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Evaluating the Impact of Urban Road Pricing on the Use of Green Transport Modes: The Case of Milan

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EVALUATING THE IMPACT OF URBAN ROAD PRICING ON THE USE OF GREEN TRANSPORT MODES: THE CASE OF MILAN – ENVIRONMENT WORKING PAPER N° 143

by Elisabetta Cornago (1), Alexandros Dimitropoulos (1) and Walid Oueslati (1)

(1) OECD Environment Directorate

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Keywords: *Congestion pricing, urban road pricing, bike sharing, sustainable mobility.*

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Abstract

Concerns for the environmental and economic implications of road congestion, air pollution and climate change are growing in cities across the world. This has led local and national authorities to take various initiatives, implementing road pricing and supporting the extension of public transport networks and the provision of non-polluting mobility services. These policies have often been rolled out in parallel, with the aim of inducing city dwellers to opt for greener transport options, thereby reducing congestion and emissions. Understanding how the interplay between these policies affects individual travel behaviour is fundamental for evaluating their effectiveness in achieving their environmental and economic objectives.

The purpose of this study is to investigate the effect of congestion pricing on the demand for zero-emission transport modes. To this end, it draws on an empirical analysis of the effect of Milan’s congestion charge on the use of bike sharing, focusing on two sudden policy changes resulting in a shift from priced to unpriced road use: a temporary suspension of the congestion charge, and a permanent reduction in the application schedule of the charge.

The analysis indicates that congestion pricing increases daily bike-sharing use by 5% to 5.8% in the short term, depending on the model specification. Extending the schedule of the congestion charge in the early evening increases bike-sharing use in the affected time window by 12%. Congestion pricing increases the cost of using private motor vehicles: this induces a modal shift away from car use and towards alternative transport options. This, in turn, reduces road traffic congestion, contributing to a safer and more pleasant environment for cycling. This “congestion” effect is estimated to be more important in inducing additional bike-sharing use than the “price” effect, i.e. the increase of the relative cost of car use.

Estimates vary significantly along multiple dimensions. First, congestion pricing affects most importantly daily bike-sharing traffic within the congestion pricing area, whereas trips outside of it are largely unaffected. Bike-sharing trips entering and exiting the congestion charge zone are influenced to a lesser extent than trips within the zone. Second, bike-sharing departures from stations located in close proximity to metro stations are unaffected by congestion pricing, whereas the policy impact is increasing in distance to the closest metro stop. This indicates the complementarity between bike-sharing and metro networks. Third, bike-sharing use is more strongly affected by congestion pricing in the evening than in the rest of the day: this underscores the fact that travellers with different values of time will not respond to the policy in the same way. Finally, bike-sharing users who have built into their mobility habits a frequent use of bike-sharing are less impacted by the policy suspension than users with infrequent use patterns.

These findings indicate that traffic mitigation measures directly aiming to reduce the use of private motor vehicles can also have positive repercussions on the uptake of non-polluting transport options. Relying solely on direct incentives for cycling, which often involve infrastructure projects, is likely not sufficient to remove barriers to bike use.

Keywords: Congestion pricing, urban road pricing, bike sharing, sustainable mobility.

JEL classification: Q58, R41, R48.

Résumé

Les préoccupations liées aux conséquences environnementales et économiques de la congestion routière, de la pollution atmosphérique et du changement climatique se développent dans plusieurs villes à travers le monde. Cela a conduit les autorités locales et nationales à prendre diverses initiatives, comme la mise en œuvre du péage urbain, l'extension des réseaux de transport public ou encore la fourniture de services de mobilité non polluants. Ces politiques ont souvent été déployées en parallèle, dans le but d'inciter les citadins à opter pour des options de transport plus écologiques, réduisant ainsi les embouteillages et les émissions. Comprendre comment l'interaction de ces politiques affecte le comportement des voyageurs en milieu urbain est fondamental pour évaluer leur efficacité économique et environnementale.

L'objet de cette étude est d'examiner l'effet de la tarification de la congestion sur la demande des modes de transport à émission nulle. À cette fin, elle s'appuie sur une analyse empirique de l'effet du péage urbain mis en œuvre par la ville de Milan sur l'utilisation du dispositif des vélos en libre-service. L'étude met l'accent sur deux changements soudains de la politique de péage urbain qui ont entraîné le passage de l'utilisation routière tarifée à une utilisation non tarifée: une suspension temporaire du péage, et une réduction permanente du calendrier de son application.

L'analyse montre que la tarification de la congestion augmente l'utilisation quotidienne du vélo en libre-service de 5% à 5,8% à court terme, en fonction des spécifications du modèle estimé. L'extension de la grille tarifaire de congestion en début de soirée augmente l'utilisation du vélo partagé dans la fenêtre de temps concernée de 12%. La tarification de la congestion augmente le coût d'utilisation des véhicules privés: cela induit un transfert modal de l'utilisation de la voiture vers des modes de transport alternatifs. Ceci, à son tour, réduit la congestion routière, contribuant ainsi à un environnement plus sûr et plus agréable pour l'utilisation du vélo. On estime que cet effet de « congestion » est plus important pour induire une utilisation supplémentaire de vélos en libre-service que l'effet « de prix », à savoir l'augmentation du coût relatif de l'utilisation de la voiture.

Les estimations varient considérablement selon plusieurs dimensions. Premièrement, la tarification de la congestion affecte surtout le trafic quotidien de vélos en libre-service dans la zone de tarification de la congestion, alors que les déplacements en dehors de celle-ci ne sont pas affectés. Les déplacements en vélos entrant et sortant de la zone à péage urbain sont moins influencés que les déplacements à l'intérieur de la zone. Deuxièmement, la tarification de la congestion n'affecte pas les départs de vélos en libre-service à partir de stations situées à proximité immédiate de stations de métro, alors que l'impact de la politique augmente avec la distance jusqu'à la station de métro la plus proche. Cela indique la complémentarité entre les vélos en libre-service et les réseaux métropolitains. Troisièmement, la tarification de la congestion en soirée a plus d'incidence sur l'utilisation du vélo en libre-service que dans le reste de la journée: cela souligne le fait que les voyageurs ayant des valeurs de temps différentes ne répondront pas à cette politique de la même manière. Enfin, les utilisateurs de vélos en libre-service qui ont intégré dans leurs habitudes de mobilité l'utilisation fréquente du vélo en libre-service sont moins touchés par la suspension de la politique que les utilisateurs dont les habitudes d'utilisation sont peu fréquentes.

Ces résultats indiquent que les mesures d'atténuation du trafic visant directement à réduire l'utilisation de véhicules à moteur peuvent également avoir des répercussions positives sur l'utilisation d'autres options de transport non polluantes. Compter uniquement sur des incitations directes pour le cyclisme, qui impliquent souvent des projets d'infrastructure, n'est probablement pas suffisant pour supprimer les obstacles à l'utilisation du vélo.

Mots clés : tarification de la congestion, péage urbain, vélos en libre-service, mobilité durable.

Classification JEL : Q58, R41, R48.

Foreword

This report has been authored by Elisabetta Cornago, Alexandros Dimitropoulos and Walid Oueslati of the OECD Environment Directorate.

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1. Introduction

Transport-related greenhouse gas emissions and air pollution are crucial environmental policy issues: fuel combustion in the transport sector generated almost a quarter of global CO_2 emissions in 2015, with road transport making up for over 70% of total transport CO_2 emissions. Among OECD countries, these figures were higher, respectively at 30% and 89% (IEA, 2017[1]). Urban populations are particularly exposed to air pollution externalities due to road transport: according to the World Health Organisation, 97% of cities in low- and middle income countries and 49% of cities in high-income countries do not meet WHO air quality guidelines (World Health Organisation, 2018[2]). Outdoor air pollution has seen an increasing trend in urban environments: between 2008 and 2013, annual mean concentrations of $PM_{2.5}$ have globally increased by 8% (World Health Organization, 2016[3]).

In the OECD, the cost of the health impact of outdoor air pollution, including both deaths and illnesses, was about USD 1.7 trillion in 2010. Road transport accounts for over 50% of the cost of these health impacts (OECD, 2014[4]; OECD, 2016[5]). Alongside costs of air pollution from road transport, urban congestion entails additional economic costs, including the cost of travel time spent in congested areas and the cost of fuel wasted in congestion.[1]

Because road transport causes such an important part of emissions in urban areas and economic losses from congestion are significant, cities face the challenge of designing transport policies to internalise pollution and congestion externalities. At the same time, providing green mobility services, such as bike sharing, facilitates behavioural change via modal shift.

The coexistence of these transport policies makes the city of Milan, Italy, an interesting context to study their interplay. In the past ten years, Milan has worked along multiple axes in order to induce a shift towards more sustainable transport options, and curb transport-related greenhouse gas emissions, air pollution and road traffic congestion. This has translated into setting up urban road pricing through pollution and congestion charges, increasing on-street parking fees, putting in place a bike-sharing scheme, extending the bike-lane network, and strengthening the public transport network.

A number of papers have analysed the impact of urban road pricing on the use of motor vehicles and, to a lesser extent, of public transport (Eliasson et al., 2009[6]; Gibson and Carnovale, 2015[7]; Leape, 2006[8]). However, the effects of road pricing on the adoption of non-motorised urban transport options remain largely unexplored. By analysing the case of Milan, this report contributes to the literature with the first assessment of how urban road pricing schemes affect the use of sustainable transport modes, such as bike sharing.

Urban road pricing can influence individual travel behaviour in several ways: users might decide to alter trip times or routes, shift to other means of transport, or even completely forgo trips (Leape, 2006[8]). The introduction of road pricing can induce behavioural change

[1] In 2017, congestion has been estimated to have cost drivers in the United States USD 305 billion in total direct and indirect costs. This figure was estimated at over GBP 37 billion in the UK, and at over EUR 80 billion in Germany (INRIX Research, 2017[37]).

through two channels, whose interplay determines the extent to which road pricing leads individuals to turn towards green transport modes:

The *price effect*: road pricing increases the cost of trips by private motor vehicles relative to trips by public transport or bike sharing: this translates into lower demand for car use and higher demand for alternative mobility services.

The *congestion effect*: road pricing directly reduces demand for travel in private motor vehicles such as cars or motorbikes. By reducing road traffic, it also reduces road congestion, rendering biking safer and more pleasant: this can induce more travellers to turn to bike sharing.

Municipalities can put in place a number of concurrent policy measures to incentivise soft mobility, i.e. cycling and walking. This can complicate the empirical estimation of the causal impact of a specific policy on the demand for a specific transport option. Simply comparing bike-sharing use before and after the introduction of congestion pricing may be misleading: confounding factors which might explain part of the variation in bike-sharing demand should be controlled for.

If the policy of interest undergoes a sudden, exogenous change, this effectively creates a quasi-experimental setting in which treatment and control groups (of individuals, groups or time periods) are randomly generated. In this study, the empirical strategy used to estimate the impact of road pricing on bike-sharing use is based on two sudden policy changes: a temporary suspension of the congestion charge in summer 2012, and a permanent reduction in the application schedule of the charge on Thursday evenings in autumn 2012. Both policy changes translate into a shift from priced to unpriced road use, either throughout the entire day or at a specific time of the day. Comparing bike-sharing use over time windows treated or untreated with congestion pricing enables the assessment of the policy impact.

As a consequence of these policy changes, car entries into the congestion charge zone are expected to increase at unpriced times. Bike-sharing use might decrease because of a price effect, as former bikers turn to cars. The price effect might also have an indirect impact on bike-sharing use: if public transport users turn to driving, less crowded public transport might attract former bikers, reducing the demand for bike-sharing use. In turn, increased street congestion within the cordon toll zone might make bike sharing less appealing for a number of reasons: biking might feel less safe or, simply, less pleasant. Thus, bike-sharing use might also decrease because of a congestion effect. One of the aims of this study is to quantify the relative impact of price signals and urban congestion on bike-sharing use.

Several policies can affect the cost of driving: fuel taxation, car ownership taxation, parking tariffs, congestion charges. However, these policies differ in several dimensions, such as governance, geographical perimeter and salience. For instance, fuel taxation is a national or state policy, while congestion pricing is a local one, which directly affects the geographical horizon of potential impacts. This report shows the behavioural implications of opting for a local, relatively salient, market-based policy which applies in an urban area.

Empirical findings indicate that congestion pricing increases daily bike-sharing use by around 5% to 5.8% in the short run, depending on the model specification. On the other hand, durable extensions of the schedule of the congestion charge increase bike-sharing use in the affected time window (in this case Thursdays, 18:00-19:30) by 12%. The report also discusses the extent to which these impacts vary along different dimensions of the urban environment (direction of bike-sharing traffic relative to the congestion charge zone;

proximity of bike-sharing stations to metro stations), to the timing of bike-sharing trips, or to the individual habits and preferences of bike-sharing users.

These findings indicate that traffic-mitigating policies, directly aimed at reducing the use of motor vehicles, can have an indirect but substantial impact on alternative transport options. As a consequence, relying solely on policy interventions which aim at directly incentivising cycling (e.g. the development of bike lanes), is likely not sufficient to remove barriers to biking.

The rest of the paper is structured as follows. Section 2 provides background on the drivers of and barriers to biking, as well as on the environmental and economic impacts of bike-sharing schemes and urban road pricing. Section 3 outlines the Milan policy context and Section 4 describes the data. Sections 5 presents the empirical approaches on which the analysis is based and discusses results. Section 6 concludes and discusses the policy implications of these results.

2. Background

2.1. Biking and bike-sharing use: drivers and barriers

Bike sharing has grown exponentially in the past 10 years. Over 1000 cities worldwide now host bike-sharing schemes, amounting to a global fleet of over 4.5 million bikes in 2017, compared to just over 1 million bikes in 2015 (Fishman and Schepers, 2018[9]).

Two main types of bike-sharing systems can be distinguished: station-based bike sharing and free-floating (or dockless) bike sharing.[2] In station-based schemes, bikes are borrowed and docked at physical stations, using badges to lock and unlock them. Free-floating schemes instead do not exploit physical docks: free-floating bikes are equipped with GPS systems, which allow users (and providers) to locate available bikes in real time thanks to smart phone apps. Free-floating systems are more recent: their flexibility of "installation" and use has driven the steep increase in the number of bike-sharing schemes in the past two years.

Recent reviews have synthesised the blossoming literature analysing bike-sharing schemes, pinpointing the main reasons for which city dwellers take up bike sharing (Ricci, 2015[10]; Fishman, 2016[11]). Evidence from actual and potential user surveys across a number of countries (e.g. Australia, China, United States and United Kingdom) indicates that convenience is the main driver of bike-sharing use: survey participants appreciate that bike sharing expands mode choice and reduces travel times and mobility costs. Proximity of stations to one's home or workplace is important in this respect. The other most frequently mentioned motivations for bike-sharing users are health, leisure and environmental benefits, as well as its lower cost of use with respect to public transport.

While it has been relatively simple to survey users, there is much less evidence on the barriers to biking for the general public. Data availability is the main constraint in this respect. However, based on focus group discussions in Australia, Fishman (2016[11]) mentions as main barriers for bike-sharing use the convenience of driving, the distance to docking stations and concerns regarding safety in traffic. The relative importance of both drivers and barriers of bike-sharing use however, is likely to be context-dependent, varying across countries and cities.

For what concerns the portrait of the typical bike-sharing user, bike-sharing schemes have been suggested to be particularly popular among employed white men, who tend to be "younger, more affluent, more educated and more likely to be already engaged in cycling independently of bike sharing" than average (Ricci (2015[10])). In countries with low cycling levels, bike-sharing ridership appears to reflect demographic patterns characterising biking more generally (i.e. in terms of gender, ethnicity and socio-economic status).

Intuitively, bike sharing should thrive in urban environments with policies favouring biking. Drivers of biking behaviour and incentives to increase its uptake have long been part of the policy debate (OECD/ECMT, 2004[12]). Ultimately, two broad sets of incentives for bike use can be distinguished: *direct incentives* for bike use, and *indirect incentives*,

[2] For a detailed discussion of different technology "generations" which have gradually enabled the evolution of bike sharing, see Ricci (2015[10]) and Fishman (2016[11]).

which hinder car use. Such incentives can be delivered through infrastructure provision as well as through a host of complementary policy tools: pricing, regulation and information provision (i.e. awareness and education campaigns). While the role of behavioural insights in the design of sustainable mobility policy has been thus far relatively limited (OECD, 2017[13]), behavioural interventions could also support policy-makers in this respect.

