Departament d'Economia Aplicada
Universitat Autònoma de Barcelona

WORKING PAPER 26-06

Here come the bikes: Cycling infrastructure and housing prices

Miquel-Àngel Garcia-López
Marianna Magagnoli
Elisabet Viladecans-Marsal

Departament d'Economia Aplicada
Edifici B
Universitat Autònoma de Barcelona
08193 Bellaterra, Barcelona, Spain.
d.econ.aplicada@uab.cat
www.uab.cat/en/applied-economics
@ecapuab.bsky.social

UAB
Universitat Autònoma de Barcelona

Here come the bikes: Cycling infrastructure and housing prices

Miquel-Àngel Garcia-López[*†]
Universitat Autònoma de Barcelona and *Institut d'Economia de Barcelona*

Marianna Magagnoli[*‡]
DIW Berlin and *Institut d'Economia de Barcelona*

Elisabet Viladecans-Marsal[*§]
Universitat de Barcelona, *Institut d'Economia de Barcelona* and *CEPR*

June 2026

Abstract: We estimate how two complementary forms of cycling infrastructure, cycle lanes and bike-sharing stations, capitalize into housing prices in Barcelona. We distinguish the presence of infrastructure from its use, which we capture recovering bike traffic across the entire street network from bike-sharing trip records. We combine geolocated sale and rental listings with digitized records of every cycle-lane segment and bike-sharing station and estimate hedonic price gradients across concentric 50-meter rings rather than a single proximity indicator. We find an asymmetry by infrastructure type and tenure. Sales respond more to stations and rents respond more to cycle lanes; station effects stay positive and fade with distance, whereas lane effects are concentrated nearby and turn negative farther out. We read this through a road-space trade-off that varies with resident characteristics. When we move from the provision of infrastructure to its use, we find that doubling local traffic raises sale prices far more than physical presence alone. This indicates that residents capitalize a well-connected, well-ridden network rather than mere adjacency. Capitalization is positive but modest, too small to support strong gentrification concerns.

Keywords: Cities, cycling, housing prices, consumption amenities, neighborhood composition
JEL classification: R31, R41, R53

[*]Financial support from the Ministerio de Ciencia e Innovación, Spain (research projects PID2021-128227OB-I00, PID2022-139878OB-I00, PID2024-162316OB-I00, TED2021-131886B-I00 and TED2021-132184B-I00), Fundació La Caixa, Spain (Social Research CAll research project LCF/PR/SR21/52560001), and ICREA Acadèmia Research Awards by Miquel-Àngel Garcia-López (2024ICREA00113) and Elisabet Viladecans-Marsal (2022) is gratefully acknowledged.

[†]Corresponding author. Department of Applied Economics, Universitat Autònoma de Barcelona, Edifici B, Facultat d'Economia i Empresa, 08193 Cerdanyola del Vallès, Spain (e-mail: miquelangel.garcia@uab.cat; phone: +34 93 581 4584; website: https://miquelangelgarcialopez.wordpress.com).

[‡]German Institute for Economic Research (DIW Berlin) - Socio-Economic Panel division (SOEP), Anton-Wilhelm-Amo-Straße 58, 10117 Berlin, Germany (e-mail: mmagagnoli@diw.de, phone: +49 30 8978 9346; website: https://sites.google.com/view/mariannamagagnoli).

[§]Department of Economics, Universitat de Barcelona, John M. Keynes 1-11, 08034 Barcelona, Spain (e-mail: eviladecans@ub.edu; phone: +34 93 403 4646; website: https://elisabetviladecans.wordpress.com/).

1. Introduction

Cycling has become an increasingly important mode of urban transport, the object of public investment and a growing body of active-mobility policy. Use has risen markedly in many cities: daily cycling in New York increased by 64% between 2013 and 2023, Paris doubled the length of its bicycle network between 2014 and 2024, or Barcelona expanded its own network from 86 km in 2011 to 158 km in 2019. At the European level, the European Declaration on Cycling (2024) identifies the mode as a strategic priority on environmental, health, and economic grounds. How this expansion is valued by residents, however, remains poorly understood, and its effects are unlikely to be uniform across space.

Like other transport infrastructure, cycling investments can shape housing markets through two opposing forces. Improved accessibility raises the attractiveness of well-connected locations and is capitalized into higher prices (Baum-Snow, 2026). At the same time, infrastructure generates local disamenities—noise, pollution, congestion, parking pressure—that reduce residential quality, so the net effect depends on the balance between the two and varies systematically across space (Garcia-López et al., 2026, Estruch-Garcia et al., 2025). This tension is especially pronounced for cycling infrastructure. A household near a new bike lane may gain from better accessibility, lower traffic noise, cleaner air, and a more active streetscape, and because cycling is a slow surface mode that lets riders stop easily, the lane can also raise the visibility of local shops. But these gains come from reallocating road space away from cars, so nearby streets may face more congestion, less parking, and harder car access—costs that fall on a different set of residents than the benefits do. Crucially, these benefits and costs have different spatial footprints, so the net effect need not even share the same sign at different distances from the intervention. Whether such infrastructure is, on net, valued positively is therefore an empirical question, and one whose answer should depend on the type of infrastructure, the distance from it, and who lives nearby.

Housing prices offer a natural lens on that question. If residents value the infrastructure, its presence should capitalize into higher prices; if local disamenities from displaced traffic, lost parking, or construction dominate, the effect may be flat or negative. Because the relevant benefits (accessibility, amenity, signaling) and costs (parking loss, traffic displacement) have different spatial footprints, the net effect need not be monotone in distance, and a single average effect can mask offsetting forces. This also bears on a growing concern that, as with other green interventions, cycling infrastructure may attract higher-income residents and contribute to displacement—a possibility that has received little direct evidence.

This paper estimates how two complementary forms of cycling infrastructure—cycle lanes and bike-sharing stations—capitalize into housing prices in Barcelona over the period 2011–2019, and asks whether the answer differs for renters and buyers. We analyze sales and rental listings separately because the two groups differ systematically in age, income, and car use, and may therefore weigh the accessibility–amenity benefits against the road-space costs differently. To recover the spatial structure of these effects, we estimate hedonic price regressions across concentric 50-meter rings extending to 300 meters from each dwelling, rather than a single proximity indicator. The ring approach is central to what we find: because positive and negative forces operate at different

distances, a binary "near/far" treatment would net them out and understate the underlying effects. We then go beyond the presence of infrastructure to its use: drawing on trip records from the bike-sharing service, we estimate bike traffic across the entire street network and ask whether prices reflect how intensively cycling infrastructure is actually ridden, not just whether it is nearby.

We study the Eixample district of Barcelona, whose regular grid provides an unusually clean setting for identification. The district is densely built and structurally homogeneous—streets are highly uniform in width, layout, housing stock, amenities, and resident composition—so cross-sectional heterogeneity that would otherwise confound the analysis is limited. During the period 2011–2019, Barcelona expanded its bike network from 86 km to 158 km in 2019, alongside the municipalization and rapid scaling of the bike-sharing system (Bicing). Within the Eixample, the number of stations grew nearly sixfold and cycle-lane length grew by about half over our sample. We argue that, within this homogeneous grid, the timing and exact placement of new infrastructure can be treated as plausibly orthogonal to pre-existing price levels and trends, and we support this with a series of tests. We find no systematic relationship between the location or timing of construction and prior price levels or trends, and no relationship with local socio-demographic or urban characteristics. We also find no evidence of anticipation, consistent with the low cost and speed of construction of the cycling infrastructure.

Barcelona is also of interest beyond its identification advantages. Its cycling transformation was large, fast, and typical of the active-mobility agendas now spreading across European and North American cities, using standard low-cost technology rather than a large-scale intervention. Because both forms of infrastructure expanded substantially within the same dense area, we can compare a space-intensive form of provision (lanes) against a lighter-footprint one (stations) holding the city, its residents, and the housing market fixed—a within-city comparison that pooling across cities cannot deliver cleanly. The mechanisms we identify are thus likely to carry over to other dense urban contexts, even if precise magnitudes will depend on local conditions.

Our data are granular on both sides. Housing listings, covering both sales and rents with precise geolocation and rich dwelling attributes, come from Idealista, the largest real-estate platform in Spain. We reconstruct the history of the cycle-lane network by digitizing official Barcelona City Council maps that record the location and construction year of each segment, and we obtain station locations from OpenStreetMap. To measure use rather than provision, we employ a routing algorithm that recovers bike-traffic flows across the entire street network. Drawing on trip-level origin–destination records from the bike-sharing service, aggregated by hour, day, and month, we assign each trip to a least-cost path in which the cost of traversing a segment depends on its bike-friendliness—so that riders are routed onto safer, more rideable streets—and aggregate the resulting paths to obtain a flow measure for every segment. We validate these estimated flows against the city's bike-traffic sensor counts.

