10} RDiT-OLS (1)	NO_2 RDiT-OLS (2)	SO_2 RDiT-OLS (3)	O_3 RDiT-OLS (4)
PTD policy	0.014 (0.069)	−0.062 (0.080)	0.102 (0.080)	−0.063 (0.051)
Calima	Yes	No	No	No
Biomass combustion	Yes	No	No	No
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	30 121	30 121	30 121	30 121
R^2	0.48	0.57	0.07	0.56

Notes: The table reports estimates from 4 separate RDiT-OLS regressions from fitting Eq. (2). The unit of observation is the daily median, and the sample for all regressions extends from January 1, 2019, to December 31, 2022. The dependent variables are the pollutants' concentration levels in logs, where PM_{10} is particulate matter, NO_2 is nitrogen dioxide, SO_2 is sulfur dioxide, and O_3 is ground-level ozone. Specifications also include a third-order polynomial time trend, as well as current and 1-day lags of quartics in temperature, atmospheric pressure, humidity, and wind speed, plus the average number of measurements recorded by the monitoring stations. Time fixed effects include indicator variables for day of the week, day of the month, week of the year, month of the year, quarter of the year, and year, as well as interactions between week of the year and years and day of the week and months. Standard errors clustered at the city level appear in parentheses. Significance values: ***p < 0.01, **p < 0.05, *p < 0.10.

as suggested by the work of Porter (2003). Ranging from −0.06 to 0.10, the coefficients are in line with the previous OLS estimates; once again, none of them are statistically significant. Hence, the RDiT-OLS estimates provide no evidence that the PTD policy has improved the air quality.

Given that regression discontinuity in time estimates can be sensitive to changes in the polynomial time trend, it is important to evaluate alternative specifications. Hence, Table A.2 reports estimates using alternative polynomials ranging from first- to fifth-order,[17] while Table A.3 reports estimates using interactions between the same alternative polynomials and the treatment variable to allow the time trend in pollution to differ on either side of the day of the implementation of the PTD policy. Overall, the estimated coefficients and both Akaike's information criteria (AIC) and the Bayesian information criteria (BIC) are very similar to our baseline, suggesting that our results are not driven either by the choice of the polynomial order or by the interacted functional form.

5.3. Robustness checks

In this section, we provide some robustness checks to corroborate our baseline results. For this purpose, Table 4 reports other RDiT-OLS results by repeating our main estimation model for different specifications. The first specification (Panel A) includes standard errors clustered at the 5-week level within cities to take into account serial correlation. The second specification (Panel B) consists of a restricted sample that excludes all observations for the year 2020 where the severity of the COVID-19 pandemic significantly changed the mobility patterns of commuters. The third specification (Panel C) adopts a nonparametric estimation.

The rationale for the latter is that our main identification strategy consists of a global parametric approach that implicitly departs from local randomisation by including observations that are far away from the cut-off determined by the implementation date of the PTD policy. Indeed, they are needed to credibly control for seasonal patterns. We further check the robustness of the results obtained in Table 3 by estimating the local estimation of the treatment effect within a closer bandwidth around the implementation date using a local linear regression on the residualised daily median pollutant concentration levels, in line with the methodology discussed in Lee and Lemieux (2010). More specifically, we construct the residualised outcome variables by estimating a model for each pollutant that includes all covariates described in Eq. (2) except the treatment variable and the polynomial time trend.

Then, we subtract the prediction of such models from the original outcome variables to keep the variability unexplained by the included confounder factors. By doing so, we explicitly incorporate the bias in

[17] The work of Gelman and Imbens (2019) suggests that polynomials that are too high should not be used in regression discontinuity designs.

Table 4
Effect of the PTD policy on pollutants' concentration levels: RDiT-OLS with alternative specifications.

Model:	PM_{10} RDiT-OLS (1)	NO_2 RDiT-OLS (2)	SO_2 RDiT-OLS (3)	O_3 RDiT-OLS (4)
Panel A: alternative standard errors				
PTD policy	0.014	−0.062	0.102	−0.063
	(0.071)	(0.077)	(0.081)	(0.048)
Observations	30 121	30 121	30 121	30 121
R^2	0.48	0.57	0.07	0.56
Panel B: restricted time window				
PTD policy	0.044	0.009	0.119	−0.032
	(0.066)	(0.085)	(0.084)	(0.062)
Observations	22 515	22 515	22 515	22 515
R^2	0.49	0.55	0.07	0.57
Panel C: local linear regression on the residualized outcomes				
PTD policy	−0.014	−0.050	0.001	−0.022
	(0.045)	(0.055)	(0.060)	(0.036)
Observations	30 121	30 121	30 121	30 121
No-treated | Treated	820 | 834	711 | 731	908 | 917	711 | 731
Optimal bandwidth (days)	39.56	34.26	43.89	34.42
Robust p-value	0.75	0.36	0.99	0.53
Calima	Yes	No	No	No
Biomass combustion	Yes	No	No	No
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: The table reports estimates from 12 separate RDiT-OLS regressions fitting Eq. (2). The unit of observation is the daily median. The dependent variables are the pollutants' concentration levels in logs, where PM_{10} is particulate matter, NO_2 is nitrogen dioxide, SO_2 is sulfur dioxide, and O_3 is ground-level ozone. Specifications also include a third-order polynomial time trend, as well as current and 1-day lags of quartics in temperature, atmospheric pressure, humidity, and wind speed, plus the average number of measurements recorded by the monitoring stations. Time fixed effects include indicator variables for day of the week, day of the month, week of the year, month of the year, quarter of the year, and year, as well as interactions between week of the year and years and day of the week and months. In Panel A, the sample for all regressions extends from January 1, 2019, to December 31, 2022, and standard errors clustered at the 5-week level within cities appear in parentheses. In Panel B, observations for the year 2020 are excluded for all regressions, and standard errors clustered at the city level appear in parentheses. In Panel C, coefficients report the local estimations of the treatment effect using a local linear regression on the residualised daily median pollutants' concentration levels with a uniform kernel; estimates are computed using the data-driven MSE optimal bandwidth choice and robust bias-corrected statistics proposed in Calonico et al. (2018, 2022). Significance values: ***p < 0.01, **p < 0.05, *p < 0.10.