Table 1 summarises the key policies and infrastructure projects aimed at promoting cycling as a safe and convenient means of transport. The table builds upon policy typologies provided by academic literature reviews summarising evidence of the impacts of cycle-friendly policies (Pucher and Buehler, 2008[14]; Heinen, van Wee and Maat, 2010[15]), as well as policy publications (OECD/ECMT, 2004[12]). The reviewed literature refers to evidence from Australia, Canada and the United States, as well as from various European countries, including Austria, Denmark, Germany, the Netherlands, Sweden and the United Kingdom.

Urban road pricing belongs to the set of indirect incentives to bike use, as a pricing tool aimed at dissuading car use thus reducing traffic. The objective of this study is to assess to what extent congestion pricing can incentivize biking, observing bike-sharing use patterns.

Table 1. Direct and indirect policy incentives for bike use

	Direct incentives	Indirect incentives
Infrastructure	Separate cycling lanes	Road speed bumps
	Bike parking spaces	
	Bike-sharing schemes	
	Intersection modifications	
	Signing and lighting	
Regulation	Traffic priority rules favouring cyclists	Road speed limits
		Car parking restrictions
Pricing		Urban road pricing (e.g. congestion pricing and pollution pricing)
		On-street parking fees
		Taxation: motor fuel, car ownership and use
Information provision	Education and training	

Source: Based on ECMT (2004), Heinen, van Wee and Maat (2010), and Pucher and Buehler (2008).

2.2. The impacts of bike-sharing use

Introducing bike sharing as an additional mobility option in the urban environment can potentially alter the modal split, as travellers reassess their transport choices. This, in turn, can impact urban congestion.

Evidence from user surveys from five cities in Australia, the United Kingdom and the United States seems to indicate that only up to 9% of bike-sharing trips are additional trips (Fishman, Washington and Haworth, 2014[16]). The uptake of bike sharing mainly replaces public transport use (between 20% in Minneapolis and just under 60% in London) and walking (around 20% in Brisbane and 40% in Minneapolis). Car use is replaced to a smaller extent: only about 2% of bike-sharing trips replace car trips in London, 7% in Washington D.C. and around 20% in Brisbane, Minneapolis and Melbourne.

A shortcoming of the literature to date is that most studies jointly analyse trip data and survey data in a before-after setting, which does not enable the causal interpretation of findings. However, some recent papers have causally identified how the introduction of bike-sharing schemes in urban environments affects mobility patterns.

A recent analysis of bike-sharing expansion in Washington, D.C., provides an empirical assessment of the causal effect of the presence of bike-sharing stations on car congestion (measured at the route segment level as the ratio between constant reference speed, which depends on historical patterns, and observed speed). Findings indicate that the presence of bike-sharing stations reduces congestion by 4%, and that these benefits are concentrated in highly congested neighbourhoods (Hamilton and Wichman, 2018[17]).

For what concerns public transport, previous evidence seems to indicate that bike sharing can act as its substitute, decreasing its use (Fishman, Washington and Haworth, 2014[16]). However, if additional bike-sharing trips are performed in conjunction with public transport, there might be an element of complementarity between the two mobility options: hence, bike sharing's total impact on public transport use is a priori unclear. A recent empirical analysis quantifies the impact of New York City's bike-sharing scheme on public transport use by exploiting the scheme's expansion in time and controlling for bike lane infrastructure (Campbell and Brakewood, 2017[18]). Because bike-sharing stations differ in the number of docks they hold, the authors consider docks as their observation unit. They find that the number of daily bus trips drops by 1.7% every thousand bike-sharing docks along a bus route, which corresponds to about 12 600 trips.

2.3. The consequences of urban road pricing

Urban road pricing policies are aimed at internalising the local external costs of motor vehicle use, notably air pollution and time losses due to congestion (OECD/ECMT, 2007[19]). Such policies are most often defined as cordon tolls, whereby inbound trips (and in certain cases, outbound trips) to a given delimited urban area are charged a flat fee. While cordon tolls are distance-invariant, urban road pricing can also be implemented through a distance-based tax, such as a flat kilometre tax. This type of tax can be levied on motor vehicle use within predetermined boundaries like a cordon toll, but acknowledging the external costs which increase in trip's length (OECD, 2018[20]).

Across OECD countries, cordon tolls are the most popular form of urban road pricing, but their design has seen substantial differences in the few cities which have implemented them (International Transport Forum, 2010[21]). In 2003, London introduced congestion pricing as a flat fee applying upon entry into the city centre. Similarly, in Milan congestion pricing involves a flat fee for entering the city centre during daytime on weekdays, but a number of exceptions apply: details are discussed in Section 3. Milan's scheme started as a pollution charge in 2008; it was transformed to a congestion charge scheme in 2012. Stockholm implemented congestion pricing in 2007, following a 6-month trial in the first half of 2006. Its congestion charge applies both upon entering and exiting the inner city, and it varies throughout the day, involving a higher price at peak time. These congestion pricing schemes also vary in their geographical extension: the congestion charge zone in London covers an area of 20.7 km^2, Stockholm's charge applies over 30 km^2, and Milan's over 8.2 km^2 (Croci, 2016[22]). Urban road pricing is also applied in several Norwegian cities, as well as in cities outside of the OECD, such as Singapore.

Following the introduction of urban road pricing, travellers can alter their transport behaviour along different axes: changing the time, route and means of transport of their trip, or forgoing the trip altogether. In turn, these behavioural changes have broader environmental and economic consequences. The empirical literature has tried to estimate these effects by assessing specific case studies. The vast majority of empirical papers on the impact of urban road pricing on individual transport behaviour have considered the cases of London, Stockholm and Milan.

Given the object of this study is the effect of road pricing on the use of green transport modes, this section reviews in greater detail the empirical evidence on the behavioural consequences of urban road pricing. However, road pricing generates a range of broader environmental and economic impacts, which are discussed in turn more concisely.

2.3.1. Behavioural consequences of urban road pricing

Most papers assessing the behavioural consequences of urban road pricing have focused on the use of motor vehicles, which is directly priced under such policies (Percoco, 2014[23]; Gibson and Carnovale, 2015[7]). Conversely, the indirect impact of urban road pricing on the use of public transport and green mobility options, such as biking, has rarely been assessed (Eliasson et al., 2009[6]; Leape, 2006[8]; Karlström and Franklin, 2009[24]).

A few studies on the direct impact of congestion charges on motor vehicle use have exploited sudden policy shocks building upon quasi-experimental methodologies. Several studies analysing the impact of Milan's congestion charge are based on its sudden suspension in 2012: this has been found to significantly increase car entries into the area where the congestion charge applies (Gibson and Carnovale, 2015[7]), and to reduce the use of motorbikes and alternative fuel vehicles, which are normally exempt from the charge (Percoco, 2014[23]). For more details on the results of these studies, see Box 1.

In Stockholm, the implementation of the congestion charge in 2007 has been preceded by a 6-month trial. Within one month of the trial's start, the number of vehicles crossing the cordon dropped by 27% relatively to the previous year (Eliasson et al., 2009[6]). This is based on the assumption that the congestion charge is the only element of variation that might have affected the decision to drive into the centre, supported by a time-series study assessing the role of fuel prices, employment and car ownership.

For what concerns the choice of travel time, there is evidence that congestion pricing in Milan induced intertemporal substitution towards driving outside of the application schedule of the charge (Gibson and Carnovale, 2015[7]). Evidence of peak spreading has also been found in Stockholm, where drivers react to the charge by delaying their entry in the priced zone (Karlström and Franklin, 2009[24]).

Some studies have looked at the extent to which road pricing drives spatial substitution to roads outside the priced zone. For what concerns London, traffic increased by 2-6% in neighbouring areas only in the first year of congestion charge application, but this trend was reverted in the second year. However, traffic management efforts were put in place to adjust traffic flows more efficiently, which might have contributed to this effect (Leape, 2006[8]). In Milan, a temporary suspension of congestion pricing reduced traffic on roads within 1 km of the congestion zone's perimeter by 18%, suggesting that these drivers might have avoided crossing the zone when the charge was applied (Gibson and Carnovale, 2015[7]).

While counterfactual-based analyses of the impact of road pricing on car traffic are rare, they are absent for what concerns impacts on public transport and bike use. Evidence in this respect has primarily drawn upon before-after comparisons. While these can be informative, they do not allow disentangling the effect of the policy itself from that of confounders, hence they should be interpreted with caution.

In London, bus passengers entering the zone at morning peak time increased by 38% between 2002 and 2003: however, only half of this increase has been estimated to be due to the congestion charge, given that improved bus service has also played a substantial role in increasing ridership (Leape, 2006[8]). Likewise, in Stockholm, the number of public transport passengers increased by 6% between spring 2005 and 2006; however, only a 4.5% increase can be associated with the road toll, while the rest might have been driven by changes in petrol prices and business-cycle effects (Eliasson et al., 2009[6]).

Finally, our knowledge of the extent to which active and potential cyclists react to road pricing is very limited. Evidence on the impact of road pricing on bicycle use is sparse and solely based on aggregate statistics rather than on microdata: for example, bike traffic inside London's congestion charge zone increased by 28% in 2003, the charge's first year, relatively to 2002 (Leape, 2006[8]).

This paper contributes to the empirical literature assessing the effects of congestion pricing on individual transport behaviour by providing the first assessment of changes in demand for a zero-emission transport option in response to road pricing.

2.3.2. Environmental and economic consequences of urban road pricing

According to whether urban road pricing induces travellers to change transport mode, trip time or route, the environmental implications of the same policy can be very different. Box 1 discusses how the design of different road pricing schemes has affected air pollution in Milan. In Stockholm, congestion pricing led to a 5% to 7.5% reduction in nitrogen dioxide (NO_2) levels and to a 15 to 20% reduction in PM_{10} levels (Simeonova et al., 2018[25]). In London, NO_x decreased by 8%, PM_{10} by 6% and CO_2 by 16% in the first year of operation of the congestion charge. Because of improvements in the emissions performance of the vehicle fleet, environmental benefits of the policy have been found to decrease over time (Transport for London, 2008[26]).

The direct benefits of road pricing go beyond reduced air pollution: time savings from reduced congestion and improved journey time reliability have been estimated to amount to EUR 18.2 million in Milan over the first 11 months of application of pollution pricing (Rotaris et al., 2010[27]). In London, estimates of annual benefits of congestion pricing from time savings and reliability amounted to GBP 202 million (Leape, 2006[8]).

The impact of road pricing on road safety and car accidents is *ex-ante* ambiguous. On the one hand, road pricing can reduce total vehicle kilometres travelled and therefore lead to fewer accidents. On the other hand, reduced congestion may result in higher speeds and more accidents (Shefer and Rietveld, 1997[28]). While a downward trend in car accidents is visible in London and Milan (Croci, 2016[22]), it is hard to precisely pin down the role of road pricing in favouring this improvement. This is due to a number of confounding factors which also contribute to a downward trend in accidents: improvement in road infrastructure and signalling, in vehicle technology, and in social norms and practices around road safety. A rigorous study of the impact of London's congestion charge zone on motor vehicle accidents revealed that the policy not only reduced the number of accidents within the charge zone, but also in adjacent zones (Green, Heywood and Navarro, 2016[29]). Within the charge zone, the policy reduced serious and fatal accidents by 25% and 35% respectively. Accident rates, i.e. the number of accidents per kilometre driven in a jurisdiction, also declined by about 27% due to the policy.

Box 1. The effects of congestion pricing in Milan

Previous studies of Milan's road pricing schemes have focused on their impact on traffic volume and composition, as well as on pollution. Most studies exploit the quasi-experimental framework provided by the sudden suspension of the congestion pricing scheme, AreaC, in 2012 (see Section 3 for details) in order to quantify such impacts.

Concerning traffic volume, empirical evidence shows that suspending the congestion charge increases vehicle entries into AreaC by 14.5% (Gibson and Carnovale, 2015[7]). Traffic composition also changes throughout the charge suspension, with lower use of alternative fuel vehicles, which are usually exempt from the charge, (-17%) and higher use of Euro 0-3 vehicles (+13%). Motorbike use, usually unpriced, also decreases by 21% (Percoco, 2014[23]).

Suspending AreaC also affects temporal and geographical features of motor vehicle traffic: entries into AreaC undergo a 23% reduction in the 15 minutes preceding its start at 7:30 and following its end at 19:30, compared to traffic during the application of the charge. There is also evidence that the policy suspension induces geographical substitution, with traffic along roads within 1 km of the AreaC perimeter dropping by 18% (Gibson and Carnovale, 2015[7]).

In terms of pollution impacts, the suspension of the congestion charge has been found to increase CO inside AreaC by 6% and PM_{10} outside AreaC by 17% (Gibson and Carnovale, 2015[7]). Implementing the pollution charge (Ecopass) as opposed to a congestion charge (AreaC) yields different impacts on air pollution, which further differ between the short and long run. Compared to neighbouring provinces, NO_x concentration in Milan undergoes a stronger short-term reduction (i.e. in the first quarter after the policy launch) under the pollution charge (-8.6%) than under the congestion charge (-5.1% to -8%) (Cerruti, 2015[30]). In the longer run (i.e. within two years of the policy launch), the congestion charge is found to be more effective than the pollution charge at curbing NO_x concentration; however, both impacts eventually shrink, due to the evolution of the vehicle stock.

Sources: Cerruti (2015); Gibson and Carnovale (2015); Percoco (2014).

3. The policy context of Milan

Milan is the second largest city in Italy: in 2011, the metropolitan area totalled just over 3 million inhabitants, of which 1.2 million resided within the municipality of Milan.[3] Over 470 thousand commuters enter the municipality of Milan on weekdays for study and work (Comune di Milano, 2011[31]). The urban public transport network consists of 4 metro lines and 154 surface lines (buses, trams, trolley buses), totalling 1286 kilometres. For what concerns trips within the perimeter of the city of Milan, the modal split favours public transport: according to 2013 data, public transport is chosen for 57% of trips, followed by cars (30%). Motorcycle and bike trips have similar modal shares, 7% and 6% respectively (Comune di Milano, 2016[32]).

Air pollution is a critical issue in Milan. While between 2002 and 2007 the yearly average concentration of PM_{10} in Milan dropped from 59 to 50 µg/m^3, it was consistently well above the annual limit of 40 µg/m^3 set by EU legislation on air quality (Directive 2008/50/EC). While EU legislation states that a daily average PM_{10} concentration of 50 µg/m^3 should not be exceeded more than 35 days per year, in 2007 this threshold was exceeded on 125 days.[4]

In order to tackle air pollution, a pollution charge labelled Ecopass was put in place in January 2008 within the city centre, covering an area of about 8.2 square kilometres, about 4.5% of the municipal surface (Agenzia Mobilità Ambiente e Territorio, 2011[33]). The charge was levied upon entering the Ecopass zone, and effectively functioned as a daily pass for unlimited travel into and within the zone. It mandated motor vehicles entering the city centre on weekdays between 7:30 and 19:30 to pay a fee varying between EUR 2 and 10 according to the pollution class to which a vehicle belonged, as defined by European emission standards. Certain categories of vehicles were exempted from paying the charge, notably motorbikes, electric, hybrid and other alternative fuel vehicles.

As the pollution charge provided an incentive in favour of shifting to vehicles generating lower emissions, by June 2010 the share of vehicles subject to the charge when entering the Ecopass area had dropped to about 15% (Cerruti, 2015[30]). Furthermore, assessing the impact of Ecopass, the municipal Agency of Mobility, Environment and Territory stated that following the evolution of the vehicle fleet, 66% of traffic related PM_{10} emissions were estimated to be non-exhaust, originating from tyre, brake and road surface wear (Agenzia Mobilità Ambiente e Territorio, 2011[33]).

Road pricing became an important topic during the campaign for the 2011 municipal elections. While purely advisory in nature, a referendum promoted by local advocacy groups and held in June 2011 (in conjunction with local elections) proposed to expand the surface of the road pricing area, and to shift from pollution to congestion pricing, in order to reduce both congestion and pollution. It also proposed a number of policy and infrastructural measures aimed at supporting the shift towards urban green mobility. Eligible voters were residents in the Milan municipality: 49% of citizens with voting rights

[3] Source: www.dati.lombardia.it. Last accessed on 20 January 2018.