The results show an asymmetry by infrastructure type and tenure. Sales respond more to bike sharing stations than to cycle lanes, while rents respond more to cycle lanes than to stations. Doubling the number of Bicing stations in close proximity raises sales by 0.74% and rents by 0.14%—about 3,815€ and 1.97€ per month for an average flat—while doubling cycle-lane length

raises sales by 0.56% and rents by 0.67%, roughly 2,848€ and 9.4€ per month. The spatial impact differs as well: Bicing effects stay positive and fade with distance, whereas cycle-lane effects are concentrated nearby and turn negative farther out, partly offsetting the gains close to the dwelling. We read these patterns through a trade-off in the allocation of public space that varies with both infrastructure type and socio-demographic composition by tenure type. Cycle lanes require a larger reallocation of road space than stations, so their benefits at the street are accompanied by stronger costs—lost parking, displaced traffic—in the surrounding area. Renters in the Eixample tend to be younger and lower-income, and thus less likely to commute by car, so they may value cycle lanes more than buyers, while buyers, more exposed to the road-space cost, value the lighter-footprint stations relatively more.

We then ask whether prices reflect not just the presence of infrastructure but its use. Doubling local bike traffic within 50 meters is associated with a 3.53% increase in sales prices—about 16,178€ for an average dwelling, and far larger than the effect of physical presence alone—while the effect on rents is weak and largely insignificant. We read the gap as evidence that traffic captures the functionally relevant features of the network—connectivity and bike-friendliness—and that high observed use signals to buyers that the infrastructure works.

Although the literature on the causal effects of cycling infrastructure is growing, it remains thin, and what exists has largely studied effects other than capitalization. One strand examines traffic, safety, and the environment, with mixed verdicts on whether lanes ease or worsen car conditions: London's Cycle Superhighways appear to have done little or even raised congestion (Bhuyan et al., 2021, Bernard, 2022), while Berlin's pop-up lanes slowed car speeds (Schrauth, 2022) and New York's bike-share rollout coincided with lower black-carbon and nitric-oxide concentrations (Thorne, 2022). Taking a general-equilibrium view, Hendrich et al. (2025) show that removing the Netherlands' cycleway network would lengthen commutes, worsen car congestion, and lower welfare.

A small but growing literature estimates how cycling infrastructure capitalizes into housing prices, with mixed results that depend on what is measured and where. For bike-sharing, Shr et al. (2022) find that proximity to a station raises rents by about 2.6% within 150 meters in Kaohsiung, using station presence as the treatment and rents as the only outcome. For cycle lanes, Shang (2024) finds price gains of up to 5% within 100 meters of a lane in Seattle under a binary near-versus-far treatment, with a spatial model recovering an amenity value of segregated lanes near 4% against a counterfactual congestion cost. We advance on both, we study stations and cycle lanes jointly within a single market, estimate effects on sales as well as rents, and replace binary proximity with a full distance gradient. The gradient is what lets us separate forces that a near/far indicator averages together—showing that the station effect decays smoothly with distance while the lane effect turns negative farther out, as the road-space cost begins to dominate the local amenity gain.

A second, unresolved question is whether what capitalizes is access or amenity, and estimates prove highly sensitive to context. In Paris, Daniele et al. (2022) find no effect of a modeled bike-market-access index on prices but a positive effect of built cycle-lane density, which they read as amenity rather than accessibility; across eleven US cities, Dahir and Le (2025) find positive,

negative, and null effects depending on facility and property type. We contribute on both fronts. Rather than the count of nearby assets or a modeled access index, we measure realized bike traffic recovered from observed trips: that traffic capitalizes strongly while physical infrastructure capitalizes weakly indicates residents pay for a high-quality, well-connected network, but not as much for one which is merely built - a distinction neither built density nor modeled access alone can draw. And rather than pool cities with different built environments, we hold the urban fabric nearly fixed within a single homogeneous grid, isolating the infrastructure's role and helping explain why estimates diverge so widely across settings.

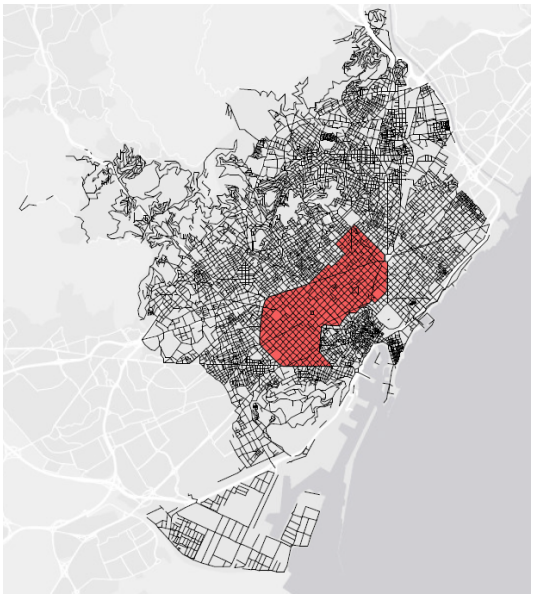
Against this backdrop, our contribution is threefold. First, and most distinctively, we price the use of cycling infrastructure rather than its mere provision. Almost all of this literature treats a built lane or a sited station as the treatment, implicitly assuming that provision generates ridership—that because a lane exists, it is ridden. But the value of infrastructure to residents depends on whether a street is well connected within the network and pleasant to cycle, and these are exactly the features that determine whether it is used at all. By measuring realized network-wide flows and showing that they capitalize far more strongly than physical presence, we provide what is, to our knowledge, the first valuation of cycling infrastructure through housing prices based on observed use rather than the existence of nearby assets or a modeled accessibility index. Second, we study cycle lanes and bike-sharing jointly within a single setting, showing that the two capitalize differently and that the difference maps onto the road-space trade-off each entails. Third, rather than pooling tenure groups, we estimate distance gradients separately for renters and buyers. This lets us trace the asymmetry in results across infrastructure back to compositional differences between the two groups — in age, income, and car ownership, for example — and accounts for the sign reversals over distance that a single pooled estimate would obscure. Our results also bear on the equity debate: capitalization is positive but modest, too small to underpin strong gentrification concerns, suggesting that cycling infrastructure of this kind can improve urban environments without displacing residents.

The paper is organized as follows. Section 2 describes the cycling infrastructure in Barcelona. Section 3 sets out the empirical strategy. Section 4 presents the main results. Section 5 develops the bike-traffic measure and estimates its effects. Section 6 concludes.

2. Cycling infrastructure in the Eixample district of Barcelona

To provide a comprehensive overview of the empirical setting, we draw on a rich and highly granular dataset combining information on cycling infrastructure in Barcelona over the period 2011–2019. The analysis focuses on the Eixample district, a central and structurally homogeneous area that offers a particularly suitable context for identification (see Figure 1). As detailed in Section 3.2, its grid-shaped layout ensures a high degree of uniformity across streets in terms of structure, housing characteristics, amenities, and resident population, resulting in substantially lower variability than in the rest of the city. The Eixample is also one of Barcelona's most densely connected areas, with a highly developed infrastructure network, and accounted for around 16% of the city's population in 2021 despite covering only 7.48 km^2 (about 7.3% of the total area).

Figure 1: Barcelona and the Eixample district (in red)



A bike-sharing service is a mobility system through which subscribers can use bicycles in exchange for a fee, with specific characteristics varying across cities. In Barcelona, the public service, known as Bicing, was introduced in 2007 and operates as a dock-based system, meaning that bicycles must be picked up and returned at designated stations. The service, which offers both mechanical and electric bicycles, is primarily designed for short trips and targets local residents, as registration requires specific documentation. Subscribers pay an annual fee, while variable costs depend on usage time and bicycle type.

Complementing this service provision, cycling infrastructure also includes dedicated lanes for bicycle traffic. These cycle lanes have evolved over time in terms of standards and design, and may be located either on the roadway or on the pavement, with variations in segregation from motorized traffic and directionality. Figure 2 illustrates these two key components: a Bicing station (Figure 2a), which enhances accessibility and network connectivity, and a segregated cycle lane (Figure 2b), which improves safety and comfort by providing dedicated space for cyclists. Together, they exemplify the integrated approach adopted in Barcelona, combining service availability with physical infrastructure to promote cycling as a viable and sustainable mode of urban transport.

The geolocation of the Bicing stations are collected from Open Street Map (OSM) starting from 2011. This source contains the stations present each year as reported by the community of contributors to the database. The Open Data portal of the city of Barcelona also provides information about the number of docks and types of bikes available at each station, but it is only available in more recent years (starting from 2019). We use this year to compare the two sources, as shown in Figure A.1 in Appendix A. According to OSM, there were 121 stations in the Eixample in 2019. The Open Data source reports 104 stations. The spatial overlap between the two sources is satisfactory. We manually digitize an historical map from the City Council of Barcelona to obtain information about the cycling network since the construction of the first cycle lane in 1983.