the distributional approximation introduced by the nonparametric approach near the cut-off under a data-driven mean squared error (MSE) optimal bandwidth choice, and we report the estimates using a uniform kernel with robust bias-corrected statistics, as proposed in Calonico et al. (2018, 2022).

Overall, the results across the three panels are consistent with our baseline estimates and provide no evidence that the PTD policy has improved daily median pollution concentration levels. Moreover, note that the results in Panel C are robust to alternative specifications using zero and quadratic polynomial time trends, as well as to specifications using different bandwidths set arbitrarily.

Additionally, we are aware that a possible threat to our identification strategy is the potential dynamic effect of the measure we are analysing. If travellers changed their behaviour anticipating the PTD policy or if its impact built up or faded out after the implementation date, our estimates would be biased. However, any anticipation effect is unlikely as transit discounts were not effective until the implementation date, making hard for travellers to adapt in the absence of the cost reduction. Dynamic effects could potentially occur if commuters had changed their travel behaviour at any point during the four-month period of validity of the voucher, but the uncertainty associated with the long-term duration of the policy made such postpone decisions less likely to occur. In any case, to assess the magnitude of this potential issue, we visually inspect the relationship between the residualised daily median pollutant concentration levels (as described in the previous paragraph) and the running variable (i.e., time) in a symmetric time window (i.e., within four months before and after the implementation date). Figs. 3a–3d suggest that during this eight months time span, there are no clear dynamic patterns in the variability of pollutant concentration levels not explained by the confounding factors included in our empirical model, which limits the concerns about this possible source of bias.[18]

Finally, we also acknowledge that the policy timing might bias our estimates if the sharp change in the cost of ridership that occurred on September 1, 2022 interacts with other factors determining ridership (and air pollution) levels over time, making the expected discontinuity either grow or shrink over time by other factors rather than the evaluated policy. Given that Fig. 1 shows how the PTD policy was introduced around the end of the summer holiday period, we gathered descriptive evidence on potential year-to-year changes in holiday patterns to check whether the distribution of vacations changed in Spain after the COVID-19 pandemic. Based on a survey on the tourist behaviour of Spanish residents, we see no year-to-year differences in the way residents allocate their summer holidays despite the behavioural and work changes induced by the aforementioned pandemic.[19]

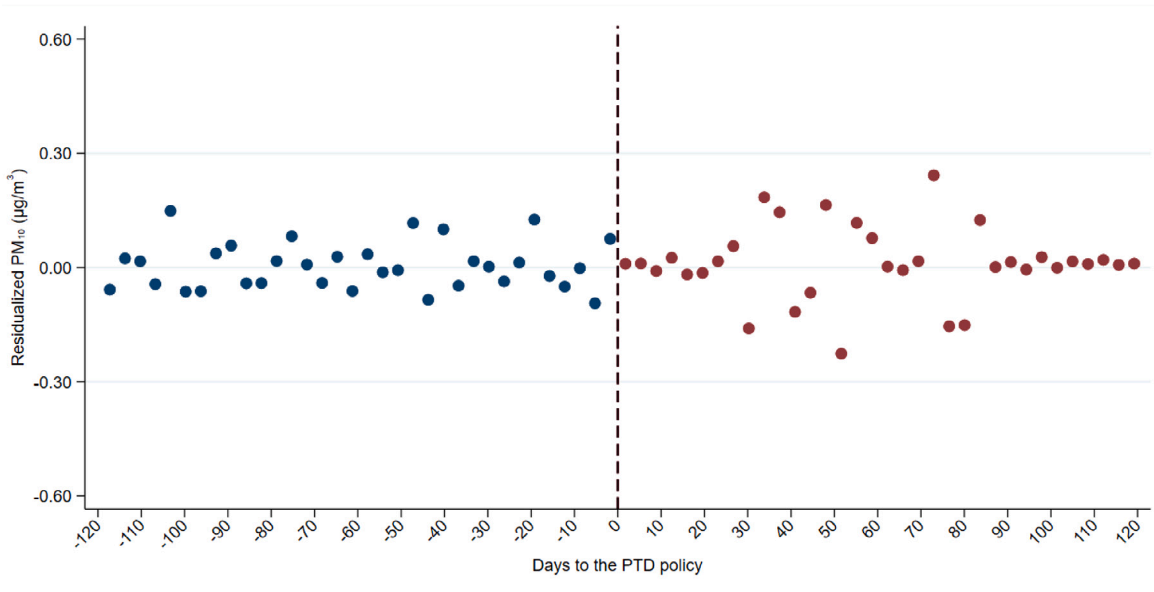
6. Mechanisms and discussion

As discussed throughout the paper, the mechanism underlying our research question is that the increased accessibility in transit ridership thanks to massive public transport fare discounts should induce a modal shift from private modes of transport and, consequently, improve the air quality. Given that our estimates provide no evidence that the PTD

[18] Moreover, note that the transit industry applies a rule of thumb for the ramp-up in demand after transport service improvements equal to three months, which is within the period of our analysis.