[4] Source: data relative to the Verziere pollution monitoring station (central Milan), available at www.arpalombardia.it/sites/qaria/_layouts/15/qaria/Inquinanti.aspx. Last accessed on 20 January 2018.

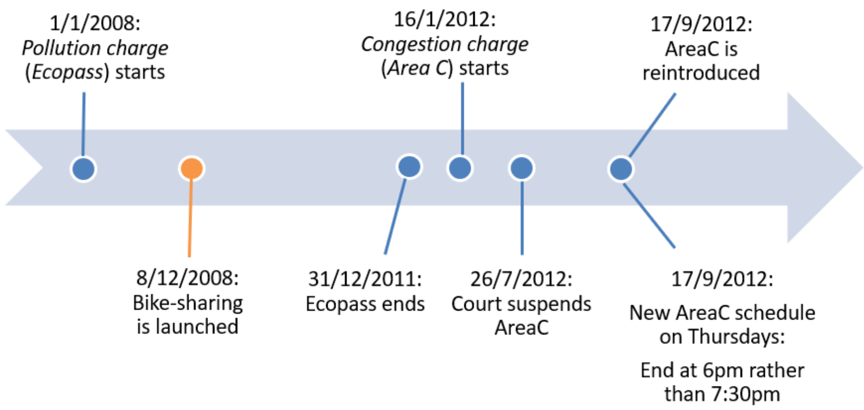
went to the polls and about 79% of voters voted in favour of this proposal. The positive result of the advisory referendum was instrumental in verifying public support for the evolution of the road pricing scheme: in January 2012, the pollution charge was replaced by a congestion charge called AreaC.

The congestion charge was applied in the same geographical area and schedule as Ecopass, but it mandated all vehicles to pay a flat fee of EUR 5 to access the city centre.[5] This change in pricing was also paired with an increase in stringency, as vehicles belonging to certain categories (e.g. Euro 0-3 diesel vehicles) were banned from entering AreaC.

On 25 July 2012, an administrative court, the Council of State, suspended the congestion charge upon a lawsuit filed by one of Milan's private garages. While this came as an abrupt and unexpected shock to the city's efforts to curb pollution, the charge was eventually reintroduced on 17 September 2012 albeit with a variation in schedule. While on the rest of weekdays the original 7:30 to 19:30 schedule remained, the application of AreaC would end at 18:00 on Thursday.[6] The timeline of implementation and variation in Milan's road pricing schemes is summarized in Figure 1.

These sudden policy changes generate a quasi-experimental setting, which is at the basis of the empirical strategy adopted in this study to identify the impact of congestion pricing on bike-sharing use. The empirical strategy is described in detail in Section 5.

Figure 1. Timeline: road pricing and bike sharing in Milan



The introduction and development of road pricing policies in Milan were carried out alongside a range of complementary measures. Measures implemented immediately included increased bus frequency and parking fees, and long-term measures included major extensions to the subway network (Rotaris et al., 2010[27]) as well as the introduction of sustainable mobility services, such as bike sharing, and connected infrastructure, such as

[5] Gibson and Carnovale (2015[7]) and Cerruti (2015[30]) provide a detailed description of the pricing structure and the exceptions characterizing Ecopass and AreaC, both in terms of categories of vehicles exempted from payment and in terms of events in which the charge is suspended (e.g. public holidays, public transport strikes).

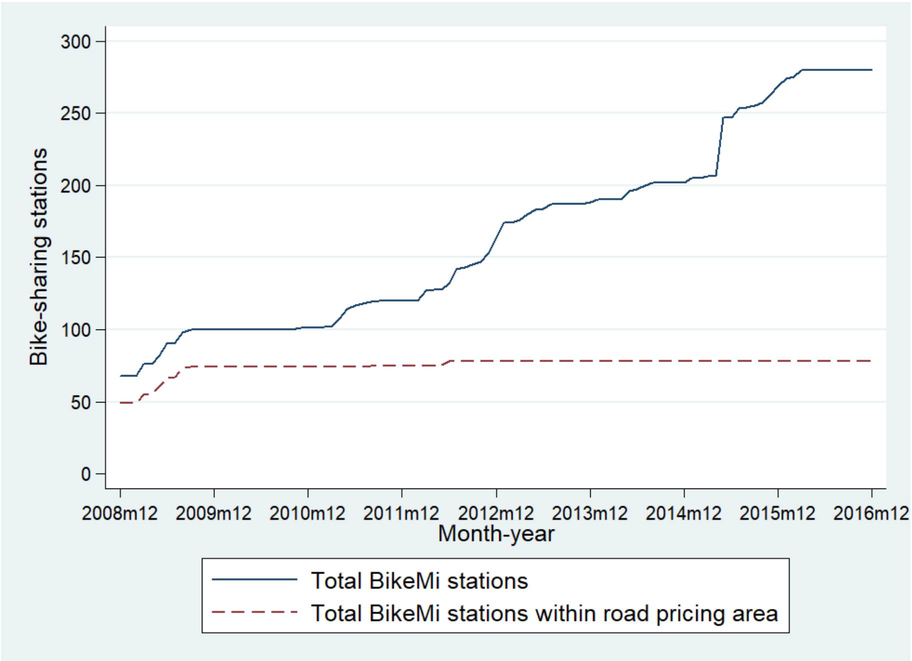
[6] The rationale for this schedule change was to enable people to freely reach the centre by car one evening per week. However, there is no specific reason why Thursday was chosen for this purpose.

bike lanes. Most importantly in the context of this analysis, the bike lane network has substantially expanded, going from 73 km in 2005 to 200 km in 2015.

A station-based bike-sharing scheme named BikeMi was launched in December 2008 with 68 stations, of which 49 located within the then-Ecopass area.[7] As Figure 2 shows, by the time the congestion charge replaced the pollution charge, the number of stations within AreaC had plateaued at 74, while 45 stations had been inaugurated outside the area. By the end of 2016, all but 78 of the 280 bike-sharing stations had been activated outside AreaC.

Users can choose between three different types of membership: daily (EUR 4.5), weekly (EUR 9), yearly (EUR 36). The use of BikeMi is free during the first 30 minutes of each trip and costs EUR 0.50 every 30 minutes beyond this threshold. The maximum duration of a bike-sharing trip is restricted to 2 hours.[8]

Figure 2. The evolution of Milan's bike-sharing scheme



Source: Authors' elaboration of Clear Channel data.

Data from a one-day bike traffic count exercise realised yearly by Ciclobby, the local association promoting bike use, points to an increasing trend in cycling: between 2002 and 2014, this has translated in a 56% observed increase in bikes passing by certain key locations in the city centre (from 21 800 in 2002 to 34 100 in 2014).[9] Over 13% of bikes counted in this context belong to the bike-sharing scheme (Ciclobby, 2014[34]).

[7] Free-floating bike-sharing operators launched their schemes in Milan over the course of 2017. While this has been an important development for the city's clean mobility capacity, it is outside the time frame of interest of this study.

[8] Source: www.bikemi.com. Last accessed on 22 January 2018.

[9] This "bike census" is performed manually by volunteers, who count bikes passing through over 20 locations on the main radial streets in the city centre between 7:30 and 19:30. All but two locations are inside AreaC.

4. Data description

The main dataset for this analysis has been provided by Clear Channel, the operator of Milan's bike-sharing scheme, BikeMi. It contains information on all bike-sharing trips carried out between BikeMi's launch in December 2008 and the end of 2016.

For each trip, the dataset provides the origin and destination station (together with their geographic coordinates) as well as the time and day of departure and arrival. Conversely, information on bike-sharing users is limited, including only their date of subscription to the bike-sharing scheme but not their personal information or socio-economic characteristics. Information on each station's inauguration date and on its number of docks has also been provided by Clear Channel.

Weather information (i.e. temperature and precipitation) and fuel prices, which are used as control variables throughout the analysis, have been gathered respectively from the websites of Lombardy's Regional Agency for Environmental Protection (ARPA),[10] and from the website of the Italian Ministry of Economic Development.[11]

Bike-sharing trips undertaken on weekends are left out of the analysis, as road pricing applies only on weekdays. Trips conducted by users of daily and weekly BikeMi passes are also excluded, and only trips conducted by users of yearly passes are retained. This choice was made because the study primarily focuses on travel behaviour of regular users. Daily and weekly pass users are likely to be tourists, whose choice set for transport options is arguably different from that of residents or regular commuters.

Throughout this section as well as throughout the analysis, days on which AreaC is suspended are alternatively dropped or exploited, according to the specific question under analysis. This includes days characterised by public transport strikes, public holidays, the interim period between the removal of Ecopass and the introduction of AreaC and the period in summer 2012 when congestion pricing was suspended because of a Court mandate. Similarly, in certain model specifications only trips connecting bike-sharing stations inaugurated before AreaC's 2012 suspension are considered (as opposed to trips connecting all stations), in order to observe how the varying implementation of the congestion charge affects the use of pre-existing BikeMi infrastructure.

According to the model specification, the sample used includes the full 2008-2016 period or a specific subset of data (2012-2013). The purpose of focusing on bike-sharing trips undertaken in 2012-2013 is two-fold. First, it allows to isolate the period in which AreaC is in place and thus abstract from variation in road *pricing* caused by the shift from a pollution to a congestion charge has entailed. Second, it allows focusing on a period in which variation in the number of bike-sharing stations and in the extension of the bike lane network is more limited with respect to the full 8-year sample.

The evolution in bike-sharing traffic across time is traced in Figure 3: seasonal trends are visible, with troughs in wintertime and around summer holidays in August, and peaks in

[10] See www.arpalombardia.it/siti/arpalombardia/meteo/richiesta-dati-misurati/Pagine/RichiestaDatiMisurati.aspx. Last accessed on 22 January 2018.

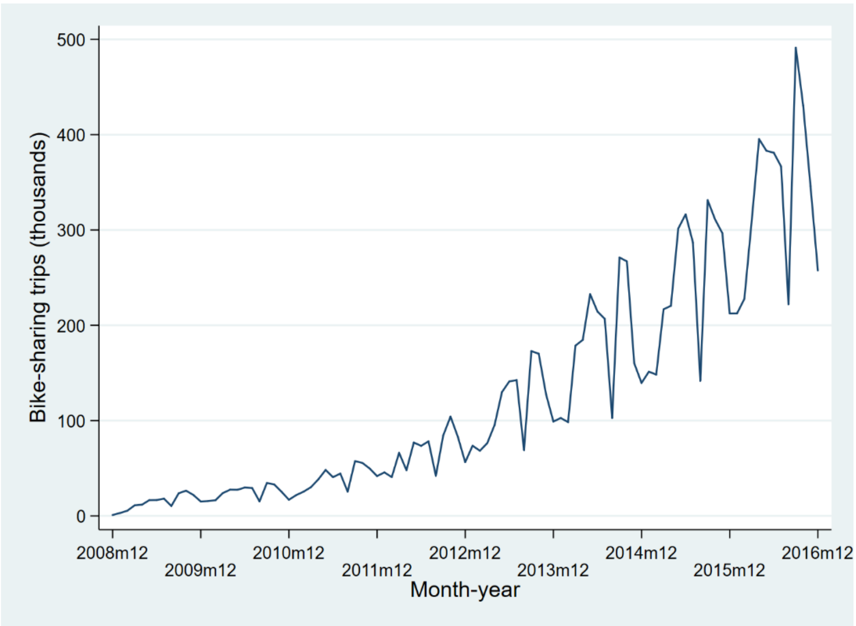
[11] See www.sviluppoeconomico.gov.it/index.php/it/mercato-e-consumatori/prezzi/mercati-dei-carburanti/struttura-del-prezzo-medio-nazionale-dei-prodotti-petroliferi. Last accessed on 16 August 2018.

September-October. After four years of operation, the monthly number of bike-sharing trips reached 100 thousand in autumn 2012; by the end of 2015, peak monthly traffic had tripled.

The impact of station distribution on bike-sharing use is shown in Figure 4, matching the evolution of the bike-sharing network pictured in Figure 2. While trips within AreaC consisted in the vast majority of BikeMi use cases until 2013, bike trips along routes outside AreaC start outnumbering them in 2014. Trips entering AreaC are in the same order of magnitude with those exiting the same zone.

Figure 3. The evolution of bike-sharing use in Milan (2008-2016)

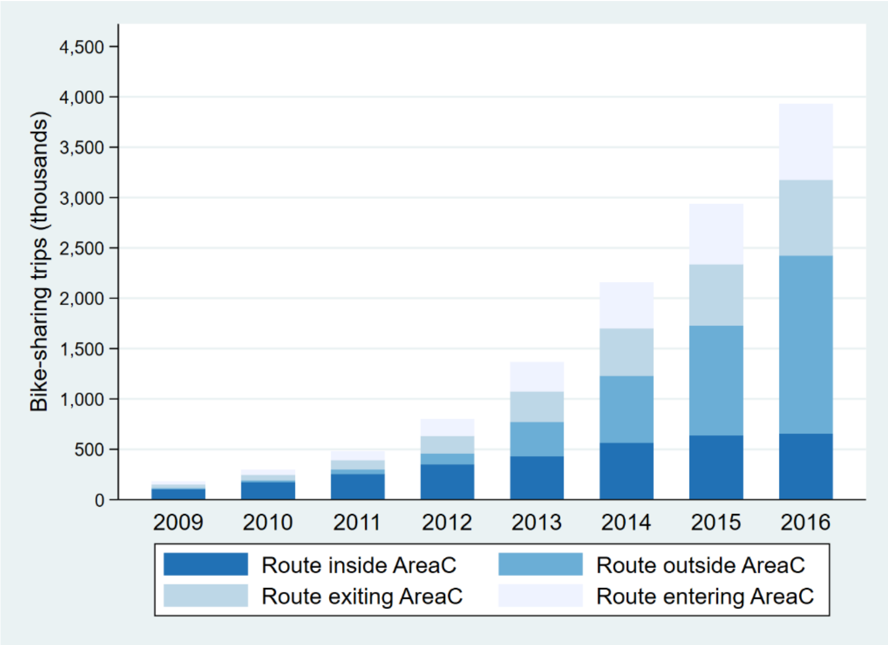
Monthly bike-sharing trips (thousands)



Source: Authors' elaboration of Clear Channel data.

Figure 4. The spatially differentiated evolution of bike-sharing demand (2009-2016)

Yearly bike-sharing trips by type of route (thousands)



Source: Authors' elaboration of Clear Channel data.

Table 2. Daily bike-sharing traffic on weekdays, per year

Year	N	Mean	Standard deviation	Min	Median	Max
2009	261	624.37	340.72	1	682	1245
2010	261	1030.77	420.06	27	1135	1772
2011	260	1661.27	642.44	124	1767	2853
2012	201	2914.04	1019.05	321	3094	4599
2013	235	4855.20	1793.35	537	5279	8092
2014	236	7516.57	2674.59	551	8074	12 019
2015	246	9936.79	3123.14	1444	10 412	14 923
2016	244	13 282.00	4098.65	1799	13 528	20 966

Note: All weekdays included, excluding days in which road pricing is suspended.
Source: Authors' elaboration of Clear Channel data.

Statistics of aggregate daily bike-sharing traffic registered on weekdays by year are reported in Table 2. Between 2009 and 2016, the average number of daily trips increased more than 20-fold, going from over 600 trips/day to over 13 000 trips/day. Heterogeneity in use due to seasonality is evident observing the quartiles as well as the minimum and maximum number of trips.

Table 3. Geographical distribution of BikeMi stations

Station Location	Spatial features of each zone	BikeMi stations on 26 July 2012
Zone 1	AreaC	74
Zone 2	Within 500m of AreaC's perimeter	42
Zone 3	Between 500m of AreaC's perimeter and the city borders	26

Note: This table presents only stations inaugurated before AreaC's 2012 suspension (i.e. until 26 July 2012), as this is the subset of stations used in most model specifications.
Source: Authors' elaboration of Clear Channel data.

As shown in Figure 2, the distribution of stations varies in time and over space. Table 3 reports the spatial references used throughout the analysis: Zone 1 is AreaC, Zone 2 is the area contained within 500 meters of AreaC's perimeter, and Zone 3 is the rest of the municipality.

Summary statistics of bike-sharing trips by the location of station of origin are reported in Table 4. The average number of daily departures per station of origin is highest for stations located in Zone 1 (i.e. AreaC), at about 20. Traffic in the rest of the city in 2012-2013 is lower. The average number of daily departures per station located in Zone 3 is higher than in Zone 2 possibly because this zone houses Milan's main train station (Milano Centrale), which makes it a pole for bike-sharing use by commuters.