Figure 2: Cycling infrastructure in Barcelona

(a) A Bicing station



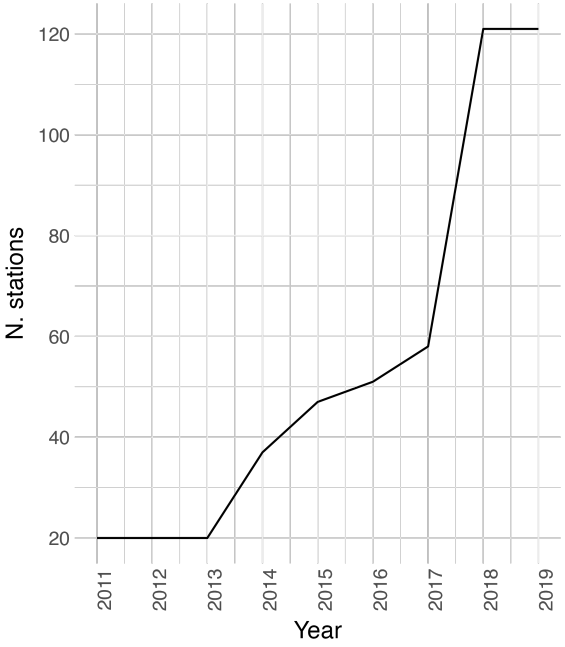
(b) A segregated cycle lane



Figure 3 depicts the evolution of cycling infrastructure in the Eixample district over the period 2011–2019, while also reflecting its relative importance within the broader urban context of Barcelona. Over this interval, the share of both Bicing stations and cycle lanes located in the Eixample declines moderately, from approximately 32% of the city total in 2011 to around 25% in 2019, indicating a gradual spatial diffusion of infrastructure across other districts. Within the Eixample itself, however, both indicators exhibit substantial growth.

Figure 3: Cycling infrastructure over time in the Eixample district: Number and length

(a) Bicing stations



(b) Cycle lanes

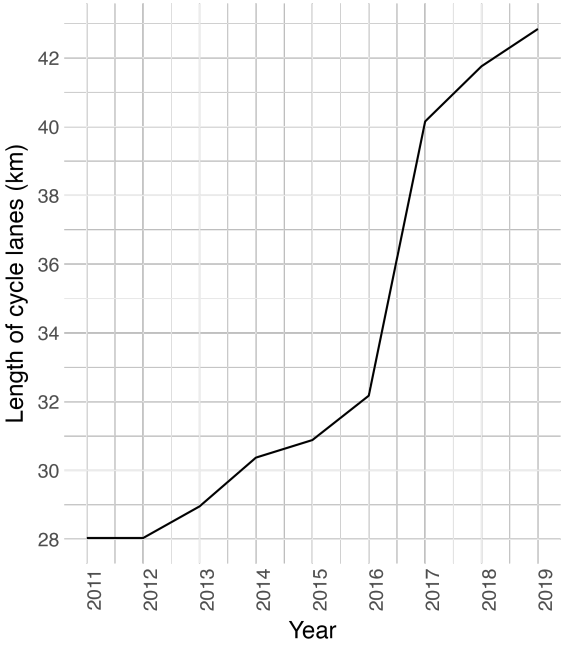


Figure 3a shows that the number of Bicing stations increased markedly, reaching a level approximately six times higher in 2019 (120) than at the beginning of the period (20), with the most pronounced expansion concentrated in 2018. This sharp increase coincides with the institutional

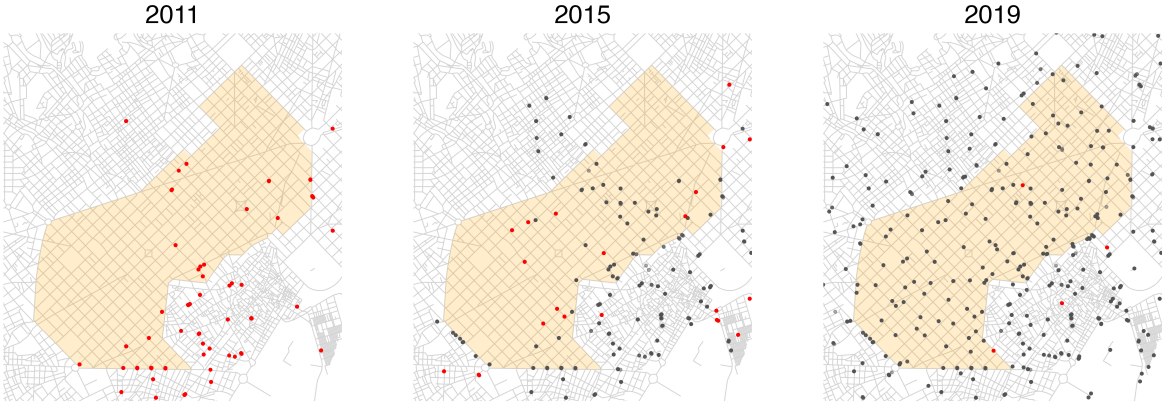
transition of the bike-sharing system from private to municipal management, suggesting a strong link between governance changes and the rapid scaling of the network.

Figure 3b, in contrast, illustrates a more gradual yet significant expansion of cycle lanes, whose total length rose from 28 km in 2011 to nearly 43 km in 2019, an increase of about 15 km, or roughly 50%. While the Eixample already had a relatively developed cycling network at the outset, as one of the first areas in the city to implement such infrastructure, the pace of expansion accelerates notably after 2015, aligning with the beginning of Ada Colau's mayoral tenure (2015-2023).

Taken together, these figures highlight distinct but complementary development patterns: a rapid and episodic deployment of Bicing stations alongside a steadier, policy-driven expansion of cycle lanes, both occurring within a context of increasing territorial dispersion of cycling infrastructure across Barcelona.

Figure 4: Cycling infrastructure over time in the Eixample district: Spatial coverage

(a) Bicing stations



(b) Cycle lanes

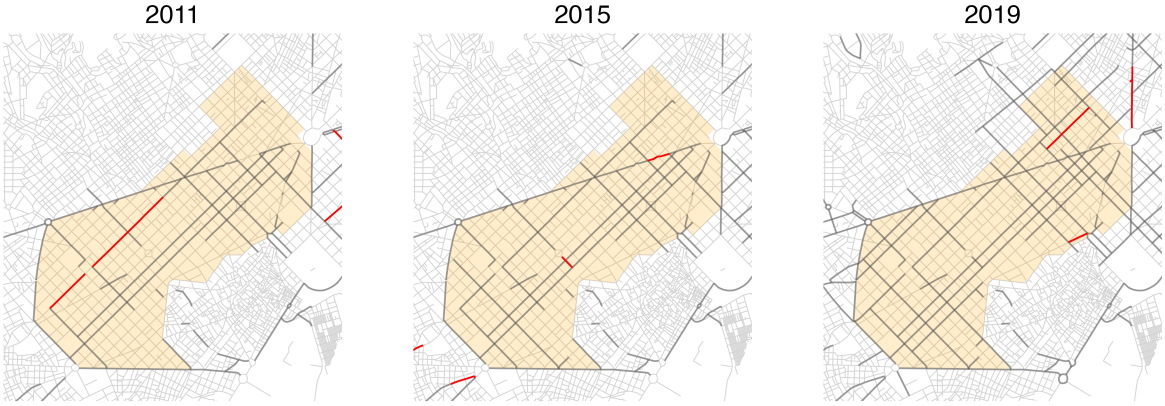
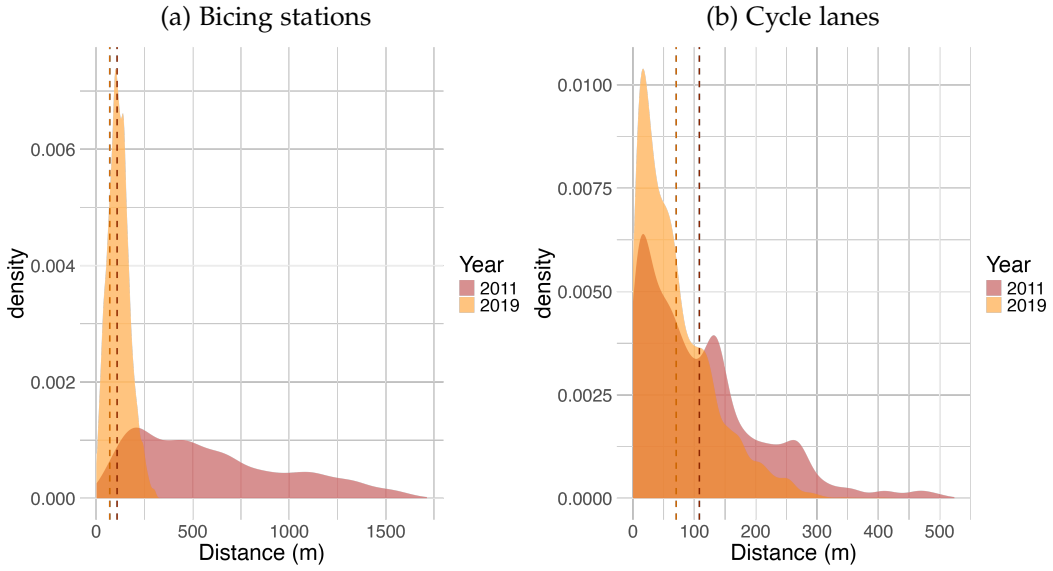


Figure 4 complements the temporal trends described above by illustrating the spatial expansion of cycling infrastructure within the Eixample between 2011 and 2019. Figure 4a shows how the distribution of Bicing stations becomes progressively denser and more evenly spread across the district, reducing initial concentrations and improving local accessibility to the service. Figure 4b depicts the corresponding development of the cycle lane network, highlighting an increasingly connected layout in which new segments extend and link pre-existing corridors. While early

infrastructure already covered key routes, subsequent additions enhance continuity and reduce fragmentation. Overall, these maps emphasise a process of spatial consolidation accompanying the quantitative growth previously documented, whereby both Bicing stations and cycle lanes evolve towards more homogeneous and integrated coverage within the district.