[19] For further details, see the publications available online at the following: https://www.ine.es/daco/daco42/etr/etr0322.pdf As an additional robustness check, we estimated Eq. (2) by adding an interaction between a September 1, 2022 dummy variable and a year trend. We find no substantial deviations from our baseline estimates.

(a) Residualised PM_{10}



(b) Residualised NO_2

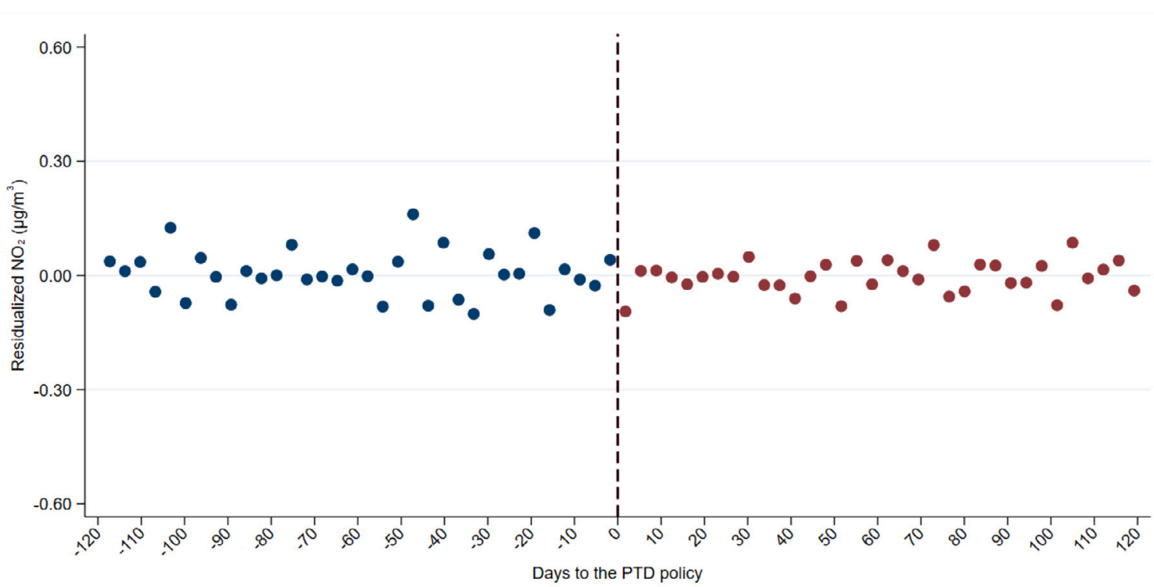


Fig. 3. Plot of the residualised daily median pollutants' concentration levels, May–December 2022. *Notes*: The residualised daily median pollutants' concentration levels are in log. *Source:* Authors' own elaboration.

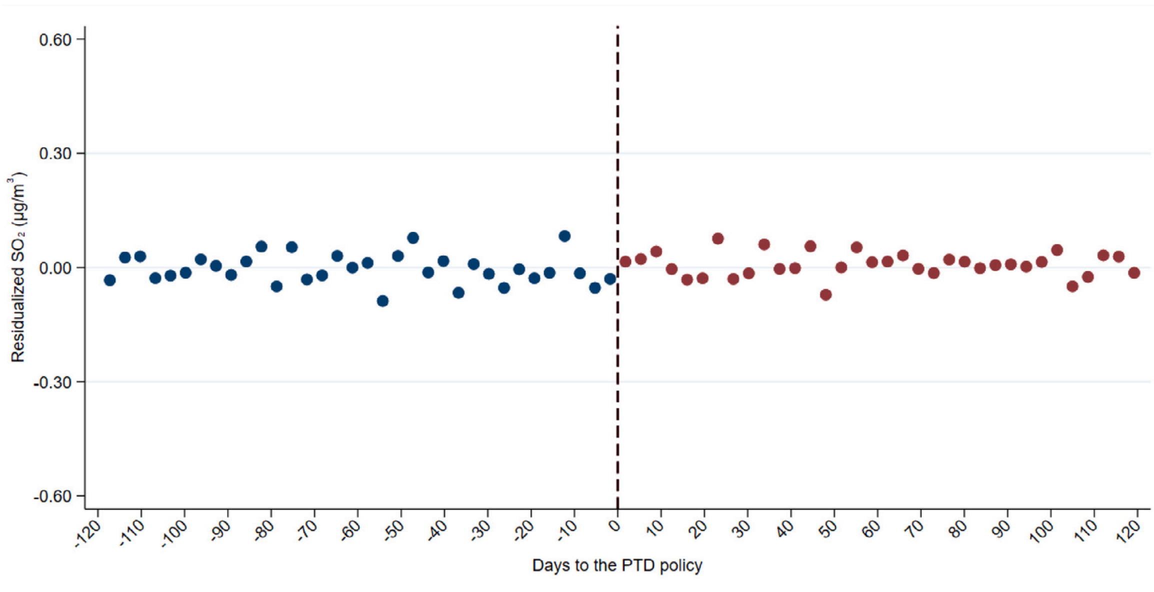
policy has reduced pollutant concentration levels, it appears that this measure has been unable to induce the aforementioned modal shift.[20] Although the absence of granular data does not allow us to credibly test for the impact of this policy directly on road traffic, we run a simple regression of monthly ridership figures at the national level (i.e., the ones used to plot Fig. 1) for the different railway services affected by the PTD policy against the treatment variable and both month and year fixed effects to assess the average difference in ridership values before and after the implementation of the policy.