While figures related to quartiles show limited heterogeneity across zones, the traffic peak differs substantially across zones: the most congested bike-sharing stations within AreaC can reach 191 departures per day, whereas the maximum number of departures per day from stations situated within 500m of AreaC's border is 62.

Table 4. Daily bike-sharing trips per station of origin, by location

Station location	No of trips	No of stations	Mean	Standard deviation	Min	Median	Max
Zone 1	31926	74	19.91	19.84	0	15	191
Zone 2	17523	42	12.46	8.37	0	11	62
Zone 3	10246	26	14.86	11.18	0	12	68
Total	59695	142	16.85	16.25	0	13	191

Note: Sample: 2012-2013, weekdays. Excludes days in which road pricing is suspended. Only trips connecting stations built prior to 26 July 2012.
Source: Authors' elaboration of Clear Channel data.

In order to investigate temporal variation in bike-sharing use, weekdays (7:30-19:30) are segmented into four different timeslots: 7:30-9:30; 9:30-13:30; 13:30-17:30; 17:30-19:30.[12] Descriptive statistics of aggregate bike-sharing use during each timeslot, normalised at the hourly level for comparability, are reported in Table 5. During the morning peak (7:30-9:30), the mean hourly number of trips is above 500, with peaks over

[12] Attention is restricted to the time window 7:30-19:30, in which road pricing applies on weekdays.

1000 in days of high bike-sharing demand. Between 9:30 and 17:30 bike-sharing traffic drops, with mean hourly trips under 200, before spiking up again for the evening peak.

Hourly traffic significantly differs in the morning and evening peak: this suggests two potential explanations. First, bike-sharing commuters might exploit this means of transport only one-way, and not necessarily perform a return trip every day. This is precisely the advantage given by bike sharing as opposed to using one's own bike. Second, while morning commuting travel appears to be relatively concentrated around , return travel might be more widely spread throughout the late afternoon and evening (e.g. part of it may occur before 17:30 and part after 19:30).

Table 5. Hourly bike-sharing trips, by timeslot

Timeslot	Mean	Standard deviation	Min	Median	Max
7:30-9:30	537.1	250.2	6.5	530.75	1070.5
9:30-13:30	174.5	81.8	4	163	366.75
13:30-17:30	198.5	91.3	11.5	185.25	432.5
17:30-19:30	394.9	183.5	4.5	369.25	886.5
Total	326.2	223.5	4	271.5	1070.5

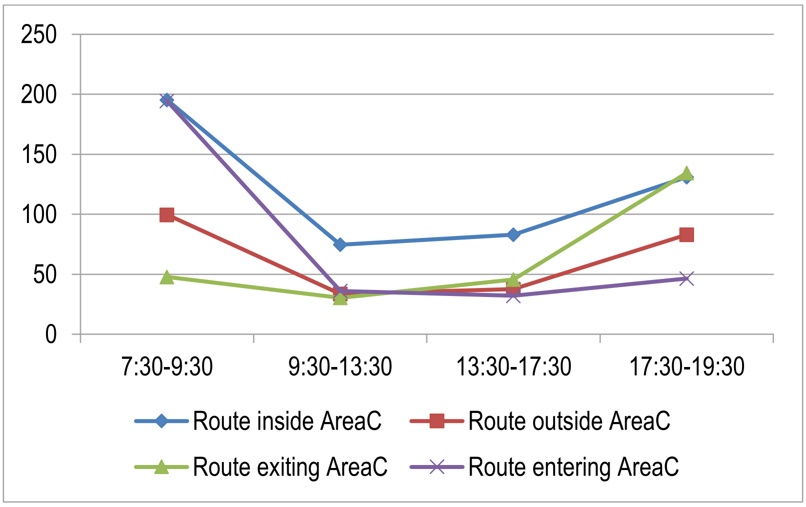
Note: Sample: 2012-2013, weekdays. Excludes days in which road pricing is suspended.
Source: Authors' elaboration of Clear Channel data.

Temporal and geographical variation in bike-sharing use are represented in Figure 5, which reports the average hourly number of trips along a given type of route, within a certain timeslot. Bike-sharing traffic is highest along routes within AreaC and entering AreaC during the morning peak, signalling the flow of commuters reaching offices in the city centre. Between 9:30 and 17:30, bike-sharing demand drops in the entire city, albeit less so within AreaC, and picks up during the evening peak along routes which exit the congestion charge zone (leaving the city centre to go towards the periphery) and routes within AreaC.

Another element of heterogeneity in bike-sharing demand relates to patterns of use of bike-sharing subscribers. Table 6 reports statistics on the average weekly frequency of use, based on different time horizons, for subscribers who joined the bike-sharing scheme prior to the policy changes analysed in this study. The first line reports the average frequency of use in the entire pre-treatment period, i.e. from a user's first bike-sharing trip until the end of July 2012, when AreaC's suspension takes place. This averages around 2.62 bike-sharing trips per week, with 75% of users performing up to 3.8 trips per week. Focusing only on frequency of use in the year prior to the policy suspension does not dramatically change the picture, but it shows a slightly lower median frequency of use.

Figure 5. Spatially and temporally differentiated demand for bike sharing (2012-2013)

Average hourly number of trips per type of route/timeslot



Note: Sample: 2012-2013, weekdays. Excludes days in which road pricing is suspended.
Source: Authors' elaboration of Clear Channel data.

Table 6. Individual frequency of bike-sharing use

	Mean	Standard deviation	Min	25th percentile	Median	75th percentile	Max
Average number of trips per week (Join date-July 2012)	2.62	2.54	0.01	0.75	1.76	3.82	19.18
Average number of trips per week (July 2011-July 2012)	2.62	2.65	0.00	0.66	1.68	3.89	19.00

Note: Figures refer to users who first used bike sharing prior to AreaC's suspension on 26 July 2012.
Source: Authors' elaboration of Clear Channel data.

5. The impact of congestion pricing on bike-sharing use

5.1. The impact of introducing a congestion charge

Individuals make transport mode choices based on the costs, travel times, comfort and other attributes of the modes available to them and on their preferences. Individual preferences for these attributes vary with age, income, type of employment and other personal characteristics. Introducing or removing a congestion charge alters the cost of driving and consequently also road traffic congestion levels. Varying street congestion might induce modal shifts between cars, public transport, biking and walking.

Demand for travel with other transport modes is influenced by both the change in relative prices and the one in congestion levels. Analysing the impacts of road pricing on the use of greener transport options, such as public and non-motorised transport, is an essential part of evaluating the potential of this policy instrument to induce more sustainable mobility patterns and contribute to environmental goals.

The objective of this report is to identify the impact of the congestion charge on the use of bike sharing. As this impact might exhibit variation in space and time (i.e. across the city and throughout the day), heterogeneous impacts are also tested for. Because different categories of users might react differently to congestion pricing according to their prior transport habits, variations of the impact according to frequency of bike-sharing use are also investigated.

The impact of interest can be identified if it can be argued that the remaining variation in bike-sharing use (i.e. after controlling for other possible determining factors) is caused by the congestion charge's suspension. This assumes that no unobserved (from the analyst's perspective) policy initiatives affecting bike-sharing use (or biking more broadly) have been implemented in the time horizon of the analysis. Likewise, if additional policies were implemented to increase the cost of urban driving relative to other transport options, this might contribute to reduced car congestion and confound the impact of the congestion charge.

In order to abstract from other time-varying factors affecting mode choice, most of the analysis exploits only the 2012-2013 sample. The rationale for focusing on the 2012-2013 period is two-fold. First, this excludes the period of application of the pollution charge Ecopass (2008-2011), removing the potentially confounding effect of shifting from pollution to congestion pricing. Second, it allows focusing on a period in which variation in the number of bike-sharing stations and in the extension of the bike lane network is more limited with respect to the full 8-year sample. Thus, unless otherwise specified, the 2012-2013 sample is usually adopted in the following analysis.

Installing, maintaining and expanding a network of bike-sharing stations is an important incentive for bike use. The evolution of the bike-sharing network is discussed in Section 3. Because a larger availability of docking stations can facilitate and increase access to bike sharing, it is controlled for by including in all specifications the number of bike-sharing stations active at all points in time inside and outside AreaC.

Furthermore, the city authorities pushed for an important expansion of the bike lane network, from 97 km in 2008 to 200 km in 2015. However, detailed documentation on the expansion of bike lanes is limited.[13] This motivates the focus on the 2012-2013 time window, given bike lane extension has seen a more limited increase between beginning 2012 and end 2013 (from 128 km to 166 km).

Between 2008 and 2016, gasoline prices hovered between EUR 1.1 and 1.9 per litre, with the lowest price observed in January 2009 and the highest in September 2012. The 2012-2013 time window generally saw relatively high gasoline prices. As this increases the relative price of car use, it is controlled for by including the average weekly gasoline price in all models.

Other policies affecting the cost of using private motor vehicles (e.g. parking fees) and the cost of public transport use (e.g. ticket prices) have been implemented outside the 2012-2013 period of reference, hence they arguably do not affect travel choices in this time window.[14]

5.1.1. Suspending congestion pricing reduces aggregate bike-sharing use

The main empirical approach used to identify the impact of the congestion charge on the use of bike sharing relies on the 2012 sudden suspension of AreaC. As explained in Section 3, AreaC was suspended on 26 July 2012 and reintroduced on 17 September 2012.[15] This strategy builds on the assumption that behavioural responses to the introduction and to the suspension of congestion pricing are perfectly symmetric. As the duration of the suspension is less than eight weeks, the findings of this analysis should be interpreted as estimates of the *short-term* effect of changes in road pricing.

The estimation strategy revolves around a series of econometric models with the following structure:

[13] A systematic mapping of this evolution at a more temporally and geographically disaggregated level does not exist. The only type of data available is a GIS-based snapshot of the current state of the network, which is too recent to be informative of the state of the network at the time of AreaC's suspension in 2012. General statistics on the yearly evolution of the extension of the bike lane network are too aggregate to be used as a control variable in this model.

[14] Concerning policies discouraging the use of private motor vehicles, the city authorities approved an increase in curb-side parking tariffs to be applied within AreaC in July 2013. However, this came into force only in December 2013, hence it does not concern the period under analysis.

An important increase in the price of single-run tickets for subway, bus and tram use was implemented in September 2011, bringing the ticket price from EUR 1 to 1.5 (prices of monthly and yearly passes remained intact). This price change is likely to have affected congestion in the local public transport network. However, because it was introduced four months prior to the implementation of AreaC and about one year prior to its suspension, it is not of primary importance in the period under consideration.

In February 2013, a new metro line with 7 stations was opened in the north of the city (in Zone 3, according to Table 3). Because the first bike-sharing stations in proximity of the metro line were inaugurated only in 2015, it is safe to say that the opening of this metro line did not immediately affect bike-sharing use.

[15] Because bike sharing was introduced in Milan in late 2008, when a pollution charge was already in place, bike-sharing use is not observed before the introduction of urban road pricing.

$$B_{id} = \beta S_d + \boldsymbol{\gamma W_d} + \boldsymbol{\theta X_d} + \boldsymbol{\varphi T_d} + \boldsymbol{\alpha_i} + \varepsilon_{id} \quad (1)$$

The dependent variable B_{id} is the number of bike-sharing trips over calendar day *d*. According to the specification, the observational unit *i* is either the route along which the trip takes place (*i* = *r*), or the station at which it originates (*i* = *s*).[16] The variable of interest is S_d, a binary variable equal to one during AreaC's 2012 suspension and zero otherwise. Vector $\boldsymbol{W_d}$ includes a set of factor variables controlling for weather conditions, i.e. precipitation and temperature.[17] Vector $\boldsymbol{X_d}$ includes a set of time-varying control variables: the weekly average gasoline price, the number of bike-sharing stations in the network (both inside and outside AreaC) and indicators of regular suspensions of the congestion charge (e.g. during holiday periods and public transport strikes).[18] Vector $\boldsymbol{T_d}$ includes a set of dummies (day of the week, week of the year, month, year) to control for regular patterns of use due to e.g. seasonality and for yearly changes which affect all stations evenly. Route or station of origin fixed effects are captured by $\boldsymbol{\alpha_i}$, which absorbs unobserved characteristics of bike-sharing use which do not vary across days. Term ε_{id} is a random error.

The impact of the sudden suspension of congestion pricing in 2012 is identified by coefficient β in model (1). This coefficient quantifies the percentage difference between bike-sharing traffic in the period affected by the policy shock and traffic in the periods when AreaC is in place. Because removing congestion pricing reduces the price of car use relative to other means of transport, it is likely to increase congestion: thus, this policy change is expected to reduce bike-sharing use.

Table 7 reports estimates of different specifications of fixed effects Poisson model (1),[19] in which the dependent variable is bike-sharing traffic originating at station *i* on day *t* between 7:30 and 18:00.[20] For ease of consultation, only the coefficient of interest is reported – full results including control variables are presented in the Appendix.

16 The number of trips is a count variable, which can only take non-negative integer values: it is unreasonable to assume a normal distribution for such a variable. Conversely, count variables are typically assumed to follow a Poisson distribution (Wooldridge, 2010[36]). The exponential function is an appropriate functional form for a non-negative discrete variable, hence the model can be formalised as follows:

$$\mathbb{E}(B_{id} \mid S_d, \boldsymbol{W_d}, \boldsymbol{X_d}, \boldsymbol{T_d}, \boldsymbol{\alpha_i}) = exp(\beta S_d + \boldsymbol{\gamma W_d} + \boldsymbol{\theta X_d} + \boldsymbol{\varphi T_d} + \boldsymbol{\alpha_i} + \varepsilon_{id}).$$

17 The precipitation factor variable indicates whether cumulative precipitation (measured in millimetres) in the period of reference falls in one of the following bins: (0, 2]; (2, 4]; (4, 6]; (6, 8]; (8, 10]; (higher than 10), with days with zero precipitation being the reference category. The temperature factor variable indicates whether the average temperature in the period of reference (measured in degrees Celsius), falls in one of the following bins: (0, 5]; (5, 10]; (10, 15]; (15, 20]; (20, 25]; (25, 30]; (higher than 30), where the (below or equal to 0) bin is the reference category.

18 Congestion pricing is regularly suspended for two weeks in August, at the peak of summer holidays, as well as during the Christmas school break.

19 The Poisson quasi-maximum likelihood estimator is fully robust to distributional misspecification, i.e. it yields consistent estimates even if the Poisson distributional features are not respected (Wooldridge, 2010[36]). All tables report results based on this estimation methodology unless otherwise specified.

20 The period 18:00-19:30 is excluded in these specifications as traffic at this time of day might differ before and after the policy suspension due to the schedule change applying on Thursday evenings starting in September 2012. This change in congestion pricing application is analysed in section 5.2. Furthermore, the period 19:30-7:30 is excluded because it is always exempt from congestion pricing.

Table 7. Aggregate effect of the policy suspension on daily bike-sharing traffic

Only bike-sharing stations built prior to the policy suspension

	(1)	(2)	(3)	(4)
	Trips per origin station / weekday (7:30-18:00)			
Time window:	2012-2013		2008-2016	
AreaC 2012 suspension	-0.060***	-0.019	-0.090***	-0.088***
	(0.014)	(0.012)	(0.023)	(0.022)
Thursdays included		x		x
Year, month, week, day of week FE	x	x	x	x
Station of origin FE	x	x	x	x
Controls: weather, number of stations, weekly average gas price	x	x	x	x
Controls: type of road pricing policy in place			x	x
Observations	54 370	67 967	198 757	248 530
Clusters	141	141	142	142

Note: Fixed effects Poisson model. Dep. var.: number of trips per origin station/weekday (7:30-18). Only stations built prior to the policy suspension are considered. Robust standard errors in parentheses are clustered at the origin level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

The sample of the analysis is always restricted to weekdays, as weekends are exempt from congestion pricing. Furthermore, it is initially restricted to trips connecting bike-sharing stations built prior to the policy suspension (i.e. "pre-existing stations"), ensuring comparability throughout the period of the analysis. In specifications (1) and (2), the sample includes only years 2012-2013, whereas the full sample (December 2008 - December 2016) is used for the estimation of specifications (3) and (4).