Figure 5: Distribution and mean of the distance to closest cycling infrastructure



As a consequence of the expansion of cycling infrastructure documented in the previous figures, the share of residents located in close proximity to a Bicing station or a cycle lane increased substantially over time. Figure 5 illustrates this improvement by mapping the distribution of distances from residential locations to the nearest infrastructure in the first and last years of the sample (2011 and 2019). Over this period, the distribution shifts markedly towards shorter distances, indicating enhanced accessibility and a reduction in spatial disparities. In particular, the maximum distance to the nearest Bicing station decreases sharply from 1.7 km in 2011 to 313 metres in 2019 (Figure 5a), while for cycle lanes the reduction is more moderate, from 524 metres to 420 metres (Figure 5b). Taken together, these patterns point to a clear and generalised improvement in spatial access to cycling facilities, consistent with the broader process of infrastructure expansion and consolidation observed across the district.

3. Empirical strategy

The main objective of this article is to examine the impact of cycling infrastructure on housing prices in the Eixample district of Barcelona over the period 2011–2019, exploiting highly granular spatial data to identify effects at different distance thresholds. The relevance of this analysis stems from the fact that, from a theoretical perspective, the overall capitalization of cycling infrastructure into housing prices is ambiguous in both direction and magnitude. On the one hand, proximity to such infrastructure provides direct access to the cycling network, which may be positively valued by residents, particularly those who actively use these facilities. On the other hand, the reallocation of urban space towards cycling often comes at the expense of road capacity and

parking availability. If this leads to increased congestion, traffic displacement, or reduced parking supply, car-dependent residents may perceive these changes negatively.

However, these potential drawbacks may be offset by broader urban benefits. If the expansion of cycling infrastructure induces a modal shift away from private motorised transport towards active mobility, it may contribute to reductions in traffic congestion, air pollution, and noise levels. Furthermore, the presence of cycle lanes and bike-sharing stations can increase street activity and visibility, potentially enhancing perceived safety and overall neighbourhood attractiveness. These changes may also influence the composition and quality of local amenities, thereby reinforcing the extent to which infrastructure improvements are capitalised into housing prices. Building on these considerations, the empirical analysis is designed to capture how these potentially offsetting effects vary with distance to the infrastructure.

3.1 Main equation

We adopt a ring-based approach, whereby we define concentric distance bands around each dwelling. As illustrated in Figure A.2 in Appendix A, we construct rings of 50 metres up to a maximum distance of 300 metres. This distance threshold is motivated by two considerations. First, as shown in Figure 5, the farthest Bicing station observed at the end of the sample period is located just above 300 metres from a dwelling. Second, evidence from Moovit (2019) indicates that the average commuter in Barcelona walks approximately 300 metres per trip.

Accordingly, the analysis considers six distance intervals: 0–50, 50–100, 100–150, 150–200, 200–250, and 250–300 metres from each property. For each ring, we compute two measures of infrastructure intensity: the total length of cycle lanes and the number of Bicing stations falling within the corresponding distance band.

We estimate the following empirical model:

$$\ln(\text{Price})_{isjt} = \beta_0 + \beta_1 \times \text{Bikes}_{irt} + \beta_2 \times \text{Dwelling}_i + \beta_3 \times \text{Socio-demographics}_{jt} + \theta_s + \gamma_t + \epsilon_{st} \quad (1)$$

where $\ln(\text{P})_{isjt}$ is the log of price per square meter of dwelling i on street section s in Basic Statistical Area (BSA) j and year t. Data on housing prices come from posted sales and rents from www.idealista.com, one of the major real estate websites used in Spain.

Bikes_{irt} represents a vector capturing cycling infrastructure around dwelling i within ring r in year t, including both the log of length of cycle lanes and the number of Bicing stations. As such, it comprises 12 elements, corresponding to the two types of infrastructure measured across six distance rings. Consequently, the parameter of interest, β_1, is itself a vector of coefficients with the same dimensionality as Bikes_{irt}, capturing the heterogeneous effects of each infrastructure type at different distance thresholds.

Dwelling_i controls for the characteristics of the dwelling i: size, floor, number of rooms, presence of air conditioning, lift and boxroom, and type of property (studio, penthouse, duplex). $\text{Socio-demographics}_{jt}$ captures the socio-demographic characteristics of Basic Statistical Area (BSA) j at time t. The Population Census of Barcelona provides detailed information at this spatial scale, which comprises 233 small statistical units designed to be relatively homogeneous in terms of population size, urban structure, and socio-economic composition. The Eixample district is

subdivided into 36 such areas. Using this information, we construct a set of time-varying socio-demographic controls, including mean age, share of population between 20 and 35 years old, percentage of population with university studies, share of foreigners, mean household size and population density. Additional variables such as unemployment and relative household income are only available at the neighborhood level, which represents a more aggregated territorial unit. Barcelona is divided into 73 neighborhoods, six of which are located within the Eixample district. θ_s and γ_t are street section and year fixed-effects, respectively. Following Baum-Snow (2007) and Dippel et al. (2021), we weight each observation by the share of listings it represents within a given ring–year. We cluster standard errors at the street-year level.

Table 1 summarises the main time-varying variables used in the empirical analysis for the beginning, midpoint, and end of the study period, reporting their mean and standard deviation. Housing price variables exhibit a pronounced temporal pattern across the three years. In 2011, prices remain relatively depressed in the aftermath of the financial crisis, and by 2015 they are still close to their lowest levels, with average values around 4,132 €/m^2 for sales and approximately 15 €/m^2 for rents. By 2019, however, both indicators have recovered substantially, reaching about 5,284 €/m^2 for sales and 20 €/m^2 for rents, thus surpassing pre-crisis levels. This evolution reflects a clear decline-and-recovery cycle, with substantial dispersion throughout the period, indicative of persistent heterogeneity across dwellings.

Table 1: Descriptive statistics: Eixample - Selected years

	2011	2015	2019
Housing prices			
Sales (€/m^2) - Mean (sd)	4,031.61 (1,407.92)	4,131.51 (4,005.60)	5,283.88 (2,080.34)
obs	2,483	3,878	4,024
Rents (€/m^2) - Mean (sd)	12.94 (4.01)	14.90 (7.44)	20.30 (9.36)
obs	2,354	3,364	2,542
Cycling infrastructure			
Bicing stations (#)	20	47	121
Cycle lanes (km)	28.03	30.88	42.84
Socio-demographics - BSA - Mean (sd)			
% Foreign population	18.06 (2.71)	18.72 (3.08)	23.67 (4.86)
% Population 20-35 yo	26.88 (1.96)	25.40 (1.59)	27.00 (2.79)
% Unemployed	8.43 (0.72)	7.07 (0.72)	5.15 (0.57)
% Population w/ university studies	36.04 (7.13)	41.57 (7.67)	45.21 (6.56)
Age	44.62 (1.05)	44.77 (0.88)	44.46 (0.98)
Household size	2.34 (0.08)	2.34 (0.06)	2.38 (0.10)
Population density (inh./m^2)	32,986 (12,281)	30,820 (13,297)	27,762 (14,018)
Relative household income	117.28 (22.09)	122.43 (27.76)	117.42 (13.37)

Notes: This table reports descriptive statistics of the Eixample district over select years of our sample. It shows mean and count values, as well as standard deviations in parentheses. Source: Idealista, City Council of Barcelona, OpenStreetMap.

The cycling infrastructure measures, including the length of cycle lanes and the number of Bicing stations, also display meaningful variation over time and across space, in line with the

expansion documented in Section 2. Additional descriptive statistics at the ring level are reported in Table B.1 in Appendix B.

By contrast, socio-demographic variables evolve more gradually over the same period. Indicators such as mean age, the share of individuals aged 20–35, the proportion of residents with university education, and the share of foreign population show only moderate changes across years. Overall, these variables remain relatively stable, consistent with the structural homogeneity of the Eixample, while still capturing limited but relevant variation in local population characteristics.

3.2 *Testing the assumption of quasi-random assignment*

Estimating the causal effects of infrastructure is inherently challenging, as its location is not random but typically reflects political, economic, and socio-demographic characteristics of the underlying area. This endogeneity complicates the identification of causal relationships between infrastructure provision and housing outcomes.

In this context, the grid-shaped layout of the Eixample district provides a particularly advantageous setting for identification. Streets in the area are highly uniform in terms of physical structure, housing characteristics, amenities, and resident composition, reducing cross-sectional heterogeneity that could otherwise confound the analysis.