Consistent with the evidence provided by MITMA (2023), Table 5 shows a statistically nonsignificant increase in public transportation use for short-distance railway services (either for the cities of Madrid and Barcelona when considered individually), while it shows a 29.1% increase for medium-distance railway services operated by conventional trains.[21] This confirms that the PTD policy may have concentrated its impact on medium-distance railway services only, which represent a very limited share of trips compared to the bulk of mobility that occurs

[20] For the sake of clarity, note that data limitations prevent us from including carbon monoxide (CO) in the analysis. This can be considered a limitation of our study in assessing the ability of the PTD policy to improve air quality through a reduction in road traffic. Indeed, CO is the pollutant most linked to car usage (Chen and Whalley, 2012; Davis, 2008; Gallego et al., 2013).

[21] Unfortunately, *Renfe* has not been able to fulfil our request for passenger data at the daily and city levels that are needed for a proper causal analysis of the PTD policy on ridership.

(c) Residualised SO_2



(d) Residualised O_3

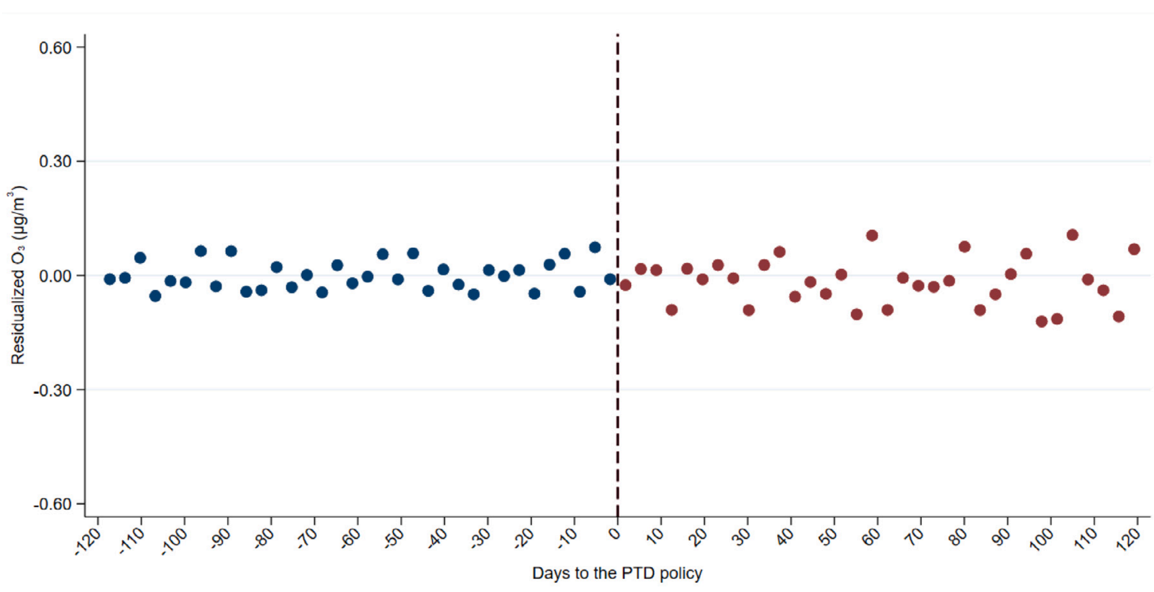


Fig. 3. (*continued*).

within metropolitan areas. Hence, the policy may have made a slim contribution to improving the air quality.

It is important to clearly state what might be driving such outcomes. Public transport fare demand elasticity roughly moves in the range between −0.2 and −0.75 in the short run, which implies an inelastic demand, as fare reductions would increase ridership less than proportionally to the fare change made (Matas, 2004; Holmgren, 2007). In addition, car usage cross elasticity to public transport fares is close to zero, which implies that changes in transit fares would only marginally attract car users (Asensio, 2002). This is in line with evidence showing that ridership growth under massive public transport fare discount schemes develops mainly from (i) travellers shifting away from other slower or low-cost transportation modes (such as walking and cycling) and (ii) induced demand, rather than from travellers shifting away from their cars (Fearnley, 2013).

Supporting this argument, the results of a travel survey that was recently made available and focused on the metropolitan area of Barcelona shows that only 1.2% of respondents switched to public transport after the implementation of the PTD policy, and only 8.4% of them increased transit usage (EMEF, 2023). By monitoring car access in the Catalan capital, the level of traffic reduction has been almost imperceptible from September 2022 onwards[22]

[22] For further details, see the articles by Dani Cordero on *La Vanguardia* (available online at the following: https://elpais.com/espana/catalunya/2022-10-10/la-gratuidad-de-rodalies-deja-indiferente-a-los-conductores.html) and David Guerrero on *La Vanguardia* (available online at the following: https://www.lavanguardia.com/local/catalunya/20230210/8746626/usuarios-transporte-publico-iba-coche-gratuidad.html).

Table 5
Correlation between the PTD policy and ridership: OLS.

	Passengers		
	Short-distance	Medium-distance (conventional)	Medium-distance (high-speed)
Model:	OLS (1)	OLS (2)	OLS (3)
PTD policy	0.052 (0.133)	0.291* (0.161)	0.090 (0.251)
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	48	48	48
R^2	0.58	0.64	0.60

Notes: The table reports estimates from 3 separate regressions by OLS. The unit of observation is the month and the sample for all regressions is from January 2019 to December 2022. The dependent variables are the number of passengers (in logs) carried by (i) short-distance, (ii) medium-distance (conventional) and (iii) medium-distance (high-speed) railway services. Robust standard errors appear in parentheses. Significance values: ***p < 0.01, **p < 0.05, *p < 0.10.