Because the schedule change applying on Thursday evening as of September 2012 might affect bike-sharing use throughout the entire day, Thursdays are excluded from the sample in specifications 1 and 3. This approach is adopted in all specifications using day-level data unless otherwise specified.

Results from Table 7 indicate that the impact of the 2012 policy suspension on daily bike-sharing traffic during weekdays is negative and statistically significant. The magnitude of this impact slightly varies across specifications: the policy suspension is found to reduce daily bike-sharing traffic by 5.8% in specification (1), which focuses on the 2012-2013 period and disregards Thursday trips.[21] Specification (3) mimics (1) but is estimated in a wider sample: considering the broader time frame 2008-2016, the impact of the policy suspension is estimated to be larger, leading to an 8.6% drop in bike-sharing use. This is partly explained by the important growth in the number of bike-sharing users throughout this time frame.

Including Thursdays, the result does not vary considerably when considering evidence drawn from the full sample, which includes trips carried out in 2008-2016 (-8.4%). However, the impact is statistically insignificant when considering only trips carried out in

[21] The Poisson coefficient β of a binary variable can be interpreted as a percentage change by transforming it as follows: 100[exp(β) - 1]. Here, the coefficient is calculated as 100[exp(-0.06) - 1] = -5.8% .

2012-2013 and including Thursdays: the effect of the Thursday schedule change is further investigated in section 5.2.

What are the implications of considering the set of pre-existing stations as opposed to all stations? Suppose that a bike-sharing user habitually travels between station A and station B. If a more convenient station C is opened in the vicinity of A, this user will shift from route A-B to route C-B. This would lead to reduced traffic from and towards pre-existing stations, which might inflate the effect of the suspension of congestion pricing as measured in Table 7. Estimating model (1) based on the full sample of stations allows to identify whether and to what extent that effect is inflated: results are reported in Table 8. Note that only the preferred specifications excluding Thursday bike-sharing traffic are reported.

Findings are consistent with those from the analysis based on the subset of pre-existing stations, reported in Table 7. Focusing on the 2012-2013 time window, the impact of AreaC's suspension is estimated to be slightly smaller than when only considering trips between pre-existing stations (-5% vs -5.8%). The difference between these two estimates indicates that the expansion of the bike-sharing network could explain about one percentage point of the drop in traffic between pre-existing stations, by shifting it towards new stations.

Extending the time window to include the full 2008-2016 period, the impact of the suspension is estimated to be virtually equal to the impact found from focusing traffic between pre-existing stations (-9.1% vs -8.6%). This small difference indicates that in the longer run, the positive effect of additional bike-sharing stations is larger than the negative effect of traffic shifting to new routes.

In the remainder of this section, results are based on the sample of stations built before the policy suspension (26/7/2012) unless otherwise specified. As specification (1) of Table 8 indicates, in 2012-2013, these estimates can be considered as an upper bound of the suspension effect.

Table 8. Aggregate effect of the suspension on daily bike-sharing traffic

All stations

	(1)	(2)
Trips per origin station / weekday (7:30-18:00)	Sample: 2012-2013	Sample: 2008-2016
AreaC 2012 suspension	-0.051***	-0.095***
	(0.015)	(0.024)
Year, month, week, day of week FE	x	x
Station of origin FE	x	x
Controls: weather, number of stations, weekly average gas price	x	x
Controls: type of road pricing policy in place		x
Observations	62 424	262 016
Clusters	187	275

Note: Fixed effects Poisson model. Dep. var.: number of trips per station of origin/day (7:30-18). Specification (1): 2012-2013 sample. Specification (2): 2008-2016 sample. Thursdays are excluded. All stations are considered, regardless of their activation date. Robust standard errors in parentheses are clustered at the origin level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

5.1.2. The congestion effect prevails over the price effect

Following the suspension of congestion pricing, bike-sharing use is expected to drop for two reasons. First, as the price of driving a motor vehicle relative to biking drops, bike-sharing users might revert to driving: this is the *price effect*. The price effect might also arise in an indirect way: as the relative cost of motor vehicle use drops, travellers might shift from public transport to car travel. Less crowded public transport might attract bike-sharing users, inducing their modal shift. Second, as car congestion increases inside AreaC and in its immediate surroundings, bike-sharing users might turn to alternative means of transport to avoid biking in intense traffic: this is the *congestion effect*.[22]

While the shift between transport options is unobserved, one can infer the relative importance of the two effects by separately estimating model (1) in four subsamples, each comprising only trips along a specific type of route: within AreaC, outside AreaC, entering AreaC and exiting AreaC. Because congestion pricing applies only upon entering the congestion charge zone, the price effect would only materialize for inbound bike-sharing trips. Conversely, the congestion effect would affect all types of trips: trips originating and ending outside AreaC are, however, expected to be affected to a lesser extent. If a low relative cost of driving is a more important barrier to bike-sharing use than road traffic congestion, the price effect will be larger (in absolute terms) than the congestion effect: variation in traffic will be stronger along routes entering the congestion charge zone than along routes within it.

Table 9 reports results from the estimation of model (1) in four different subsamples: each specification assesses the impact of the policy suspension on trips along a specific type of route. This can provide some insight into the magnitude of the congestion and price effects induced by the policy suspension. In this model, bike-sharing traffic is not measured at the origin level, but at the route (origin-destination pair) level.

In order to assess the importance of the congestion effect, one needs to focus on routes departing and arriving within AreaC. Along such routes, the effect of suspending congestion pricing is negative and statistically significant, indicating that the policy shock leads travellers to reduce their bike-sharing use by 8.1% because of the disutility caused by increased congestion.

Assessing the magnitude of the price effect is more complex. While this effect is only observable along routes entering AreaC (i.e. departing from a station located outside the congestion charge zone and arriving inside it), traffic along such routes is also influenced by the congestion effect. Consequently, it is not possible to precisely quantify the extent to which the suspension impact in specification (4) is due to the price effect.

Comparing specifications (1) and (4) we see that the drop in bike-sharing traffic is stronger on routes within AreaC than along routes entering AreaC: this signals that the congestion effect is stronger than the price effect. The price effect is thus a secondary driver of the behavioural response to the suspension of congestion pricing: few travellers substitute bike-sharing use with motor vehicle or public transport use as a direct consequence of the lower price of car travel.

[22] The magnitude of the modal shift from bike sharing to driving depends on the cross-elasticity of bike-sharing demand to the price of driving and to travel time by car. These cross-elasticities determine the relative importance of the congestion and price effects.

A more moderate reduction in bike-sharing use is observed along routes exiting AreaC (i.e. originating within the congestion charge zone but directed outside it). There is no statistically significant impact on bike traffic along routes outside AreaC: this is intuitive as the impact of the policy suspension should be limited to traffic inside AreaC, hence a very modest congestion effect should arise outside of the congestion charge zone.

Table 9. Impact of the policy suspension by direction of the trip: congestion effect and price effect

	(1)	(2)	(3)	(4)
	Route inside AreaC	Route outside AreaC	Route exiting AreaC	Route entering AreaC
	Trips per route / weekday (7:30-18:00)			
AreaC 2012 suspension	-0.085***	-0.035	-0.071***	-0.055***
	(0.014)	(0.027)	(0.024)	(0.021)
Year, month, week, day of week FE	x	x	x	x
Route (origin-destination pair) FE	x	x	x	x
Controls: weather, number of stations, weekly average gas price	x	x	x	x
Observations	2 096 441	1 177 962	1 591 075	1 636 506
Clusters	5400	3777	4556	4662

Note: Fixed effects Poisson model. Dep. var.: number of trips per route/weekday (7:30-18:00). Thursdays are excluded. Sample: 2012-2013. Only routes connecting stations built before the policy suspension (26/07/2012) are considered. Robust standard errors in parentheses are clustered at the route level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

5.1.3. The effect of the congestion charge's suspension is larger in the evening

Variation in the impact of the policy suspension across the day may arise as travellers have different values of time for different trip purposes. For users with a high value of time, such as commuters, mode choice is likely to be more sensitive to congestion variation, which directly affects travel time, and less sensitive to changes in the relative price of their transport option. This is due to the fact that the value of time constitutes a greater part of the total travel cost. The opposite is true for users with a low value of time, such as leisure travellers. Because the value of time is likely to differ between peak and off-peak times, one can expect that the impact of suspending congestion pricing will vary across the day.

Temporal variation can be investigated by estimating a model in which bike-sharing traffic is measured at a higher frequency: each weekday is segmented into four "timeslots" (7:30-9:30; 9:30-13:30; 13:30-17:30; 17:30-19:30)[23] and the number of bike-sharing trips is normalised at hourly level for comparability.

$$B_{itd} = \beta S_d + \boldsymbol{\gamma W_t} + \boldsymbol{\theta X_d} + \boldsymbol{\varphi T_d} + \boldsymbol{\alpha_{it}} + \varepsilon_{itd} \quad (2)$$

In model (2), subscript t indicates the timeslot, while d indicates the day and i indicates route or station of origin as previously discussed. To identify temporal variation in the policy impact, this model is separately estimated in four samples reporting observations of hourly bike-sharing traffic in each of the above four timeslots. Note that weather variables

[23] In contrast to previous specifications, trips occurring between 18:00 and 19:30 are included.

in $\boldsymbol{W_t}$ are measured at the timeslot level. $\boldsymbol{\alpha_{it}}$ is a vector of origin-timeslot (if i = s) or route-timeslot (if i = r) fixed effects.

Table 10 presents estimates of β, the coefficient of interest in model (2), which measures the impact of the policy suspension. In Panel A, the dependent variable is the hourly number of bike-sharing trips measured by station of origin, while in Panel B it is measured at the route level. Analysis at the station of origin level indicates that the most important drop in bike-sharing traffic occurs in the evening (17:30-19:30), when during the policy suspension bike-sharing use drops by 12.2%. The impact of the policy suspension across the rest of the day (7:30-17:30) is considerably lower, as the reduction in bike-sharing use varies between 4.8% and 5.9%. The analysis at the route level presented in Panel B leads to very similar results.

The larger bike-sharing use reduction in the late afternoon might be explained by the fact that the value of time savings is lower in the evening, when city dwellers come back from work or go for leisure activities. This is in contrast with morning peak time, when commuters need to reach their work places by a given time. When the policy suspension alters the relative price of transport options, bike-sharing users might opt for public transport to avoid increased congestion, if they are more sensitive to the congestion effect, or shift to car use if they are more sensitive to the price effect. From Table 9, we know that the price effect has a minor role in explaining the aggregate impact of the congestion pricing on bike-sharing demand. The main mechanism explaining behavioural change in this respect is the congestion effect.

Table 10. Impact of the policy suspension by time of day

Panel A

	(1)	(2)	(3)	(4)
	Trips per *origin-timeslot* (normalised per hour)			
	7:30-9:30	9:30-13:30	13:30-17:30	17:30-19:30
AreaC 2012 suspension	-0.061***	-0.049**	-0.058***	-0.130***
	(0.021)	(0.019)	(0.017)	(0.018)
Year, month, week, day of week FE	x	x	x	x
Controls: weather, # stations, weekly average gas price	x	x	x	x
Station of origin - timeslot FE	x	x	x	x
Observations	54 100	54 127	54 151	54 094
Clusters	141	141	141	141

Note: Fixed effects Poisson model. Dep. var.: number of trips per origin/hour (normalised). Only routes between stations constructed prior to 26/7/2012 are considered. Thursdays are excluded. Robust standard errors in parentheses are clustered at the origin-timeslot level. Sample: 2012-2013. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Panel B

	(1)	(2)	(3)	(4)
	Trips per *route/timeslot* (normalised per hour)			
	7:30-9:30	9:30-13:30	13:30-17:30	17:30-19:30
AreaC 2012 suspension	-0.046***	-0.038**	-0.045***	-0.134***
	(0.015)	(0.015)	(0.015)	(0.015)
Year, month, week, day of week FE	x	x	x	x
Controls: weather, # stations, weekly average gas price	x	x	x	x
Route - timeslot FE	x	x	x	x
Observations	5 102 829	6 349 167	6 469 444	5 975 546
Clusters	19 744	23 757	24 334	22 938

Note: Fixed effects Poisson model. Dep. var.: number of trips per route/hour (normalised). Only routes between stations constructed prior to 26/7/2012 are considered. Thursdays are excluded. Robust standard errors in parentheses are clustered at the route-timeslot level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

5.1.4. Suspending congestion pricing leads to lower bike-sharing use from infrequent users; behavioural reactions from frequent users are more contained

Different categories of bike-sharing users might react differently to the sudden policy suspension. Frequent users, having effectively incorporated bike sharing in their travel habits, might have a less elastic demand, i.e. they might be less sensitive to relative price changes. This can be investigated by estimating the following model in a different set-up of the dataset, where the observation unit u is the bike-sharing scheme user:

$$B_{ud} = \boldsymbol{\beta frequency_u} * S_d + \boldsymbol{\gamma W_d} + \boldsymbol{\theta X_d} + \boldsymbol{\varphi T_d} + \boldsymbol{\alpha_u} + \varepsilon_{ud} \qquad (3)$$

In model (3), the policy suspension variable is interacted with factor variable $\boldsymbol{frequency_u}$, indicating a user u's average weekly frequency of bike-sharing use prior to the policy suspension (e.g. 0.75 to 1.75 trips/week). Attention is restricted to the subset of users who enrolled in the bike-sharing scheme prior to the policy suspension, for whom such frequency data is available. The term α_u denotes user fixed effects, which control for user characteristics that do not change over time.

Table 11. Impact of the policy suspension by frequency of use

Dependent variable: trips per user/day			
(1)		(2)	
Frequency of use from join date to July 2012		Frequency of use from July 2011 to July 2012	
(0-0.75 trips/week] * Suspension	-0.215***	(0-0.65 trips/week] * Suspension	-0.229***
	(0.050)		(0.052)
(0.75-1.75 trips/week] * Suspension	-0.155***	(0.65-1.65 trips/week] * Suspension	-0.154***
	(0.031)		(0.032)
(1.75-3.8 trips/week] * Suspension	-0.054**	(1.65-3.8 trips/week] * Suspension	-0.049**
	(0.023)		(0.022)
Above 3.8 trips/week * Suspension	-0.037***	Above 3.8 trips/week * Suspension	-0.040***
	(0.013)		(0.013)
Year, month, week, day of week FE	x		x
Controls: weather, # stations, weekly average gas price	x		x
User FE	x		x
Observations	2 427 259		2 427 259
Clusters	6383		6383

Note: Fixed effects Poisson model. Dep. var.: number of trips per user/day. Subset of users who joined before 26/7/2012. All stations. All weekdays excl. Thursdays. Robust standard errors in parentheses are clustered at the user level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 11 presents results on the impact of the policy suspension according to the frequency of use of bike sharing for users who joined the BikeMi scheme before the policy suspension. Frequency of use is defined with a four-tier indicator, with each tier indicating a quartile of the average weekly frequency distribution. The table includes two specifications of model (3): in specification (1), this indicator is based on frequency of use from the day the user joins the bike-sharing scheme until the policy suspension ("long-term" frequency of use); in specification (2), the indicator is based on frequency of use in the year prior to the policy suspension ("recent" frequency of use).

Results indicate that the policy suspension induces a substantially higher reduction in bike-sharing use among low-frequency users, whereas high-frequency users do not alter their travel behaviour as much. More specifically, users who carry out more than an average of 1.75 trips per week (1.65 trips per week in specification 2) reduce their bike-sharing use by 3.6% to 5.2%, according to the specification. Conversely, travellers with a low long-term frequency of use reduce their bike-sharing trips by three to four times as much, leading to drops ranging from -14.2% to -20.5%. Users who have more solidly built bike sharing into their travel habits are less affected by the policy suspension.

5.1.5. The bike-sharing and metro networks are complementary mobility options

Bike sharing can act as a complement to or as a substitute of public transport for specific routes, according to the city's morphology and infrastructure as well as travellers' preferences. The extent to which the impact of congestion pricing varies with proximity to public transport can be investigated with the following model:

$$B_{sd} = \boldsymbol{\beta Mdist_s} * S_d + \boldsymbol{\gamma W_d} + \boldsymbol{\theta X_d} + \boldsymbol{\varphi T_d} + \boldsymbol{\alpha_s} + \varepsilon_{sd} \quad (4)$$

The policy suspension variable is interacted with $\boldsymbol{Mdist_s}$, a variable indicating the distance between a bike-sharing station s and the closest metro station (expressed in intervals, e.g. between 400 and 600 metres).