Table 2: Characteristics of Eixample vs Rest of the districts, 2011

	Eixample			Rest of the districts (N = 9)		
District characteristics	Mean	SD	N. AEB	Mean(Mean)	Mean(SD)	Mean(N. AEB)
Socio-demographics						
% Foreign population	18.06	2.71	36	17.57	6.06	22
% Population 20-35 yo	26.88	1.96	36	26.70	3.39	22
% Unemployed	8.43	0.72	36	10.02	1.37	22
% Population w/ university studies	36.04	7.13	36	25.45	6.42	22
Age	44.62	1.05	36	43.07	2.04	22
Household size	2.34	0.08	36	2.50	0.21	22
Population density	32,650.76	12,968.30	36	26,638.29	16,522.57	22
Relative household Income	117.28	22.09	36	99.39	16.61	22
Urban features						
Mean street gradient	1.28	0.41	36	3.13	1.64	22
Mean street width	27.08	8.97	36	24.53	12.04	22
N. intersections/km^2	76.44	29.48	36	167.47	89.80	22
N. urban trees/km^2	3,100.88	629.00	36	2,329.77	1,079.70	22
N. metro stations	2.89	3.48	36	1.48	1.78	22
N. bus stations	11.47	6.57	36	14.05	11.48	22

Note: This table compares the Eixample to the rest of 9 districts in which the city of Barcelona is divided. It shows the within-district average and standard deviation in socio-demographic characteristics and urban features at the AEB level. N. AEB stands for the number of Basic Statistical Area contained in each district. Columns 5 to 7 report the average of within-district values. Source: Barcelona City Council and own elaboration.

Table 2 compares the characteristics of the Eixample with those of the rest of the districts in 2011. In addition to relatively small differences in mean values, the table shows that the dispersion of key variables, measured by their standard deviations, is substantially lower within the Eixample than across Barcelona as a whole, further underscoring the district's relative homogeneity.

We argue that the homogeneity of the Eixample in terms of shape and characteristics allows us to consider the timing and exact placement of the cycling infrastructure in this area to be as-good-as-random. In other words, orthogonal to price levels and trends. We perform a couple of exercises aimed at assessing the validity of these assumptions, which we describe in the next subsection.

We first look at whether there is a direct correlation between the construction of the cycling infrastructure and price levels or trends. If this was built where prices were already different than elsewhere or on a specific trend, our results would be biased. In order to test for this hypothesis, we estimate the following regressions at the street section level:

$$\mathbb{I}[\text{Treatment year} = t]_{st \leq \text{Treatment year}} = \alpha_0 + \alpha_1 \overline{\ln(\text{Price})_{st}} + \theta_s + \gamma_t + \epsilon_{st} \tag{2}$$

$$\mathbb{I}[\text{Treatment year} = t]_{st \leq \text{Treatment year}} = \alpha_0 + \alpha_1 \frac{\overline{\ln(\text{Price})_{st}}}{\overline{\ln(\text{Price})_{st-1}}} + \theta_s + \gamma_t + \epsilon_{st} \tag{3}$$

where s refers to each street section in the Eixample and t indicates the sample year. The treatment year is defined as the year in which the first Bicing station was open or the cycle lane was built on s. θ_s and γ_t are street section and year fixed effects, respectively. $\overline{\ln(\text{Price})_{st}}$ is the average log of price per square meter in street section s in year t. The coefficients α_1 indicate whether there is a relationship between the mean price level (2) or the price trend (3) and the placement of the infrastructure (binary indicator). We exclude the observations where the sample years is after the treatment year, as these would bear the treatment effect.

Figure 6: Correlation with prices

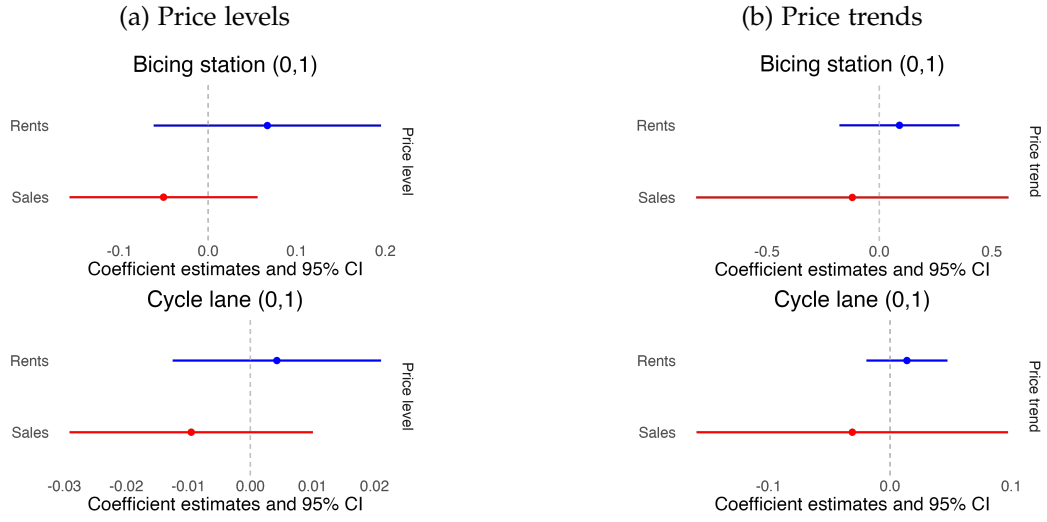


Figure 6 plots the estimation results. None of the estimated α_1 coefficients is statistically significant. We interpret these findings as evidence of the absence of a systematic correlation

between the location and timing of treatment and housing prices. This, in turn, supports the assumption that the evolution of cycling infrastructure can be treated as orthogonal to price dynamics.

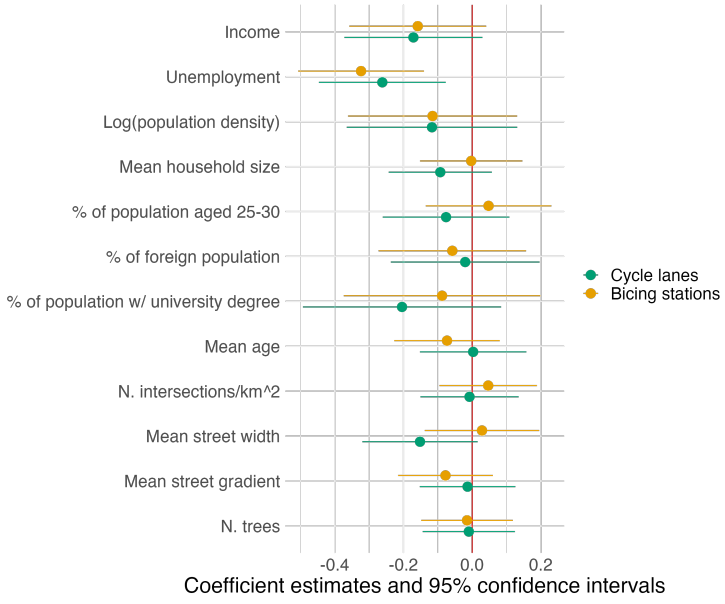
Although these previous results are reassuring, we further explore whether socio-demographic characteristics and urban features of the area explain the location and timing of the construction of the cycling infrastructure. Such sort of correlation could bias our results, as population characteristics would relate to both infrastructure and housing prices. It is important to control for urban features of the area, as these may play a role in the decision of where to place the infrastructure and correlate to socio-demographic characteristics. We perform this test at the BSA level, as this is the smallest geographic specification at which population data is available. We run the following regressions:

$$\text{Bikes}_{jt} = \delta_0 + \delta_1 \times \text{Socio-demographics}_{jt} + \beta_2 \times \text{Urban features}_j + \epsilon_{jt} \tag{4}$$

where Bikes denotes either the number of Bicing stations opened each year t in BSA j or the length of cycle lanes built. To account for differences in the size of BSAs, both outcome variables are normalized by the area of the corresponding unit.

We estimate the regressions separately for each type of infrastructure, with all explanatory variables standardized. The results are reported in Figure 7. Among the covariates considered, only unemployment is statistically significant: BSAs with higher unemployment levels experienced a lower expansion of cycling infrastructure between 2011 and 2019. It is important to note, however, that this variable, like income, is measured at the neighborhood level, which is more aggregated than the BSA classification. As a result, the estimated relationship may be subject to measurement error. While this limitation should be borne in mind, we account for it in the empirical analysis by including a comprehensive set of time-varying socio-demographic controls.

Figure 7: Correlation with socio-demographics and urban features



Lastly, we are confident excluding anticipation effects. We found no anecdotal evidence of public announcement of the location and timing of construction of the infrastructure. The cheap costs of construction and relatively easy construction works required made the development of the infrastructure very agile and left little space for anticipation.

4. Effects of cycling infrastructure on housing prices

We study the effects of cycling infrastructure on housing prices by estimating Equation (1). Tables 3 and 4 report the OLS estimation results. Columns 1 and 2 present specifications that separately include only one type of cycling infrastructure within the first ring (0–50 m): the number of Bicing stations and the length of cycle lanes, respectively. These specifications do not include control variables. Column 3 includes both types of cycling infrastructure within 50 m, while Column 4 additionally incorporates dwelling characteristics and BSA socio-demographic controls. Finally, Columns 5–9 progressively add concentric distance rings. Standard errors are clustered at the street-year level.