Thus, it seems unlikely that the PTD policy has led to a sizable modal shift in favour of short-distance transit trips, while it might have led to such a shift in favour of medium-distance transit trips for which the monetary cost is more relevant than the travel time. In short, even though a upward trend in ridership figures exists, it is hardly coming from a significant volume of users shifting away from their cars. Indeed, an increase in transit does not necessary entail a reduction in road traffic, also because a possible reduction in congestion could attract additional car trips that were previously not undertaken (Downs, 1998).

In contrast with the results obtained by Aydin and Kürschner Rauck (2023) and Gohl and Schrauth (2024), our empirical analysis does not support the positive relation between transit fares and air quality. Compared to these works, we believe that our regression discontinuity in time approach is much more effective than other methods in detecting the causal effect of public transportation fare subsidies on air quality because all the monitoring stations are affected by the policy.[23] We believe that including this identification strategy in these previous works would corroborate the validity of their differences-in-differences methods and could shed light on the potential biases introduced by the previous issue. In any case, differences in the methodologies, policy designs, and characteristics of the transport system make it difficult to discuss the divergences across studies, which opens up interesting lines of further research.

7. Conclusions

Within urban areas, automobile pollution poses significant negative effects on human health. With the aim of reducing vehicle traffic and improving air quality, policy-makers are promoting more sustainable transport modes by — for instance — reducing the monetary cost of public transport. However, little is known about the air pollution effects of such measures. This paper seeks to fill this gap by quantifying the impact of public transportation low-cost or free-of-charge financing schemes on air quality by taking advantage of a four-month period during which massive discounts (starting on September 1, 2022) were applied to transit fares in Spain.

By exploiting the sharp discontinuity in the cost of ridership that occurred on the implementation day of the policy through a regression discontinuity in time approach, our analysis provides no evidence that the PTD policy has reduced the concentration levels of any pollutant examined. Hence, our results suggest that measures aimed at reducing transit prices may fail to either induce a significant modal shift from private to collective modes of transport or yield environmental benefits that are worth the use of public funds.

[23] Particularly when potential dynamic effects are ruled out, as discussed in Section 5.3.

Table A.1
List of cities.

City
Barcelona
Bilbao
Burgos
Castellón de la Plana
Córdoba
Granada
Huelva
Palmas de Gran Canaria
Madrid
Murcia
Málaga
Oviedo
Palma
Pamplona
Salamanca
San Sebastián
Santa Cruz de Tenerife
Santander
Sevilla
Valencia
Valladolid
Vitoria
Zaragoza

If we compare the PTD policy outcomes with those obtained by public transport supply-oriented interventions in the available literature, it becomes clear that the latter are much more effective in tackling the air pollution issue. Our results have a high policy relevance, as we show that the often-claimed positive relationship between transit fares and air pollution does not necessarily broadly apply. In light of our results, it seems fair to conclude that heavily subsidised public transportation fares might not represent an efficient use of resources to address air quality in urban environments.

From an overall policy analysis perspective, it is important to mention the other objectives of the PTD policy. As a pure transfer between agents in the society with no effect on welfare, the other main goal of the evaluated policy was to mitigate inflationary pressures related to the economic consequences of the *Russo-Ukrainian War* and, consequently, increase households' disposable income. Therefore, while any equity evaluation is beyond the scope of this paper, the PTD policy may have effectively addressed the rising cost of living through an economic relief to low-income travellers, who are more used to rely on public transportation.

CRediT authorship contribution statement

Daniel Albalate: Writing – original draft, Validation, Supervision, Funding acquisition, Data curation, Conceptualization. **Mattia Borsati:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Albert Gragera:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We are very grateful for comments and suggestions that substantially improved the paper by the Editor and one anonymous Referee. We are also very grateful to the team members of the *Air Quality Open Data Platform* (AQICN) for the publicly available data, as well as for their support and clarifications. We thank participants at ITEA 2023 (Santander), ERSA 2024 (Terceira), and the seminar held at the Department of Business Administration of the University of Gothenburg. All remaining errors are our own. Financial support from the Spanish Ministry of Science and Innovation (PID2021-128237OB-I00, TED2021-130638A-I00, PID2022-138866OB-I00, ERDF/EU), the Generalitat de Catalunya, and the research group on Governments and Markets (SGR2021-00261) is gratefully acknowledged.

Appendix A. Additional tables

See Tables A.1–A.3.

Appendix B. Additional figures

See Fig. B.1.

Table A.2
Effect of the PTD policy on pollutants' concentration levels: RDiT-OLS with alternative polynomials.