If the bike-sharing and metro networks are complements, suspending congestion pricing will affect to a lesser extent bike-sharing departures from stations in close proximity to metro stops. Conversely, departures from bike-sharing stations further away from metro stops might decrease: as they are less tightly connected to the metro network, complementarity might be weaker.

Table 12 provides results from the estimation of model (4), investigating whether the effect of the policy suspension on bike-sharing use varies by proximity of bike-sharing stations to metro stations. Results indicate that the policy suspension does not affect bike-sharing use originating in close proximity to metro stations (i.e. whenever the closest metro station is located within 200 metres of the bike-sharing one). Beyond this threshold, however, the impact is statistically significant and increasing in distance to metro stations. These findings indicate that bike sharing and metro are complements rather than substitutes. We can imagine that travellers opt for bike sharing for the first or last "mile" of one's trip, in order to connect to the metro network.

Table 12. Impact of the policy suspension by proximity to metro stations

	Trips per origin per day	
(0-200m from closest metro station) * Suspension	-0.011	(0.025)
[200m-400m) * Suspension	-0.089***	(0.032)
[400m-600m) * Suspension	-0.106**	(0.045)
Further than 600m * Suspension	-0.109***	(0.033)
Year, month, week, day of week FE	x	
Controls: weather, # stations, weekly average gas price	x	
Station of origin FE	x	
Observations	54 370	
Clusters	141	

Note: Fixed effects Poisson model. Dep. var.: number of trips per origin station/day (7:30-18). Thursdays are excluded. Only stations built prior to the policy suspension are considered. Sample: 2012-2013. Robust standard errors in parentheses are clustered at the origin level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

5.2. The impact of congestion charge design

Section 5.1 assessed the impact of congestion pricing on bike-sharing use by analysing the effect of a temporary policy shock which results in unpriced congestion. This section instead discusses the behavioural implications of certain design choices, in particular the design of the schedule of congestion pricing implementation.

The following analysis is based on a different empirical strategy from the one in section 5.1: building upon a different source of variation in the implementation of the congestion charge, it complements and corroborates previous findings by exploiting a difference-in-differences (DiD) design.

As previously explained, in September 2012 city authorities suddenly altered the schedule of application of the congestion charge on Thursdays, changing it from 7:30-19:30 to 7:30-18:00. This policy change creates a 90-minute timeslot (18:00-19:30) during which entry into the city centre is unpriced for all motor vehicles. Thus, Thursday evening can be defined as the *treated* timeslot, where the treatment is the change in schedule. An appropriate set of *control* timeslots (all 90-minute timeslots on Wednesday between 10:30-18:00) is identified as explained in detail in the Appendix.

The impact of the schedule change on bike-sharing use can be estimated by exploiting a difference-in-differences (DiD) design, estimating the following model:

$$B_{std} = \delta_1 treated_{td} + \delta_2 after_d + \delta_3 (after_d * treated_{td}) + \boldsymbol{\gamma W_{td}} + \boldsymbol{\theta X_d} + \boldsymbol{\varphi T_d} + \boldsymbol{\alpha_{st}} + \varepsilon_{std} \quad (5)$$

The idea of this difference-in-differences model is to compare the difference in bike-sharing traffic during the treated timeslot (i.e. Thursday 18:00-19:30) before and after the schedule change, to the difference in traffic during the control timeslot (i.e. Wednesday, 10:30-18:00) before and after the same policy change. Concretely, in model (5), the parameter of interest is δ_3, which represents the difference-in-difference estimate of the average impact of the September 2012 change in the schedule of congestion pricing on bike-sharing use:

$$\delta_3 = [\mathbb{E}(B_{std} \mid treated_{td} = 1, after_d = 1) - \mathbb{E}(B_{std} \mid treated_{td} = 1, after_d = 0)] - [\mathbb{E}(B_{std} \mid treated_{td} = 0, after_d = 1) - \mathbb{E}(B_{std} \mid treated_{td} = 0, after_d = 0)]$$

Control variables included in vector $\boldsymbol{X_d}$ have been defined in section 5.1. Weather variables included in vector $\boldsymbol{W_{td}}$ (cumulative precipitations and average temperature) are measured at the timeslot level. Vector $\boldsymbol{T_d}$ includes month and year dummies. Vector $\boldsymbol{\alpha_{st}}$ denotes station of origin-timeslot fixed effects. For what concerns unobserved variables which might confound the identification of this impact (e.g. the evolution of cycle paths), the same considerations discussed in section 5.1 also hold in the context of this identification strategy.

5.2.1. Removing congestion pricing from a specific timeslot reduces bike-sharing use in that time window

Anticipating the end of congestion pricing at an earlier time on Thursdays induces a congestion and a price effect, reducing bike-sharing use as in the policy suspension case, albeit in a more limited time period. In contrast with the short-term nature of the effect of the policy suspension, the findings presented in this subsection can be interpreted as estimates of the *long-term* effects of the schedule change on the use of bike-sharing.

Table 13. Impact of AreaC's schedule change on bike-sharing use on Thursday evening

	(1)	(2)
	Trips per station of origin-timeslot	
Sample period:	2012-2013	Jan-July 2012-13
After=1 * Treated=1	-0.128***	-0.194***
	(0.030)	(0.032)
Station-timeslot FE	x	x
Month, year FE	x	x
Controls: weather, number of stations, weekly average gas price	x	x
Observations	70 628	42 244
Clusters	846	846

Note: Fixed effects Poisson model. Dep. var.: number of trips per timeslot/station. Only stations built prior to 26/07/2012 are considered. Robust standard errors in parentheses are clustered at the station-timeslot level. Control group: Wednesday 10:30-18:00. Days in which AreaC is suspended are always excluded.
* p < 0.10, ** p < 0.05, *** p < 0.01

(1) Aggregate effect. Period covered: 2012-2013.
(2) Aggregate effect. Period covered: January 2012-July 2012; January 2013-July 2013.

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 13 reports results from the estimates of the coefficient of interest in model (5). While specification (1) comprises the entire period 2012-2013, specification (2) is more conservative in that it uses the same months for pre- and post-treatment period (January-July 2012 and January-July 2013 respectively).

The aggregate effect highlighted in specification (1) signals that bike-sharing use has dropped by 12% on Thursday evening following the change in schedule of the congestion pricing scheme. This effect is estimated to be 17.6% in specification (2), signalling that the behavioural reaction leading to lower bike-sharing use is not constant over time: this is further investigated with model (6). The main message from these findings is that seemingly small design details can have an important impact on demand for specific mobility options. Variation of this impact throughout the day is further investigated in Table 16.

Finally, it may be tempting to compare the findings from specification (1) in Table 13 to those in specification (4) in Table 10, Panel A. Because the impact assessment of the policy suspension is performed with a different empirical approach and a slightly different timeslot length (trips per hour vs. trip per 90 minutes) from that of the schedule change, the two impacts cannot be compared one-to-one. The durable nature of the schedule change also implies a long-term effect on bike-sharing behaviour, while the temporary suspension of the congestion charge only has a short-term effect. However, the closeness of the two effects in magnitude and statistical significance indicates the robustness of the findings of the report.

5.2.2. The impact of the change in congestion pricing schedule exhibits seasonal variation

While model (5) provides an estimate of the average effect of the schedule change over the time horizon of the sample at hand (2012-2013), this impact might also evolve over time, as bike-sharing users adapt their mobility behaviour to the updated pricing schedule. This is tested by estimating the following model:

$$B_{std} = \delta_1 treated_{td} + \delta_2 after_d + \boldsymbol{\delta_3}(\boldsymbol{Q_d} * treated_{td}) + \boldsymbol{\gamma W_{td}} + \boldsymbol{\theta X_d} + \boldsymbol{\varphi T_d} + \boldsymbol{\alpha_{st}} + \varepsilon_{std} \quad (6)$$

The vector of coefficients of interest, $\boldsymbol{\delta_3}$, is associated with the interaction term between the *treated* binary variable and a factor variable $\boldsymbol{Q_d}$ indicating the quarter in which a given trip has taken place (e.g. Q4 of 2012). This allows observing how the impact of the AreaC schedule change varies over time.

Table 14 illustrates results from the estimation of model (6). Findings indicate that the drop in bike-sharing use following the reduction in the schedule of congestion pricing exhibits seasonal variation. More specifically, the effect in spring (Q2) is twice as large as the effect in autumn and winter (Q4 and Q1), whereas there is no statistically significant effect in summertime (Q3), when bike-sharing use generally drops because of the August holiday period in Milan (see Figure 3).

Table 14. Time-varying impact of AreaC's schedule change on bike-sharing use

	Trips per station of origin-timeslot	
Treated=1 * Q4 2012=1	-0.138***	(0.028)
Treated=1 * Q1 2013=1	-0.137***	(0.036)
Treated=1 * Q2 2013=1	-0.251***	(0.035)
Treated=1 * Q3 2013=1	-0.004	(0.037)
Treated=1 * Q4 2013=1	-0.130***	(0.039)
Station-timeslot FE	x	
Month, year FE	x	
Controls: weather, number of stations, weekly average gas price	x	
Observations	70 628	
Clusters	846	

Note: Fixed effects Poisson model. Dep. var.: number of trips per timeslot/station. Only stations built prior to 26/07/2012 are considered. Sample: 2012-2013. Robust standard errors in parentheses are clustered at the station-timeslot level. Control group: Wednesday 10:30-18:00. Days in which AreaC is suspended are always excluded. In this specification, Q4 of year 2012 also includes the period from 17 September 2012 to 30 September 2012, in order to include the first two weeks of application of the new AreaC schedule.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

5.2.3. The schedule change has additional repercussions on bike-sharing use at other times of the day

Finally, it is important to assess to what extent the schedule change influences travel behaviour outside the directly affected time window. Removing congestion pricing between 18:00 and 19:30, which constitutes the return commute time, might also affect transport choices at morning peak-time.

Table 15 illustrates findings on the impact of the schedule change on bike-sharing use at a different time of day. If part of the travellers who forego bike-sharing use on Thursday evening following the schedule change usually rely on the same means of transport for their morning commute, a reduction in traffic might be visible also during the morning peak time (7:30-9:00). This can be tested by estimating model (5), assuming that the Thursday morning peak timeslot is "treated" (with the spill-over effects of the schedule change directly affecting evening traffic), after having identified an appropriate control group.

Findings indicate that traffic during the morning peak does decrease by 8.3% following the schedule change, but to a lesser extent than in the directly-affected timeslot, during which bike-sharing use drops by 12% (as indicated in spec. (1), Table 13). This can have two potential explanations: first, thanks to the flexibility provided by shared mobility options, commuters might not necessarily use bike-sharing both for their morning and evening commute, and might adapt their mode choice to a number of contingent factors including congestion conditions. Second, the time of the evening commute might be more spread out than that of the less flexible morning commute – and this analysis only includes bike-sharing trips carried out until 19:30.

Table 15. Effect of AreaC's schedule change on bike-sharing use on Thursday morning

	(1)	(2)
	Trips per station of origin-timeslot	
Sample period:	2012-2013	Jan-July 2012-13
After=1 * Peak time=1	-0.088*	-0.133***
	(0.049)	(0.046)
Station-timeslot FE	x	x
Month, year, day of week FE	x	x
Controls: weather, number of stations, weekly average gas price	x	x
Observations	148 019	87 677
Clusters	987	987

Note: Fixed effects Poisson model. Dep. var.: number of trips per timeslot/station. Only stations built prior to 26/07/2012 are considered. Robust standard errors in parentheses are clustered at the station-timeslot level. Control group: Monday (9:00-13:30, 15:00-16:30), Tuesday (7:30-10:30), Friday (9:00-18:00). Days in which AreaC is suspended are always excluded.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(1) Aggregate effect. Period covered: 2012-2013.

(2) Aggregate effect. Period covered: January 2012-July 2012; January 2013-July 2013.

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

6. Discussion and policy implications

Urban road pricing is often implemented alongside incentives for soft mobility: these policy interventions aim to induce individuals to reduce their use of private motor vehicles and opt for alternative transport options. In this sense, behavioural change is the cornerstone of successful urban mobility policies.

Road pricing is a fundamental part of the toolbox available to local policy makers to tackle local externalities such as congestion and air pollution. While policies supporting the adoption of zero- or low-emission motor vehicles aim to curb emissions from exhaust sources, policies such as congestion pricing can contribute to reducing congestion and air pollution from non-exhaust sources (i.e. tyre and brake wear). The extent to which corrective policies can internalise congestion and air pollution externalities depends on whether they induce individuals to adopt non-polluting transport options.

This is the first study assessing how the implementation and evolution of congestion pricing influence the use of bike sharing, a green mobility option whose uptake has exponentially increased in the past decade. The analysis builds upon the case of the city of Milan, where road pricing has been in place for over ten years. Two sudden changes in the way congestion pricing is implemented – an unexpected suspension and a schedule change – generate a quasi-experimental setting, which enables the assessment of the effects of congestion pricing on bike-sharing use.

Both policy changes result in the removal of congestion pricing. However, while the analysis of the impact of the suspension enables a better understanding of how urban travel behaviour adapts to *temporary* policy shocks, the analysis of the change in schedule explores the behavioural responses to *durable* changes in the policy implementation. In this vein, the former analysis quantifies the short-term effect of changes in road pricing, while the latter their longer term impact.

Because the city of Milan installed the first bike-sharing stations when road pricing was already in place, bike-sharing use patterns are not observed in the absence of road pricing. However, it is legitimate to assume that the introduction of congestion pricing would have had an equally sized impact of the opposite sign on bike-sharing use. Consequently, the findings of this study can be interpreted as a mirror-like picture of behavioural adaptation to the implementation of urban road pricing through the use of bike sharing.

Empirical findings based on data from a narrow window around the policy change (2012-2013) reveal that introducing congestion pricing increases daily bike-sharing use by 5% to 5.8% in the short term, according to the model specification used. On the other hand, the long-term impact of an extension in the schedule of the congestion charge is a 12% increase in bike-sharing use in the affected timeslot. Estimates vary significantly along multiple dimensions: removing congestion pricing differently impacts bike-sharing use according to geographical features of the trip, the time of day when the trip takes place, and users' personal habits.

These findings have direct implications for urban mobility policy. First, policies directly aiming to reduce the use of private motor vehicles, such as congestion pricing, can have significant repercussions on the uptake of sustainable transport options such as bike sharing. Indirect, market-based incentives for cycling should thus be seen as a complement to direct, infrastructure-based incentives (e.g. development of bike lanes).

Second, once the aggregate effect of congestion pricing on bike-sharing use is identified, it is important to understand the mechanisms driving this impact. This study disentangles the extent to which variation in biking patterns is due to the price or to the congestion effect. In the context of the city of Milan, congestion pricing mainly impacts bike-sharing use through the reduction of road traffic congestion, which makes cycling safer and more pleasant. The direct effect of the increased relative cost of car use is secondary in individual decisions to use bike-sharing. More generally, the relative importance of these effects is likely to be context-specific, according to the baseline level of urban congestion, the broader policy mix affecting the cost of using private motor vehicles and the design of the congestion pricing scheme.

Third, applying congestion pricing to a specific time of day and within a delimited geographical area means the cost of driving is altered within specific temporal and geographical boundaries. Consequently, policy impacts on individual travel behaviour will reflect these geographical and temporal policy features. This is a fundamental difference from changes in the relative price of car use due to complementary market-based tools, such as e.g. a durable, country-level increase in motor fuel taxes.

This study also has more general policy implications for the design, regulation and evaluation of mobility policies and infrastructure systems. While the main dataset exploited in the analysis contains detailed information on geographical and temporal features of bike-sharing trips, it does not allow assessing policy repercussions on the use of other modes. Integrating data on motor vehicle traffic (including entries into the congestion charge zone) with data on public transport use (surface and underground) and on cycling (including bike-sharing use) would present a more complete picture of mobility patterns. This, in turn, would translate in a better understanding of demand for mobility services, and of complementarity/substitutability patterns among various transport options.

While many mobility services automatically generate vast datasets through their reliance on cards or mobile phone apps, data with this level of granularity may not be available for all transport options, such as for private means of transport. This indicates that travel surveys are a fundamental tool to gather information on evolving travel choices, related to both commuting and leisure trips.