A comparison of column 3 with columns 1 and 2 indicates that jointly accounting for both types of cycling infrastructure does not materially alter the estimated coefficient for the first ring. Furthermore, the results remain robust to the inclusion of dwelling and BSA time-varying socio-demographic controls, as reported in Column 4.

Our preferred specification is reported in column 9 of Tables 3 and 4 and Figure 8. Interestingly, adding concentric rings reveals clear patterns over the distance gradient. For bike-sharing stations, the effects on sales prices are positive and statistically significant between 50 and 200 m, with the largest impact observed within the 50–100 m ring. The coefficient in this range suggests an increase of around 2.5% in sales prices for one additional station. These positive effects gradually decline with distance and become insignificant beyond 200 m. For rents, the impact of bike-sharing stations is more concentrated within shorter distances. While the effect within 50 m is not statistically significant, we observe positive and marginally significant effects between 50 and 100 m. Beyond this range, the pattern becomes more mixed, with no clear monotonic decay and some positive effects reappearing at 200–250 m.

For cycle lanes, the results display a more nuanced pattern. In both sales and rents, there is no statistically significant effect within immediate proximity. Positive effects emerge between 50 and 150 m. For sales, these positive effects are strongest within the 50–100 m ring, but are partly offset by negative effects between 150 and 200 m, resulting in a more ambiguous overall pattern. For rents, positive and statistically significant effects are observed between 50 and 150 m, with coefficients indicating that a 1% increase in cycle lane length raises rents by approximately 0.007%. However, these gains are partially offset by negative effects at greater distances, particularly between 200 and 250 m.

Table 3: Effects of cycling infrastructure on housing prices: Sales, 2011-2019

Dependent variable:	ln(Price (€/m^2))								
	OLS [1]	OLS [2]	OLS [3]	OLS [4]	OLS [5]	OLS [6]	OLS [7]	OLS [8]	OLS [9]
No. Bicing stations 50 m	0.0250		0.0034	0.0018	-0.0008	0.0162	0.0198	0.0189	0.0162
	(0.0170)		(0.0133)	(0.0128)	(0.0126)	(0.0134)	(0.0148)	(0.0149)	(0.0151)
No. Bicing stations 50-100 m					0.0137^c	0.0233^a	0.0248^a	0.0239^a	0.0248^a
					(0.0078)	(0.0086)	(0.0092)	(0.0092)	(0.0091)
No. Bicing stations 100-150 m						0.0095	0.0119^c	0.0124^c	0.0136^b
						(0.0060)	(0.0065)	(0.0064)	(0.0066)
No. Bicing stations 150-200 m							0.0066	0.0093^c	0.0100^b
							(0.0047)	(0.0050)	(0.0050)
No. Bicing stations 200-250 m								0.0043	0.0057
								(0.0044)	(0.0045)
No. Bicing stations 250-300 m									0.0032
									(0.0043)
log(km Cycle lanes 50 m)		0.0001	0.0001	-0.0006	-0.0016	-0.0023	-0.0021	-0.0028	-0.0026
		(0.0017)	(0.0017)	(0.0016)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
log(km Cycle lanes 50-100 m)					0.0035^b	0.0041^b	0.0049^b	0.0056^a	0.0056^a
					(0.0017)	(0.0018)	(0.0019)	(0.0019)	(0.0019)
log(km Cycle lanes 100-150 m)						-0.0015	0.0024	0.0034	0.0042
						(0.0023)	(0.0028)	(0.0027)	(0.0028)
log(km Cycle lanes 150-200 m)							-0.0066^b	-0.0058^c	-0.0061^c
							(0.0028)	(0.0031)	(0.0031)
log(km Cycle lanes 200-250 m)								-0.0019	-0.0008
								(0.0039)	(0.0048)
log(km Cycle lanes 250-300 m)									-0.0012
									(0.0077)
Adjusted R^2	0.434	0.512	0.512	0.561	0.580	0.580	0.588	0.587	0.590
Dwelling controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
BSA controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 31,450 observations. All regressions include Year and Street fixed-effects. Dwelling controls include size, condition, number of rooms, floor, whether the flat has air conditioning, a lift, a boxroom, and whether it is a studio or a penthouse. BSA controls include socio-demographic characteristics such as mean age, household size, income, population density, percentage of residents with university studies, foreign nationality, aged between 20 and 35, and unemployed. Clustered standard errors (at street section-year level) in parentheses ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

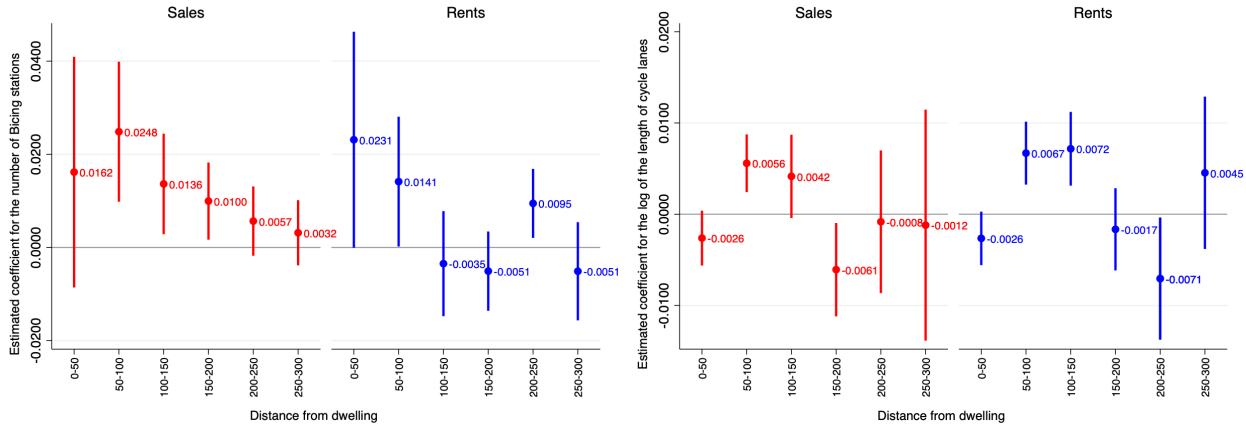
Table 4: Effects of cycling infrastructure on housing prices: Rents, 2011-2019

Dependent variable:	ln(Rents (€/m^2))								
	OLS [1]	OLS [2]	OLS [3]	OLS [4]	OLS [5]	OLS [6]	OLS [7]	OLS [8]	OLS [9]
No. Bicing stations 50 m	0.0315^b		0.0312^b	0.0236^c	0.0215	0.0215	0.0189	0.0213	0.0231
	(0.0141)		(0.0141)	(0.0137)	(0.0139)	(0.0132)	(0.0131)	(0.0135)	(0.0141)
No. Bicing stations 50-100 m					0.0097	0.0151^c	0.0142^c	0.0145^c	0.0141^c
					(0.0079)	(0.0081)	(0.0083)	(0.0083)	(0.0085)
No. Bicing stations 100-150 m						-0.0005	-0.0042	-0.0038	-0.0035
						(0.0063)	(0.0068)	(0.0068)	(0.0069)
No. Bicing stations 150-200 m							-0.0061	-0.0047	-0.0051
							(0.0048)	(0.0051)	(0.0052)
No. Bicing stations 200-250 m								0.0105^b	0.0095^b
								(0.0044)	(0.0045)
No. Bicing stations 250-300 m									-0.0051
									(0.0064)
log(km Cycle lanes 50 m)		0.0014	0.0013	-0.0002	-0.0027	-0.0039^b	-0.0033^c	-0.0027	-0.0026
		(0.0020)	(0.0020)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0018)
log(km Cycle lanes 50-100 m)					0.0054^a	0.0060^a	0.0066^a	0.0068^a	0.0067^a
					(0.0019)	(0.0020)	(0.0021)	(0.0021)	(0.0021)
log(km Cycle lanes 100-150 m)						0.0051^b	0.0067^a	0.0078^a	0.0072^a
						(0.0020)	(0.0023)	(0.0024)	(0.0025)
log(km Cycle lanes 150-200 m)							-0.0036	-0.0018	-0.0017
							(0.0024)	(0.0027)	(0.0027)
log(km Cycle lanes 200-250 m)								-0.0059^c	-0.0071^c
								(0.0035)	(0.0041)
log(km Cycle lanes 250-300 m)									0.0045
									(0.0051)
Adjusted R^2	0.377	0.376	0.377	0.521	0.511	0.512	0.514	0.514	0.515
Dwelling controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
BSA controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 31,450 observations. All regressions include Year and Street fixed-effects. Dwelling controls include size, condition, number of rooms, floor, whether the flat has air conditioning, a lift, a boxroom, and whether it is a studio or a penthouse. BSA controls include socio-demographic characteristics such as mean age, household size, income, population density, percentage of residents with university studies, foreign nationality, aged between 20 and 35, and unemployed. Clustered standard errors (at street section-year level) in parentheses ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

Figure 8: Effects of cycling infrastructure on housing prices: Results column 9 Tables 3 and 4

(a) Bicing stations (b) Cycle lanes



In order to provide a clearer idea of the importance of these effects, one should take into account the sample means presented in Table B.1 of Appendix B. On rents, the effect of bike-sharing stations within 50-100 m translates, given the sample means, to a 0.22€ per m^2 for each new station opened within this distance. Given the average size of rented flats (90 m^2), this amounts to 20€ per month. The effect of one extra station within 50-100 m translates into 114 € per m^2 on sales, amounting to 12,616€ for a flat of average size (111 m^2). However, the sample mean of the number of stations within these distances is 0.15. This implies that one extra station corresponds to roughly seven times the sample mean, respectively.