Model:	PM_{10} RDiT-OLS (1)	NO_2 RDiT-OLS (2)	SO_2 RDiT-OLS (3)	O_3 RDiT-OLS (4)
Panel A: 1st-order polynomial				
PTD policy	0.020	−0.085	0.093	−0.074
	(0.069)	(0.080)	(0.077)	(0.051)
R^2	0.48	0.57	0.07	0.56
AIC	21 721	20 329	28 462	16 943
BIC	21 945	20 570	28 703	17 184
Panel B: 2nd-order polynomial				
PTD policy	0.024	−0.050	0.101	−0.066
	(0.069)	(0.081)	(0.080)	(0.050)
R^2	0.48	0.57	0.07	0.56
AIC	21 726	20 296	28 455	16 944
BIC	21 976	20 529	28 671	17 193
Panel C: 3rd-order polynomial (baseline estimates)				
PTD policy	0.014	−0.062	0.102	−0.063
	(0.069)	(0.080)	(0.080)	(0.051)
R^2	0.48	0.57	0.07	0.56
AIC	21 719	20 290	28 457	16 935
BIC	21 960	20 540	28 681	17 151
Panel D: 4th-order polynomial				
PTD policy	0.014	−0.061	0.103	−0.063
	(0.069)	(0.080)	(0.080)	(0.051)
R^2	0.48	0.57	0.07	0.56
AIC	21 723	20 289	28 453	16 940
BIC	21 980	20 547	28 677	17 181
Panel E: 5th-order polynomial				
PTD policy	0.013	−0.062	0.102	−0.063
	(0.069)	(0.080)	(0.079)	(0.051)
R^2	0.48	0.57	0.07	0.56
AIC	21 712	20 276	28 454	16 944
BIC	21 937	20 492	28 687	17 201
Calima	Yes	No	No	No
Biomass combustion	Yes	No	No	No
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	30 121	30 121	30 121	30 121

Notes: The table reports estimates from 20 separate RDiT-OLS regressions fitting Eq. (2). The unit of observation is the daily median, and the sample for all regressions extends from January 1, 2019, to December 31, 2022. The dependent variables are the pollutants' concentration levels in logs, where PM_{10} is particulate matter, NO_2 is nitrogen dioxide, SO_2 is sulfur dioxide, and O_3 is ground-level ozone. According to the different panels, specifications also include a 1st-, 2nd-, 3rd-, 4th-, or 5th-order polynomial time trend, as well as current and 1-day lags of quartics in temperature, atmospheric pressure, humidity, and wind speed, plus the average number of measurements recorded by the monitoring stations. Time fixed effects include indicator variables for day of the week, day of the month, week of the year, month of the year, quarter of the year, and year, as well as interactions between week of the year and years and day of the week and months. Standard errors clustered at the city level appear in parentheses. Significance values: ***p < 0.01, **p < 0.05, *p < 0.10.

Table A.3
Effect of the PTD policy on pollutants' concentration levels: RDiT-OLS with alternative polynomials interacted with the PTD policy.

Model:	PM_{10} RDiT-OLS (1)	NO_2 RDiT-OLS (2)	SO_2 RDiT-OLS (3)	O_3 RDiT-OLS (4)
Panel A: 1st-order polynomial × T				
PTD policy	0.021	−0.085	0.092	−0.074
	(0.069)	(0.081)	(0.077)	(0.051)
R^2	0.48	0.57	0.07	0.56
AIC	21 719	20 325	28 458	16 942
BIC	21 943	20 549	28 691	17 183
Panel B: 2nd-order polynomial × T				
PTD policy	0.033	−0.039	0.096	−0.068
	(0.067)	(0.082)	(0.081)	(0.049)
R^2	0.48	0.57	0.07	0.56
AIC	21 730	20 286	28 458	16 934
BIC	22 012	20 511	28 691	17 151
Panel C: 3rd-order polynomial × T				
PTD policy	0.024	−0.051	0.093	−0.068
	(0.065)	(0.080)	(0.081)	(0.051)
R^2	0.48	0.57	0.07	0.56
AIC	21 722	20 281	28 458	16 929
BIC	21 988	20 506	28 690	17 195
Panel D: 4th-order polynomial × T				
PTD policy	0.034	−0.033	0.103	−0.046
	(0.063)	(0.082)	(0.080)	(0.051)
R^2	0.48	0.57	0.07	0.56
AIC	21 713	20 272	28 453	16 914
BIC	21 945	20 529	28 677	17 155
Panel E: 5th-order polynomial × T				
PTD policy	0.023	−0.018	0.097	−0.031
	(0.063)	(0.081)	(0.076)	(0.057)
R^2	0.48	0.57	0.07	0.56
AIC	21 714	20 264	28 454	16 907
BIC	21 955	20 496	28 696	17 123
Calima	Yes	No	No	No
Biomass combustion	Yes	No	No	No
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	30 121	30 121	30 121	30 121

Notes: The table reports estimates from 20 separate RDiT-OLS regressions fitting Eq. (2). The unit of observation is the daily median, and the sample for all regressions extends from January 1, 2019, to December 31, 2022. The dependent variables are the pollutants' concentration levels in logs, where PM_{10} is particulate matter, NO_2 is nitrogen dioxide, SO_2 is sulfur dioxide, and O_3 is ground-level ozone. According to the different panels, specifications also include a 1st-, 2nd-, 3rd-, 4th-, or 5th-order polynomial time trend interacted with the PTD policy, as well as current and 1-day lags of quartics in temperature, atmospheric pressure, humidity, and wind speed, plus the average number of measurements recorded by the monitoring stations. Time fixed effects include indicator variables for day of the week, day of the month, week of the year, month of the year, quarter of the year, and year, as well as interactions between week of the year and years and day of the week and months. Standard errors clustered at the city level appear in parentheses. Significance values: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Fig. B.1. Map of short- and medium-distance railway services affected by the PTD policy. *Notes*: The yellow areas show the operational radius of short-distance railway services. The medium-distance connections operated by high-speed railway services are *Madrid–Segovia–Valladolid*, *Madrid–Ciudad Real–Puertollano*, *Madrid–Toledo*, *Salamanca–Segovia–Madrid*, *Albacete–Cuenca–Madrid*, *Barcelona–Tarragona–Lleida*, *Barcelona–Girona*, *Barcelona–Figueres Vilafant*, *Valencia–Requena Utiel*, *Calatayud–Zaragoza*, *Málaga–Córdoba–Sevilla*, *Granada–Málaga*, *Granada–Córdoba–Sevilla*, *Ourense–Santiago–A Coruña*.
Source: Wikipedia.