Whenever such data includes socio-demographic information on users, it can deepen policy makers' understanding of the urban context of reference. At the same time, the sheer size and level of detail of big data requires appropriate policies to ensure user privacy is respected throughout data-gathering and analysis efforts. The reward for striking a balance between the potential and the challenges of big data is more effective urban mobility policy.

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Annex A. Appendix to section 5.1

Table 16. Aggregate effect of the policy suspension on daily bike-sharing traffic [only bike-sharing stations built prior to the policy suspension]

Full print of Table 7

Trips per origin station / weekday (7:30-18:00)	(1)	(2)	(3)	(4)
Time window:	2012-2013		2008-2016	
AreaC 2012 suspension	-0.060***	-0.019	-0.090***	-0.088***
	(0.014)	(0.012)	(0.023)	(0.022)
N stations inside AreaC	0.002	-0.009	0.022***	0.021***
	(0.011)	(0.011)	(0.002)	(0.001)
N stations outside AreaC	-0.009***	-0.007***	0.001*	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)
Weekly average gas price (eur/liter)	-0.316***	-0.231**	-0.112**	-0.058
	(0.099)	(0.099)	(0.049)	(0.048)
Holiday	-0.329***	-0.310***	-0.336***	-0.357***
	(0.019)	(0.018)	(0.014)	(0.013)
Public transport strike	0.094***	0.093***	0.161***	0.155***
	(0.011)	(0.010)	(0.011)	(0.009)
Interim between Ecopass and AreaC	-0.084***	-0.070***	0.075**	0.082***
	(0.022)	(0.022)	(0.034)	(0.030)
Ecopass			-3.193***	-3.166***
			(0.118)	(0.111)
Temperature (baseline: temperature below 0 dC)				
(0-5dC]	0.104***	0.151***	0.072***	0.106***
	(0.016)	(0.015)	(0.027)	(0.024)
(5-10dC]	0.378***	0.412***	0.229***	0.269***
	(0.019)	(0.019)	(0.029)	(0.027)
(10-15dC]	0.448***	0.505***	0.329***	0.372***
	(0.020)	(0.020)	(0.032)	(0.030)
(15-20dC]	0.585***	0.611***	0.465***	0.513***
	(0.022)	(0.022)	(0.035)	(0.033)
(20-25dC]	0.521***	0.553***	0.483***	0.526***
	(0.024)	(0.024)	(0.035)	(0.033)
(25-30dC]	0.476***	0.505***	0.400***	0.453***
	(0.022)	(0.023)	(0.033)	(0.032)
> 30dC	0.324***	0.391***	0.343***	0.402***
	(0.026)	(0.024)	(0.029)	(0.028)
Precipitation (baseline: no rain)				
(0-2mm]	-0.162***	-0.157***	-0.103***	-0.105***
	(0.004)	(0.003)	(0.003)	(0.002)
(2-4mm]	-0.350***	-0.377***	-0.243***	-0.257***
	(0.019)	(0.013)	(0.008)	(0.007)
(4-6mm]	-0.556***	-0.486***	-0.552***	-0.527***
	(0.013)	(0.010)	(0.007)	(0.006)
(6-8mm]	-0.489***	-0.476***	-0.497***	-0.446***
	(0.010)	(0.009)	(0.007)	(0.007)
(8-10mm]	-0.506***	-0.410***	-0.750***	-0.726***
	(0.019)	(0.017)	(0.008)	(0.008)
>10mm	-1.260***	-1.349***	-0.770***	-0.799***
	(0.018)	(0.018)	(0.007)	(0.007)
Thursdays included		x		x
Year, month, week, day of week FE; Station of origin FE	x	x	x	x
Observations	54370	67967	198757	248530
Clusters	141	141	142	142

Note: Fixed effects Poisson model. Dep. var.: number of trips per origin station/weekday (7:30-18). Only stations built prior to the policy suspension are considered. Robust standard errors in parentheses are clustered at the origin level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 17. Aggregate effect of the suspension on daily bike-sharing traffic [all stations]

Full print of Table 8

	(1)	(2)
Trips per origin station / weekday (7:30-18:00)	Sample: 2012-2013	Sample: 2008-2016
AreaC 2012 suspension	-0.051***	-0.095***
	(0.015)	(0.024)
N stations inside AreaC	-0.014	0.019***
	(0.011)	(0.001)
N stations outside AreaC	-0.010***	0.000
	(0.001)	(0.000)
Weekly average gas price (eur/liter)	-0.504***	-0.221***
	(0.101)	(0.046)
Holiday	-0.379***	-0.367***
	(0.018)	(0.012)
Strike public transport	0.103***	0.181***
	(0.010)	(0.010)
Interim between Ecopass and AreaC	-0.039*	0.114***
	(0.023)	(0.034)
Temperature (baseline: temperature below 0 dC)		
(0-5dC]	0.080***	0.043
	(0.016)	(0.028)
(5-10dC]	0.343***	0.178***
	(0.018)	(0.030)
(10-15dC]	0.429***	0.273***
	(0.019)	(0.032)
(15-20dC]	0.559***	0.413***
	(0.021)	(0.034)
(20-25dC]	0.505***	0.446***
	(0.023)	(0.034)
(25-30dC]	0.455***	0.366***
	(0.021)	(0.033)
> 30dC	0.290***	0.298***
	(0.025)	(0.031)
Precipitation (baseline: no rain)		
(0-2mm]	-0.167***	-0.108***
	(0.003)	(0.002)
(2-4mm]	-0.356***	-0.234***
	(0.017)	(0.006)
(4-6mm]	-0.562***	-0.537***
	(0.012)	(0.005)
(6-8mm]	-0.489***	-0.477***
	(0.009)	(0.006)
(8-10mm]	-0.471***	-0.713***
	(0.016)	(0.007)
>10mm	-1.253***	-0.745***
	(0.016)	(0.005)
Year, month, week, day of week FE	x	x
Station of origin FE	x	x
Observations	62424	262016
Clusters	187	275

Note: Fixed effects Poisson model. Dep. var.: number of trips per station of origin/day (7:30-18).
Specification (1): 2012-2013 sample. Specification (2): 2008-2016 sample. Thursdays are excluded. All stations are considered, regardless of their activation date. Robust standard errors in parentheses are clustered at the origin level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 18. Impact of the policy suspension by direction of the trip: congestion and price effect

Full print of Table 9

	(1)	(2)	(3)	(4)
	Route inside AreaC	Route outside AreaC	Route exiting AreaC	Route entering AreaC
	Trips per route / weekday (7:30-18:00)			
AreaC 2012 suspension	-0.085***	-0.035	-0.071***	-0.055***
	(0.014)	(0.027)	(0.024)	(0.021)
N stations inside AreaC	-0.013**	-0.017*	-0.003	-0.010
	(0.006)	(0.010)	(0.009)	(0.008)
N stations outside AreaC	-0.012***	-0.017***	-0.016***	-0.012***
	(0.001)	(0.002)	(0.002)	(0.002)
Weekly average gas price (eur/liter)	-0.311***	-0.750***	-0.479***	-0.516***
	(0.078)	(0.174)	(0.137)	(0.122)
Holiday	-0.341***	-0.422***	-0.329***	-0.405***
	(0.023)	(0.046)	(0.040)	(0.035)
Interim between Ecopass and AreaC	-0.020	-0.166***	-0.042	-0.017
	(0.025)	(0.056)	(0.046)	(0.036)
Strike public transport	0.056***	0.082***	0.157***	0.110***
	(0.010)	(0.019)	(0.016)	(0.014)
Temperature (baseline: temperature below 0 dC)				
(0-5dC]	0.046***	0.170***	0.133***	0.119***
	(0.018)	(0.046)	(0.035)	(0.030)
(5-10dC]	0.317***	0.422***	0.379***	0.427***
	(0.019)	(0.048)	(0.036)	(0.031)
(10-15dC]	0.418***	0.599***	0.520***	0.556***
	(0.020)	(0.050)	(0.037)	(0.032)
(15-20dC]	0.579***	0.741***	0.670***	0.703***
	(0.021)	(0.050)	(0.038)	(0.033)
(20-25dC]	0.528***	0.691***	0.604***	0.655***
	(0.023)	(0.053)	(0.041)	(0.035)
(25-30dC]	0.489***	0.599***	0.527***	0.580***
	(0.024)	(0.056)	(0.042)	(0.037)
> 30dC	0.356***	0.409***	0.338***	0.410***
	(0.029)	(0.069)	(0.054)	(0.046)
Precipitation (baseline: no rain)				
(0-2mm]	-0.126***	-0.114***	-0.130***	-0.121***
	(0.005)	(0.010)	(0.008)	(0.007)
(2-4mm]	-0.230***	-0.279***	-0.285***	-0.252***
	(0.009)	(0.017)	(0.014)	(0.012)
(4-6mm]	-0.240***	-0.285***	-0.300***	-0.192***
	(0.010)	(0.018)	(0.016)	(0.013)
(6-8mm]	-0.353***	-0.444***	-0.502***	-0.294***
	(0.024)	(0.043)	(0.039)	(0.030)
(8-10mm]	-0.339***	-0.314***	-0.373***	-0.275***
	(0.016)	(0.030)	(0.027)	(0.021)
>10mm	-0.631***	-0.649***	-0.602***	-0.666***
	(0.008)	(0.014)	(0.013)	(0.012)
Year, month, week, day of week FE	x	x	x	x
Route FE	x	x	x	x
Observations	2096441	1177962	1591075	1636506
Cluster	5400	3777	4556	4662

Note: Fixed effects Poisson model. Dep. var.: number of trips per route/weekday (7:30-18:00). Thursdays are excluded. Sample: 2012-2013. Only routes connecting stations built before the policy suspension (26/07/2012) are considered. Robust standard errors in parentheses are clustered at the route level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 19. Impact of the policy suspension by time of day (station-level analysis)

Full print of Table 10, Panel A

	(1)	(2)	(3)	(4)
	N trips origin-timeslot (normalised per hour)			
	7:30-9:30	9:30-13:30	13:30-17:30	17:30-19:30
AreaC 2012 suspension	-0.061***	-0.049**	-0.058***	-0.130***
	(0.021)	(0.019)	(0.017)	(0.018)
Holiday	-0.436***	-0.340***	-0.255***	-0.433***
	(0.035)	(0.038)	(0.031)	(0.033)
Interim between Ecopass and AreaC	-0.113***	0.041	-0.030	-0.121***
	(0.033)	(0.033)	(0.031)	(0.029)
Strike public transport	0.095***	0.165***	0.100***	0.109***
	(0.015)	(0.019)	(0.014)	(0.016)
Weekly avg gas price (eur/liter)	-0.844***	0.021	0.080	-0.444***
	(0.149)	(0.130)	(0.123)	(0.107)
N stations inside AreaC	-0.032*	0.000	0.018**	0.030***
	(0.017)	(0.009)	(0.008)	(0.009)
N stations outside AreaC	-0.006***	-0.010***	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Temperature (baseline: temperature below 0 dC)				
(0-5dC]	0.114***	0.412***	-0.041	0.232***
	(0.016)	(0.038)	(0.034)	(0.026)
(5-10dC]	0.169***	0.557***	0.316***	0.384***
	(0.020)	(0.038)	(0.037)	(0.027)
(10-15dC]	0.257***	0.709***	0.438***	0.459***
	(0.024)	(0.038)	(0.036)	(0.029)
(15-20dC]	0.329***	0.790***	0.627***	0.590***
	(0.031)	(0.039)	(0.038)	(0.033)
(20-25dC]	0.427***	0.880***	0.753***	0.669***
	(0.038)	(0.043)	(0.038)	(0.034)
(25-30dC]	0.402***	0.846***	0.704***	0.688***
	(0.033)	(0.043)	(0.039)	(0.036)
> 30dC	0.152***	0.764***	0.650***	0.680***
	(0.057)	(0.043)	(0.041)	(0.036)
Precipitation (baseline: no rain)				
(0-2mm]	-0.490***	-0.343***	-0.367***	-0.510***
	(0.020)	(0.008)	(0.013)	(0.013)
(2-4mm]	-1.962***	-1.429***	-0.985***	-1.385***
	(0.081)	(0.035)	(0.020)	(0.042)
(4-6mm]	-2.449***	-1.190***	-1.535***	-1.116***
	(0.085)	(0.039)	(0.036)	(0.049)
(6-8mm]	-1.600***	-0.814***	-0.645***	
	(0.049)	(0.071)	(0.029)	
(8-10mm]	-2.181***	-1.835***	-1.164***	
	(0.069)	(0.059)	(0.063)	
>10mm	-2.218***	-2.097***	-0.902***	-1.950***
	(0.115)	(0.062)	(0.047)	(0.079)
Year, month, week, day of week FE	x	x	x	x
Station of origin FE	x	x	x	x
Observations	54100	54127	54151	54094
Clusters	141	141	141	141

Note: Fixed effects Poisson model. Dep. var.: number of trips per origin/hour (normalised). Only routes between stations constructed prior to 26/7/2012 are considered. Thursdays are excluded. Robust standard errors in parentheses are clustered at the origin-timeslot level. Sample: 2012-2013. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 20. Impact of the policy suspension by time of day (route-level analysis)

Full print of Table 10, Panel B

	(1)	(2)	(3)	(4)
	7:30-9:30	9:30-13:30	13:30-17:30	17:30-19:30
	Trips per route/timeslot (normalised per hour)			
AreaC 2012 suspension	-0.046***	-0.038**	-0.045***	-0.134***
	(0.015)	(0.015)	(0.015)	(0.015)
Holiday	-0.469***	-0.327***	-0.271***	-0.440***
	(0.025)	(0.028)	(0.024)	(0.026)
Interim between Ecopass and AreaC	-0.153***	-0.037	-0.076**	-0.192***
	(0.027)	(0.033)	(0.030)	(0.032)
Strike public transport	0.100***	0.165***	0.099***	0.117***
	(0.009)	(0.012)	(0.011)	(0.012)
Weekly avg gas price (eur/liter)	-0.859***	-0.011	-0.135	-0.743***
	(0.091)	(0.091)	(0.091)	(0.094)
N stations inside AreaC	-0.041***	0.000	0.003	-0.004
	(0.007)	(0.005)	(0.006)	(0.006)
N stations outside AreaC	-0.006***	-0.009***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Temperature (baseline: temperature below 0 dC)				
(0-5dC]	0.112***	0.453***	-0.010	0.255***
	(0.014)	(0.032)	(0.034)	(0.026)
(5-10dC]	0.166***	0.600***	0.338***	0.397***
	(0.015)	(0.031)	(0.034)	(0.027)
(10-15dC]	0.260***	0.761***	0.465***	0.480***
	(0.016)	(0.032)	(0.033)	(0.028)
(15-20dC]	0.324***	0.840***	0.655***	0.621***
	(0.017)	(0.033)	(0.034)	(0.029)
(20-25dC]	0.414***	0.936***	0.774***	0.692***
	(0.019)	(0.035)	(0.035)	(0.030)
(25-30dC]	0.384***	0.897***	0.730***	0.706***
	(0.020)	(0.036)	(0.036)	(0.031)
> 30dC	0.122**	0.819***	0.676***	0.699***
	(0.050)	(0.037)	(0.037)	(0.031)
Precipitation (baseline: no rain)				
(0-2mm]	-0.476***	-0.360***	-0.357***	-0.495***
	(0.008)	(0.008)	(0.010)	(0.009)
(2-4mm]	-1.981***	-1.435***	-0.992***	-1.401***
	(0.065)	(0.030)	(0.017)	(0.036)
(4-6mm]	-2.385***	-1.233***	-1.551***	-1.238***
	(0.061)	(0.030)	(0.034)	(0.050)
(6-8mm]	-1.604***	-0.738***	-0.621***	
	(0.032)	(0.065)	(0.027)	
(8-10mm]	-2.211***	-1.841***	-1.172***	
	(0.058)	(0.049)	(0.052)	
>10mm	-2.211***	-1.982***	-0.897***	-2.037***
	(0.121)	(0.054)	(0.047)	(0.078)
Year, month, week, day of week FE	x	x	x	x
Route FE	x	x	x	x
Observations	5102829	6349167	6469444	5975546
Clusters	19744	23757	24334	22938

Note: Fixed effects Poisson model. Dep. var.: number of trips per route/hour (normalised). Only routes between stations constructed prior to 26/7/2012 are considered. Thursdays are excluded. Robust standard errors in parentheses are clustered at the route-timeslot level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 21. Impact of the policy suspension by frequency of use