When considering the effect of doubling the number of bike-sharing stations within these distances, these coefficients translate to 0.14% on rents and 0.74% on sales when doubling stations within 50 - 100 m from the house. For a flat of average size, these amount to 1.97€ per monthly rents and 3,815€ for sales, respectively. As already mentioned, these effects decrease in magnitude with distance, but they are not statistically different from each other.

Doubling the extent of cycle lanes within 50 - 100 m implies a 0.67% increase in rents and a 0.56% increase in sales. For flats of average size, it translates into 9.4€ per month and 2,848€, respectively. As already mentioned, the effect of further cycle lanes is still positive on rents, before turning marginally negative or insignificantly different from zero. On sales, they offset the positive impact in closer proximity.

The reasons which may explain this change in sign could lie in the trade-off in allocation of space between driving and cycling. If the infrastructure implies less parking space or traffic displacement, these may negatively capitalize into housing prices. Unfortunately, we don't have access to complete data on traffic congestion. We have partial data on parking space from Albalate and Gragera (2020). However, the sample period of this data overlaps only partly with ours. We use the information to control for parking space within each ring and results do not change. Nevertheless, we are not able to draw solid conclusions which exclude the role of parking space as a mechanism. As the space required for cycle lanes is greater than what is required for bike-sharing stations, the trade-off is expected to be stronger. This may explain why we observe some negative results for cycle lanes but not for the bike-sharing stations.

Moreover, the trade-off could also explain why we don't find effects in the immediate proximity of the houses. If the redistribution of space towards cycling creates an amenity effect which is localized at the street section level, this first ring captures both the amenity and the connectivity factor, as well as the negative implications of the redistribution.

Overall, these results show that sales react more positively to Bicing stations than to cycle lanes, while the opposite is true for rents. What may rationalize these results is a trade-off in the allocation of public space which varies with the type of infrastructure, as well as with the preferences of residents. In other words, because the socio-demographic characteristics of renters tend to be different from buyers (renters tend to be younger and have lower income (Idealista.com, 2023), which may make them less likely to own and use a car as commuting mode), the cycling infrastructure may be more appealing to the former than the latter group. Therefore, given that cycle lanes have a higher trade-off in space, the willingness to pay for them may be higher for renters than for buyers, while the opposite may be true for the bike-sharing service.

Our results are very much in line with what is found by Shr et al. (2022) in Taiwan, who estimate an average premium of 2.6% on rents up to 150 m from a bike-sharing station but are much lower than what is estimated by Shang (2024) in Seattle, where cycle lanes increase housing prices by up to 5%. Through a bike market access approach based on cycle lanes built in Paris, Daniele et al. (2022) estimate an elasticity of 0.063 on sale prices. Our estimated elasticity is around ten times lower, but the two approaches are not directly comparable. The variability of these results demostrate the need for further research on what determines the capitalization of cycling infrastructure on housing prices.

5. Estimating bike traffic and its effects on housing prices

Not all parts of the cycling network are used with the same intensity. Streets are not all equally bike-friendly and have different relevance as connection links within the city (depending on their location relative to residential areas, job centers and amenities). Residents choose the most convenient bike route among a set of options based on their destination and the bike-friendliness of the route. This implies that the connectivity and the bike-friendliness of the street reflect into higher bike traffic. In order to explore whether these factors capitalize into housing prices, we use bike traffic as proxy.

While the City of Barcelona collects and publishes bike traffic counts which offer a precise measure on the number of users on bike lanes, their spatial coverage is limited to a small number of points. In order to obtain a measure of bike traffic which covers the entire street network, we estimate bike flows through a least cost path algorithm.

From the City Council of Barcelona we obtain a unique dataset on trips made by users of the Bicing in 2019. They contain origin-destination (OD) trips by hour and day (Wednesdays and Sundays) of each month. We use this data to obtain a measure of bike traffic over the whole cycling network of the city.

5.1 *Bike traffic*

We use a least cost path calculation in order to estimate the route taken by users of the Bicing service between each origin-destination (OD) pair we observe in the data. We choose a multimodal algorithm which is based on Open Street Map (OSM) and it allows the user to input historical networks[1]. We limit the estimation to the cycling mode and make use of the included measure of cycling Level of Traffic Stress (LTS)[2] to only include the set of streets where cyclists have dedicated lanes and only have to interact with traffic at intersections.

Figure 9: Estimated bike traffic on morning hours of working days

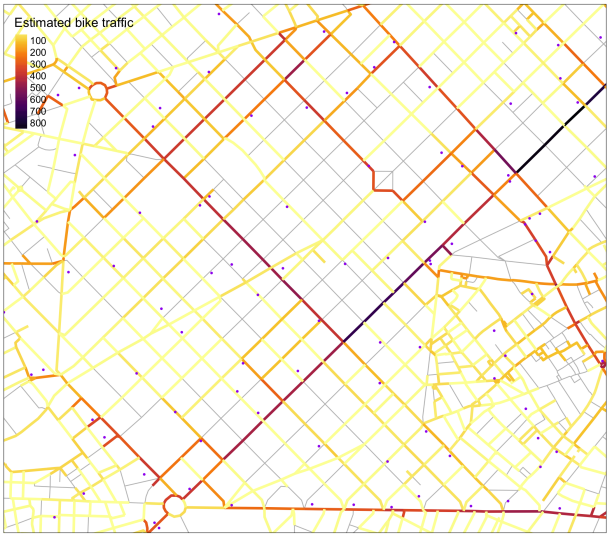


Figure 9 illustrates the output of the least cost path estimation aggregated at the street section level using 2019 averages for morning hours of a working day (Wednesday). On an average Wednesday of that year, around 40,000 trips were made using the Bicing service, of which 25,326 passed through the Eixample district, and just under 6,000 started between 7 and 10 a.m. The figure highlights the heterogeneity of cycling flows within the network, with higher concentrations observed along key corridors of the Eixample district.

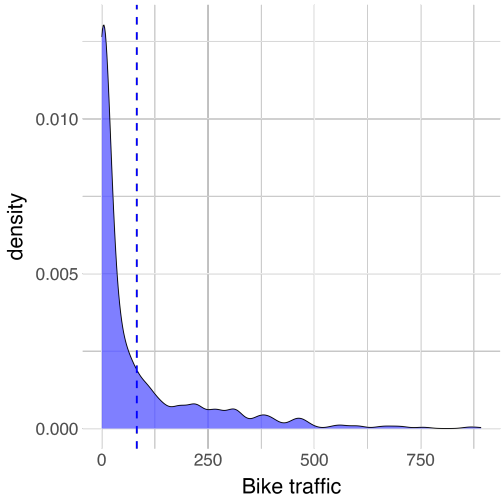
Figure 10 presents the corresponding distribution of estimated bike traffic at the street section level during these hours, revealing substantial variation in network use with a strongly right-skewed distribution. In total, 73% of street sections in the Eixample are traversed by bike trips

[1] In practice, the least cost paths calculations are done through the R package r5r developed by Pereira et al. (2021). r5r is an R package for rapid realistic routing in multimodal transport network (walk, bike, public transport and car) using Rapid Realistic Routing on Real-world and Reimagined (R^5) networks. It is a fast and open source routing engine developed by Conveyal. The `detailed_itineraries()` function returns realistic routing scenarios described by the distance traveled, the duration (by modal share, including waiting time), as well as the exact estimated itinerary.

[2] The Conveyal routing engine, on which the algorithm is based, includes a measure of cycling Level of Traffic Stress (LTS) which is applied to limit route selection to those streets which most riders would consider to be safe and more enjoyable (see details here). The LTS metric was first proposed by Mekuria et al. (2012). Based on tagged attributes of OSM ways, it classifies streets into 4 levels of traffic stress (1 representing the least stressful or safer conditions, 4 the most stressful or dangerous ones). `highway=` is the main key used in OSM to categorize any kind of road, street or path. It distinguishes ways by their function and importance within the road network as a whole. Table B.3 of Appendix B reports the description of the commonly used values of the tag. We set the maximum LTS level to 2.

in this time frame, with an average of 82 Bicing bikes per section, significantly higher than the citywide average of 20, reflecting the district's central location and high population density.

Figure 10: Distribution of estimated bike traffic on street sections of the Eixample



We validate the above estimation using bike traffic data released by the city of Barcelona. Over the whole city, there are around 250 counting points placed on cycle lanes. We aggregate traffic at the street section level and we compare the traffic counts detected by sensors to the estimated bike traffic. For this purpose, we limit the sample to sections with a traffic sensor within the whole street network of Barcelona.