References

Adler, M.W., van Ommeren, J.N., 2016. Does public transit reduce car travel externalities? Quasi-natural experiments' evidence from transit strikes. J. Urban Econom. 92, 106–119.

Albalate, D., Fageda, X., 2021. On the relationship between congestion and road safety in cities. Transp. Policy 105, 145–152.

Anderson, M.L., 2014. Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. Amer. Econ. Rev. 104 (9), 2763–2796.

Asensio, J., 2002. Transport mode choice by commuters to Barcelona's CBD. Urban Stud. 39 (10), 1881–1895.

Auffhammer, M., Kellogg, R., 2011. Clearing the air? The effects of gasoline content regulation on air quality. Amer. Econ. Rev. 101 (6), 2687–2722.

Aydin, E., Kürschner Rauck, K., 2023. Public Transport Subsidization and Air Pollution: Evidence from the 9-Euro-Ticket in Germany. SSRN Working Paper No. 4505249.

Basso, L.J., Guevara, C.A., Gschwender, A., Fuster, M., 2011. Congestion pricing, transit subsidies and dedicated bus lanes: Efficient and practical solutions to congestion. Transp. Policy 18 (5), 676–684.

Basso, L.J., Navarro, M., Silva, H.E., 2021. Public transport and urban structure. Econom. Transp. 28, 100232.

Basso, L.J., Silva, H.E., 2014. Efficiency and substitutability of transit subsidies and other urban transport policies. Am. Econ. J.: Econ. Policy 6 (4), 1–33.

Bauernschuster, S., Hener, T., Rainer, H., 2017. When labor disputes bring cities to a standstill: The impact of public transit strikes on traffic, accidents, air pollution, and health. Am. Econ. J.: Econ. Policy 9 (1), 1–37.

Beaudoin, J., Farzin, Y.H., Lawell, C.-Y.C.L., 2015. Public transit investment and sustainable transportation: A review of studies of transit's impact on traffic congestion and air quality. Res. Transp. Econom. 52, 15–22.

Bel, G., Holst, M., 2018. Evaluation of the impact of bus rapid transit on air pollution in Mexico city. Transp. Policy 63, 209–220.

Bull, O., Muñoz, J.C., Silva, H.E., 2021. The impact of fare-free public transport on travel behavior: Evidence from a randomized controlled trial. Reg. Sci. Urban Econ. 86, 103616.

Calonico, S., Cattaneo, M.D., Farrell, M.H., 2018. On the effect of bias estimation on coverage accuracy in nonparametric inference. J. Amer. Statist. Assoc. 113 (522), 767–779.

Calonico, S., Cattaneo, M.D., Farrell, M.H., 2022. Coverage error optimal confidence intervals for local polynomial regression. Bernoulli 28 (4), 2998–3022.

Cats, O., Susilo, Y.O., Reimal, T., 2017. The prospects of fare-free public transport: Evidence from Tallinn. Transportation 44, 1083–1104.

Chapman, L., 2007. Transport and climate change: A review. J. Transp. Geogr. 15 (5), 354–367.

Chay, K.Y., Greenstone, M., 2003. The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. Q. J. Econom. 118 (3), 1121–1167.

Chen, Y., Whalley, A., 2012. Green infrastructure: The effects of urban rail transit on air quality. Am. Econ. J.: Econ. Policy 4 (1), 58–97.

Davis, L.W., 2008. The effect of driving restrictions on air quality in Mexico city. J. Polit. Econ. 116 (1), 38–81.

Davis, L.W., 2017. Saturday driving restrictions fail to improve air quality in Mexico city. Sci. Rep. 7 (1), 1–9.

Davis, L.W., 2021. Estimating the price elasticity of demand for subways: Evidence from Mexico. Reg. Sci. Urban Econ. 87, 103651.

De Borger, B., Proost, S., 2015. The political economy of public transport pricing and supply decisions. Econom. Transp. 4 (1–2), 95–109.

Downs, A., 1998. The law of peak-hour expressway congestion. In: Urban Affairs and Urban Policy. Edward Elgar Publishing, pp. 1–17.

EEA, 2020. Air Quality in Europe — 2020 Report. European Environment Agency, Retrieved 20 March 2023 from https://www.eea.europa.eu/publications/air-quality-in-europe-2020-report.

EEA, 2021. Air Quality Standards. European Environment Agency, Retrieved 20 March 2023 from https://www.eea.europa.eu/themes/air/air-quality-concentrations/air-quality-standards.

EMEF, 2023. Enquesta de Mobilitat en Dia Feiner 2022. Institut d'Estudis Regionals i Metropolitans de Barcelona, Retrieved 15 August 2023 from https://bcnroc.ajuntament.barcelona.cat/jspui/bitstream/11703/131800/1/EMEF_2022_Informe_Resum_Executiu.pdf.

EPA, 2022. Overview of the Clean Air Act and Air Pollution. United States Environmental Protection Agency, Retrieved 20 March 2023 from https://www.epa.gov/clean-air-act-overview.

Fearnley, N., 2013. Free fares policies: Impact on public transport mode share and other transport policy goals. Int. J. Transp. 1 (1), 75–90.

Gagnepain, P., Massoni, S., Mayol, A., Staropoli, C., 2024. The effect of public transport pricing policy: experimental evidence. halshs-04610702.

Gallego, F., Montero, J.-P., Salas, C., 2013. The effect of transport policies on car use: Evidence from latin American cities. J. Public Econom. 107, 47–62.