Full print of Table 11

Dependent variable: trips per user/day			
	(1)		(2)
Frequency of use from join date to July 2012		*Frequency of use from July 2011 to July 2012*	
(0-0.75 trips/week] * Suspension	-0.215***	(0-0.65 trips/week] * Suspension	-0.229***
	(0.050)		(0.052)
(0.75-1.75 trips/week] * Suspension	-0.155***	(0.65-1.65 trips/week] * Suspension	-0.154***
	(0.031)		(0.032)
(1.75-3.8 trips/week] * Suspension	-0.054**	(1.65-3.8 trips/week] * Suspension	-0.049**
	(0.023)		(0.022)
Above 3.8 trips/week * Suspension	-0.037***	Above 3.8 trips/week * Suspension	-0.040***
	(0.013)		(0.013)
N stations inside AreaC	0.046***		0.046***
	(0.004)		(0.004)
N stations outside AreaC	-0.007***		-0.007***
	(0.001)		(0.001)
Weekly avg gas price (eur/l)	-0.115*		-0.115*
	(0.063)		(0.063)
Holiday	-0.345***		-0.345***
	(0.022)		(0.022)
Interim between Ecopass and AreaC	-0.051***		-0.051***
	(0.019)		(0.019)
Strike public transport	0.095***		0.095***
	(0.007)		(0.007)
Temperature (baseline: temperature below 0 dC)			
(0-5dC]	0.092***		0.092***
	(0.013)		(0.013)
(5-10dC]	0.341***		0.341***
	(0.015)		(0.015)
(10-15dC]	0.443***		0.443***
	(0.016)		(0.016)
(15-20dC]	0.606***		0.606***
	(0.017)		(0.017)
(20-25dC]	0.568***		0.568***
	(0.018)		(0.018)
(25-30dC]	0.494***		0.494***
	(0.019)		(0.019)
> 30dC	0.348***		0.348***
	(0.024)		(0.024)
Precipitation (baseline: no rain)			
(0-2mm]	-0.136***		-0.136***
	(0.004)		(0.004)
(2-4mm]	-0.222***		-0.222***
	(0.007)		(0.007)
(4-6mm]	-0.277***		-0.277***
	(0.007)		(0.007)
(6-8mm]	-0.495***		-0.495***
	(0.015)		(0.015)
(8-10mm]	-0.321***		-0.321***
	(0.011)		(0.011)
>10mm	-0.577***		-0.577***
	(0.007)		(0.007)
Year, month, week, day of week FE	x		x
User FE	x		x
Observations	2 427 259		2 427 259
Clusters	6383		6383

Note: Fixed effects Poisson model. Dep. var.: number of trips per user/day. Subset of users who joined before 26/7/2012. All stations. All weekdays excl. Thursdays. Robust standard errors in parentheses are clustered at the user level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 22. Impact of the policy suspension by proximity to metro stations
Full print of Table 12

	Trips per origin per day	
(0-200m from closest metro station) * Suspension	-0.011	(0.025)
[200m-400m) * Suspension	-0.089***	(0.032)
[400m-600m) * Suspension	-0.106**	(0.045)
Further than 600m * Suspension	-0.109***	(0.033)
N stations inside AreaC	0.002	(0.011)
N stations outside AreaC	-0.009***	(0.001)
Average weekly gas price	-0.316***	(0.099)
Holiday	-0.329***	(0.019)
Strike public transport	0.094***	(0.011)
Interim between Ecopass and AreaC	-0.084***	(0.022)
Temperature (baseline: temperature below 0 dC)		
(0-5dC]	0.104***	(0.016)
(5-10dC]	0.378***	(0.019)
(10-15dC]	0.448***	(0.020)
(15-20dC]	0.585***	(0.022)
(20-25dC]	0.521***	(0.024)
(25-30dC]	0.476***	(0.022)
> 30dC	0.324***	(0.026)
Precipitation (baseline: no rain)		
(0-2mm]	-0.162***	(0.004)
(2-4mm]	-0.350***	(0.019)
(4-6mm]	-0.556***	(0.013)
(6-8mm]	-0.489***	(0.010)
(8-10mm]	-0.506***	(0.019)
>10mm	-1.260***	(0.018)
Year, month, week, day of week FE	x	
Station of origin FE	x	
Observations	54370	
Clusters	141	

Note: Fixed effects Poisson model. Dep. var.: number of trips per origin station/day (7:30-18). Thursdays are excluded. Only stations built prior to the policy suspension are considered. Sample: 2012-2013. Robust standard errors in parentheses are clustered at the origin level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Annex B. Appendix to section 5.2

Table 23. Impact of AreaC's schedule change on bike-sharing use on Thursday evening

Full print of Table 13

	(1)	(2)
	Trips per station of origin-timeslot	
Sample period:	2012-2013	Jan-July 2012-2013
After=1	0.007	0.053
	(0.028)	(0.132)
After=1 * Treated=1	-0.128***	-0.194***
	(0.030)	(0.032)
N stations inside AreaC	0.012*	0.013*
	(0.007)	(0.007)
N stations outside AreaC	-0.002	0.004
	(0.002)	(0.003)
Weekly avg gas price (eur/liter)	-0.084	-0.213
	(0.106)	(0.136)
Temperature (baseline: temperature below 0 dC)		
(0-5dC]	0.683***	0.642***
	(0.043)	(0.044)
(5-10dC]	0.729***	0.726***
	(0.041)	(0.041)
(10-15dC]	0.847***	0.898***
	(0.040)	(0.040)
(15-20dC]	1.005***	1.121***
	(0.041)	(0.043)
(20-25dC]	1.093***	1.119***
	(0.041)	(0.042)
(25-30dC]	1.070***	1.161***
	(0.043)	(0.045)
> 30dC	1.040***	1.095***
	(0.045)	(0.047)
Precipitation (baseline: no rain)		
(0-2mm]	-1.009***	-1.050***
	(0.026)	(0.040)
(2-4mm]	-0.337***	
	(0.051)	
(4-6mm]	-1.216***	-0.777***
	(0.078)	(0.095)
>10mm	-0.575***	-0.525***
	(0.089)	(0.088)
Year, month FE	x	x
Station of origin-timeslot FE	x	x
Observations	70628	42244
Clusters	846	846

Note: Fixed effects Poisson model. Dep. var.: number of trips per timeslot/station. Only stations built prior to 26/07/2012 are considered. Robust standard errors in parentheses are clustered at the station-timeslot level. Control group: Wednesday 10:30-18:00. Days in which AreaC is suspended are always excluded.
* p < 0.10, ** p < 0.05, *** p < 0.01

(1) Aggregate effect. Period covered: 2012-2013.
(2) Aggregate effect. Period covered: January-July 2012; January-July 2013.

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 24. Time-varying impact of AreaC's schedule change on bike-sharing use

Full print of Table 14

	Trips per station of origin-timeslot	
After	0.281***	(0.077)
Treated=1 * Q4 2012=1	-0.138***	(0.028)
Treated=1 * Q1 2013=1	-0.137***	(0.036)
Treated=1 * Q2 2013=1	-0.251***	(0.035)
Treated=1 * Q3 2013=1	-0.004	(0.037)
Treated=1 * Q4 2013=1	-0.130***	(0.039)
N stations inside AreaC	-0.006	(0.009)
N stations outside AreaC	-0.003**	(0.002)
Weekly avg gas price (eur/liter)	0.120	(0.130)
Temperature (baseline: temperature below 0 dC)		
(0-5dC]	0.688***	(0.043)
(5-10dC]	0.733***	(0.041)
(10-15dC]	0.846***	(0.040)
(15-20dC]	1.005***	(0.041)
(20-25dC]	1.084***	(0.041)
(25-30dC]	1.075***	(0.043)
> 30dC	1.022***	(0.045)
Precipitation (baseline: no rain)		
(0-2mm]	-1.003***	(0.026)
(2-4mm]	-0.333***	(0.051)
(4-6mm]	-1.206***	(0.079)
>10mm	-0.571***	(0.089)
Station of origin-timeslot FE	x	
Month, quarter of year FE	x	
Observations	70628	
Clusters	846	

Note: Fixed effects Poisson model. Dep. var.: number of trips per timeslot/station. Only stations built prior to 26/07/2012 are considered. Sample: 2012-2013. Robust standard errors in parentheses are clustered at the station-timeslot level. Control group: Wednesday 10:30-18:00. Days in which AreaC is suspended are always excluded. In this specification, Q4 of year 2012 also includes the period from 17 September 2012 to 30 September 2012, in order to include the first two weeks of application of the new AreaC schedule.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Table 25. Effect of AreaC's schedule change on bike-sharing use on Thursday morning

Full print of Table 15

	(1)	(2)
	Trips per station of origin-timeslot	
Sample period:	2012-2013	Jan-July 2012-13
After=1	0.047**	0.118
	(0.022)	(0.086)
Peak time=1	0.070*	0.044
	(0.037)	(0.028)
After=1 * Peak time=1	-0.088*	-0.133***
	(0.049)	(0.046)
Temperature (baseline: temperature below 0 dC)		
(0-5dC]	0.006	0.048*
	(0.023)	(0.027)
(5-10dC]	0.206***	0.235***
	(0.020)	(0.025)
(10-15dC]	0.291***	0.366***
	(0.024)	(0.029)
(15-20dC]	0.346***	0.438***
	(0.026)	(0.034)
(20-25dC]	0.453***	0.538***
	(0.027)	(0.037)
(25-30dC]	0.435***	0.520***
	(0.028)	(0.035)
> 30dC	0.408***	0.478***
	(0.029)	(0.036)
Precipitation (baseline: no rain)		
(0-2mm]	-0.989***	-1.094***
	(0.016)	(0.017)
(2-4mm]	-1.670***	-2.095***
	(0.067)	(0.075)
(4-6mm]	-2.352***	-2.859***
	(0.083)	(0.131)
(6-8mm]	-3.610***	-3.581***
	(0.447)	(0.448)
(8-10mm]	-0.872***	-0.881***
	(0.055)	(0.053)
N stations inside AreaC	-0.040***	-0.038***
	(0.008)	(0.008)
N stations outside AreaC	-0.000	0.003*
	(0.001)	(0.002)
Weekly avg gas price (eur/liter)	-0.344***	0.023
	(0.093)	(0.132)
Station of origin-timeslot FE	x	x
Month, year, day of week FE	x	x
Observations	148 019	87 677
Clusters	987	987

Note: Fixed effects Poisson model. Dep. var.: number of trips per timeslot/station. Only stations built prior to 26/07/2012 are considered. Robust standard errors in parentheses are clustered at the station-timeslot level. Control group: Monday (9:00-13:30, 15:00-16:30), Tuesday (7:30-10:30), Friday (9:00-18:00). Days in which AreaC is suspended are always excluded.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(1) Aggregate effect. Period covered: 2012-2013.
(2) Aggregate effect. Period covered: January 2012-July 2012; January 2013-July 2013.

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

Common trends test

The identifying assumption for the estimation of a difference-in-differences model is that the dependent variable follows a common trend in the treatment and in the control group in the pre-treatment period, conditional on observed variables. Thus, in order to pin down a control timeslot, one needs to consider the historical trends in bike-sharing use prior to the schedule change.[24] This is done estimating the following model with data from all 40 timeslots between 7:30 and 19:30 on weekdays (8 timeslots of 90 minutes per day) with Thursday evening (18:00-19:30) as baseline:

$$B_{std} = \delta_1 w_d + \delta_2 (w_d * timeslot_t * doweek_d) + \boldsymbol{\gamma W_{td}} + \boldsymbol{\theta X_{td}} + \boldsymbol{\varphi T_{td}} + \boldsymbol{\alpha_{st}} + \varepsilon_{std} \quad (7)$$

The dependent variable is the number of bike-sharing trips originating at station *s* during 90-minute timeslot *t,* on day *d*. The main control variables are a weekly trend w_d and an interaction term between the trend itself and factor variables indicating during which timeslot and day of week the trip has taken place. Additional vectors of covariates, including e.g. weather-related variables, have been presented in Section 5. Vector $\boldsymbol{\alpha_{st}}$ denotes station-timeslot fixed effects, controlling for regular patterns of use characterising given stations at given times of the day. The coefficient of interest in this specification is δ_2, associated with the interaction term: using as benchmark the treated group, Thursday evening, any other timeslot for which δ_2 is not statistically different from zero is a potential control group.

Table 26. Testing for common trends in bike-sharing use in the pre-treatment period

	Trips per station of origin/timeslot/day	
	Baseline: Thursday, 18:00-19:30	
Week-year	0.022***	(0.003)
10:30-12:00 # Wednesday # Week-year	-0.003	(0.002)
12:00-13:30 # Wednesday # Week-year	-0.002	(0.002)
13:30-15:00 # Wednesday # Week-year	-0.001	(0.002)
15:00-16:30 # Wednesday # Week-year	-0.004	(0.002)
16:30-18:00 # Wednesday # Week-year	-0.002	(0.002)
18:00-19:30 # Tuesday # Week-year	0.000	(0.001)
Station-timeslot FE	x	
Month, day of week FE	x	
Controls: weather, number of stations, weekly average gas price	x	
Observations	132 580	
Cluster	1110	

Note: Fixed effects Poisson model. Dep. var.: number of trips per station of origin/timeslot. Sample: January-July 2012, excluding AreaC suspensions. Robust standard errors in parentheses are clustered at the station-timeslot level. * p < 0.10, ** p < 0.05, *** p < 0.01
Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.

[24] Restricting attention to the period where congestion pricing is in place (as opposed to pollution pricing through Ecopass), the pre-treatment period starts on 12 January 2012, with the launch of AreaC, and ends on 17 September 2012, when the Thursday change in schedule entered into force. Days in which congestion pricing is suspended (e.g. strikes, holidays, exceptional suspension in summer 2012) are excluded from the sample.

Table 26 reports selected results from the estimation of model (7): more specifically, only statistically insignificant estimates of δ_2 are reported, indicating potential control groups. These are timeslots exhibiting a common trend in bike-sharing use with the treated timeslot (Thursday 18:00-19:30). Because following the schedule change, travellers might shift trips from Thursday evening to other weekday evenings, the Tuesday 18:00-19:30 timeslot is excluded in order to avoid this potential confounding effect. The other timeslots, i.e. Wednesday 10:30-18:00, are retained as control group for the estimation of the difference-in-differences model (5) and (6).

In order to assess the impact of the schedule change on bike-sharing use at peak time, model (7) is then estimated with Thursday morning (7:30-9:00) as baseline. Table 27 reports only statistically insignificant estimates of δ_2, indicating timeslots which exhibit a common historical trend in bike-sharing use relatively to Thursday morning. Using the ensuing control group, model (5) is then estimated considering as "treated" timeslot Thursday morning (7:30-9:00): results are reported in table 15.

Table 27. Testing for common trends in bike-sharing use in the pre-treatment period

	Trips per station of origin/timeslot/day	
	Baseline: Thursday, 7:30-9:00	
Week-year	0.009***	(0.003)
7:30-9:00 # Tuesday # Week-year	0.000	(0.001)
9:00-10:30 # Monday # Week-year	0.000	(0.003)
9:00-10:30 # Tuesday # Week-year	0.002	(0.003)
9:00-10:30 # Thursday # Week-year	0.002	(0.003)
9:00-10:30 # Friday # Week-year	-0.002	(0.003)
10:30-12:00 # Monday # Week-year	0.004	(0.003)
10:30-12:00 # Friday # Week-year	0.001	(0.003)
12:00-13:30 # Monday # Week-year	0.005	(0.003)
12:00-13:30 # Friday # Week-year	0.002	(0.003)
13:30-15:00 # Friday # Week-year	0.004	(0.003)
15:00-16:30 # Monday # Week-year	0.003	(0.003)
15:00-16:30 # Friday # Week-year	0.001	(0.003)
16:30-18:00 # Friday # Week-year	0.003	(0.003)
Station-timeslot FE	x	
Month, day of week FE	x	
Controls: weather, number of stations, weekly average gas price	x	
Observations	132 580	
Cluster	1110	

Note: Fixed effects Poisson model. Dep. var.: number of trips per station of origin/timeslot. Sample: January-July 2012, excluding AreaC suspensions. Robust standard errors in parentheses are clustered at the station-timeslot level. * p < 0.10, ** p < 0.05, *** p < 0.01

Source: Authors' calculations based on data from Clear Channel, ARPA Lombardia, Ministero dello Sviluppo Economico.