Gelman, A., Imbens, G., 2019. Why high-order polynomials should not be used in regression discontinuity designs. J. Bus. Econom. Statist. 37 (3), 447–456.

Gendron-Carrier, N., Gonzalez-Navarro, M., Polloni, S., Turner, M.A., 2022. Subways and urban air pollution. Am. Econ. J.: Appl. Econom. 14 (1), 164–196.

Goel, D., Gupta, S., 2017. The effect of metro expansions on air pollution in Delhi. World Bank Econ. Rev. 31 (1), 271–294.

Gohl, N., Schrauth, P., 2024. JUE insight: Ticket to paradise? The effect of a public transport subsidy on air quality. J. Urban Econom. 103643.

Hausman, C., Rapson, D.S., 2018. Regression discontinuity in time: Considerations for empirical applications. Annu. Rev. Resour. Econom. 10, 533–552.

Holmgren, J., 2007. Meta-analysis of public transport demand. Transp. Res. A 41 (10), 1021–1035.

Hörcher, D., Tirachini, A., 2021. A review of public transport economics. Econom. Transp. 25, 100196.

Huang, C., Wang, Q., Wang, S., Ren, M., Ma, R., He, Y., 2017. Air pollution prevention and control policy in China. Ambient Air Pollut. Health Impact China 243–261.

Kaddoura, I., Nagel, K., 2018. Simultaneous internalization of traffic congestion and noise exposure costs. Transportation 45 (5), 1579–1600.

Knittel, C.R., Miller, D.L., Sanders, N.J., 2016. Caution, drivers! Children present: Traffic, pollution, and infant health. Rev. Econ. Stat. 98 (2), 350–366.

Lalive, R., Luechinger, S., Schmutzler, A., 2018. Does expanding regional train service reduce air pollution? J. Environ. Econom. Manage. 92, 744–764.

Lee, D.S., Lemieux, T., 2010. Regression discontinuity designs in economics. J. Econ. Lit. 48 (2), 281–355.

Li, S., Liu, Y., Purevjav, A.-O., Yang, L., 2019. Does subway expansion improve air quality? J. Environ. Econom. Manage. 96, 213–235.

Lu, H., Zhu, Y., Qi, Y., Yu, J., 2018. Do urban subway openings reduce PM2.5 concentrations? Evidence from China. Sustainability 10 (11), 4147.

Matas, A., 2004. Demand and revenue implications of an integrated public transport policy: The case of madrid. Transp. Rev. 24 (2), 195–217.

MITMA, 2023. Las Medidas de Fomento del Transporte Público de MITMA Hacen Posible Que el 82% de Los Viajes de Competencia Estatal Sean con Abonos Gratuitos o Descuento. Press Note, Ministerio de Transportes, Mobilidad y Agenda Urbana - Gobierno de España, Retrieved 15 August 2023 from https://www.mitma.gob.es/recursos_mfom/sala_prensa/230804_np_impacto_descuentos_transporte.pdf.

Parry, I.W., Bento, A., 2001. Revenue recycling and the welfare effects of road pricing. Scand. J. Econom. 103 (4), 645–671.

Parry, I.W., Small, K.A., 2005. Does britain or the United States have the right gasoline tax? Amer. Econ. Rev. 95 (4), 1276–1289.

Parry, I.W., Small, K.A., 2009. Should urban transit subsidies be reduced? Amer. Econ. Rev. 99 (3), 700–724.

Parry, I.W., Walls, M., Harrington, W., 2007. Automobile externalities and policies. J. Econ. Lit. 45 (2), 373–399.

Percoco, M., 2013. Is road pricing effective in abating pollution? Evidence from milan. Transp. Res. D 25, 112–118.

Porter, J., 2003. Estimation in the Regression Discontinuity Model. Vol. 2003, Department of Economics, University of Wisconsin at Madison, pp. 5–19, Unpublished Manuscript.

Proost, S., Van Dender, K., 2012. Energy and environment challenges in the transport sector. Econom. Transp. 1 (1–2), 77–87.

Sun, C., Zhang, W., Fang, X., Gao, X., Xu, M., 2019. Urban public transport and air quality: Empirical study of China cities. Energy Policy 135, 110998.

Tomeš, Z., Fitzová, H., Pařil, V., Rederer, V., Kordová, Z., Kasa, M., 2022. Fare discounts and free fares in long-distance public transport in central Europe. Case Stud. Transp. Policy 10 (1), 507–517.

UITP, 2020. Full Free Fare Public Transport: Objectives and Alternatives. The International Association of Public Transport, Retrieved 1 March 2023 from https://cms.uitp.org/wp/wp-content/uploads/2020/09/Policy-Brief-FullFreeFarePT-DEF-web.pdf.

Webster, G., 2024. Free fare for better air? Evaluating the impacts of free fare public transit on air pollution. Transp. Res. A 184, 104076.

WHO, 2019. Ambient (Outdoor) Air Pollution. World Health Organization, Retrieved 20 March 2023 from https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.

Yang, Z., Tang, M., 2018. Does the increase of public transit fares deteriorate air quality in Beijing? Transp. Res. D 63, 49–57.

Zhang, K., Batterman, S., 2013. Air pollution and health risks due to vehicle traffic. Sci. Total Environ. 450, 307–316.

Zhang, L., Long, R., Chen, H., Geng, J., 2019. A review of China's road traffic carbon emissions. J. Clean. Prod. 207, 569–581.

Zheng, S., Zhang, X., Sun, W., Wang, J., 2019. The effect of a new subway line on local air quality: A case study in Changsha. Transp. Res. D 68, 26–38.