Figure 11: Correlation between estimated traffic volumes and bike traffic counts

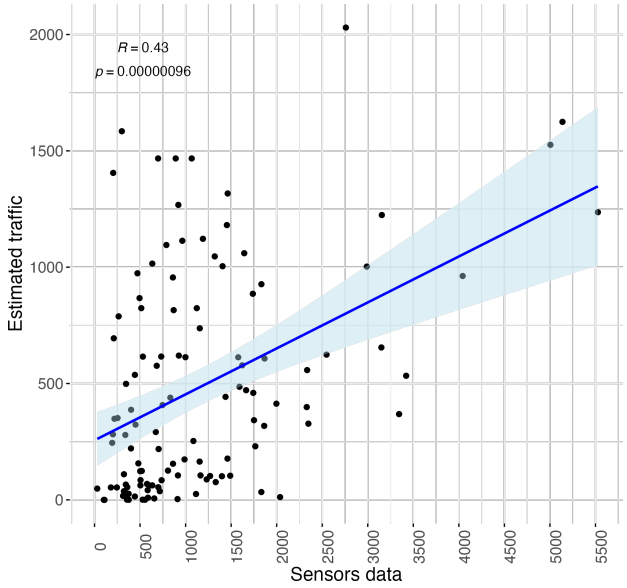


Figure 11 shows the significant correlation of 0.43 between the two measures. Within the sample we use for this test, the mean traffic volume on working days is of 1,154 and 484 as measured by the estimated shortest paths for Bicing trips and by the sensors, respectively. Taking

into account that the bike-sharing service is estimated to account for 35% of the bike trips, we consider our estimated bike flows as a good proxy for bike traffic.

This measure is a function of both cycling infrastructure (cycle lanes and Bicing stations), of the bike-friendliness of the infrastructure, and of its relevance as connection axis within the whole street network. Once the itineraries between each OD pair are computed, we create a measure of bike traffic within each ring around each house. We use an overlap with the estimated itineraries and then build a relative measure which compares each ring to the total of bike trips done in the city. This measure reflects the centrality of the local infrastructure with respect to all sets of route choices.

5.2 *Effects of bike traffic on housing prices*

To study the effects of bike traffic on housing prices, we estimate Equation (5):

$$\ln(\text{Price})_{is} = \beta_0 + \beta_1 \times \text{Traffic}_r + \beta_2 \times \text{Dwelling}_i + \theta_s + \epsilon_s \tag{5}$$

where Traffic_r refers to a relative measure of bike traffic within each ring r around dwelling i on street s. In particular, we compute the share of trips crossing each ring relative to the total number of bike trips across the city during the same time window. We compute 4 different versions of this variable using data for morning weekday trips (7am-10am Wednesday), weekday trips (24h Wednesday), weekend trips (24h Sunday) and Origin-Destination pairs. θ_s is a street section fixed-effect and standard errors are clustered at the street level. Since the analysis relies on a single year, we exclude year fixed effects and BSA socio-demographic controls.

Table 5 reports the OLS estimates of the effect of bike traffic intensity on housing prices in 2019, distinguishing between sales (columns 1-4) and rents (columns 5-8), and across the different measures of bike traffic: morning weekday (columns 1 and 5), weekday (columns 2 and 6), weekend (columns 3 and 7), and OD pairs (columns 4 and 8).

The results for property sales indicate a positive and statistically significant effect of the share of bike traffic on housing prices for distances of up to 250 meters, while the effects beyond this threshold are small and not statistically significant. The magnitude of the coefficients suggests that proximity to cycling infrastructure—particularly segments with higher connectivity and bike-friendliness, and thus greater traffic intensity—is capitalized into property values within a relatively local radius. This effect is especially pronounced in the 50–250 meter range. For instance, based on column 1, a 1% increase in the share of bike traffic within 50 meters of a property is associated with a 0.0353% increase in price per square meter. Interpreted differently, a doubling of bike traffic—approximately 130 additional cyclists according to Table B.2—would correspond to a 3.53% increase in transaction prices, equivalent to about 16,178€ for an average dwelling.

Results do not depend on the period in which traffic is measured. This implies that the effect is not driven by particular routes specific to commuting or leisure trips. The relatively large coefficient of Origin-Destination pairs indicates that a considerable part of the effect of bike traffic is explained by the variety of locations that the infrastructure connects, rather than by the volume of bikes riding those connections.

Table 5: Effects of bike traffic on housing prices, 2019

Dependent variable:	ln(Price (€/m^2))							
	Sales				Rents			
	Morning weekday	Weekday	Weekend	OD pairs	Morning weekday	Weekday	Weekend	OD pairs
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Share bike traffic 50 m	0.0353^b	0.0343^b	0.0353^b	0.0213^b	0.0156	0.0139	0.0151	0.0091
	(0.0137)	(0.0142)	(0.0150)	(0.0086)	(0.0197)	(0.0210)	(0.0241)	(0.0124)
Share bike traffic 50-100 m	0.0376^a	0.0379^a	0.0392^a	0.0238^a	0.0236	0.0188	0.0194	0.0137
	(0.0131)	(0.0138)	(0.0145)	(0.0083)	(0.0191)	(0.0199)	(0.0225)	(0.0117)
Share bike traffic 100-150 m	0.0348^a	0.0357^a	0.0372^a	0.0223^a	0.0304^c	0.0261	0.0286	0.0173
	(0.0124)	(0.0132)	(0.0140)	(0.0078)	(0.0178)	(0.0186)	(0.0213)	(0.0110)
Share bike traffic 150-200 m	0.0271^b	0.0258^b	0.0271^b	0.0161^b	0.0124	0.0095	0.0106	0.0059
	(0.0112)	(0.0119)	(0.0125)	(0.0070)	(0.0175)	(0.0181)	(0.0204)	(0.0105)
Share bike traffic 200-250 m	0.0296^a	0.0290^a	0.0304^a	0.0170^a	0.0092	0.0092	0.0109	0.0050
	(0.0085)	(0.0088)	(0.0094)	(0.0052)	(0.0141)	(0.0140)	(0.0156)	(0.0078)
Share bike traffic 250-300 m	0.0035	0.0017	0.0021	0.0001	-0.0035	-0.0075	-0.0079	-0.0052
	(0.0059)	(0.0060)	(0.0062)	(0.0035)	(0.0133)	(0.0132)	(0.0138)	(0.0077)
Adjusted R^2	0.679	0.679	0.679	0.679	0.630	0.630	0.630	0.631
Observations	4,214	4,214	4,214	4,214	2,099	2,099	2,099	2,099

Notes: All regressions include Street fixed-effects, and dwelling controls. Dwelling controls include size, condition, number of rooms, floor, whether the flat has air conditioning, a lift, a boxroom, and whether it is a studio or a penthouse. BSA controls include socio-demographic characteristics such as mean age, household size, income, population density, percentage of residents with university studies, foreign nationality, aged between 20 and 35, and unemployed. Clustered standard errors (at street section level) in parentheses ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

The relatively large magnitude of the estimated effect of bike traffic on sales prices compared to the effect of the infrastructure alone may be driven by three main factors. First, our measures of bike traffic capture not only the presence of cycling infrastructure—such as cycle lanes and Bicing stations—but also the bike-friendliness of the surrounding built environment and its connectivity within the broader street network. As such, it provides a more comprehensive and relevant proxy than simple infrastructure indicators, while also assigning greater weight to the most intensively used segments of the network. Second, higher observed traffic volumes may act as a credible signal to potential buyers of the effectiveness, usability, and success of the infrastructure. Third, given the substantial increase in the modal share of cycling over the sample period, it is plausible that the valuation of cycling infrastructure has risen over time. Focusing on the final year of the sample may therefore capture a relatively higher willingness to pay compared to the whole sample period.

In contrast, the results for rents are weaker and largely not statistically significant, although a positive and marginally significant effect is observed for bike traffic in the 100–150 meter range under the morning weekday specification. This may be explained by the fact that the bike-traffic is based on the usage of the bike-sharing service, which had statistically significant effects more

pronounced on sales than on rents. Overall, these findings suggest that the positive valuation of bike traffic is more strongly reflected in the sales market than in the rental market, and that the effect is spatially localized.

6. Conclusion

This paper studies whether and how the staggered construction of the cycling infrastructure capitalizes into housing prices. If focuses on the city of Barcelona, where the infrastructure significantly increased over the past years. It studies both cycle lanes and the public bike-sharing service of the city (Bicing). It focuses on a central area of the city of Barcelona, the district of the Eixample, where the timing and location of treatment can be considered quasi-random. We perform some validity tests to show that, within this area, the placement and the timing of the infrastructure is not related to housing prices nor to socio-demographic characteristics.

We follow a ring approach which accounts for spatial spillovers and intensity of treatment. Specifically, we construct concentric rings around each street section, extending in 50-meter increments up to 300 meters. The cycling infrastructure is defined as the length of cycle lanes and the number of Bicing stations which fall within each ring in the year in which the flat is listed. The results show that sales react more positively to Bicing stations than to cycle lanes, while the opposite is true for rents. We identify heterogeneous preferences by tenancy (renters vs buyers) and different intensity of trade-off in allocation of public space across the two infrastructure as factors possibly rationalizing the observed results.

More specifically, we observe (marginal) positive effects in the immediate proximity of the house (within 50 m) only for Bicing stations on rents. In the rest of the cases, the infrastructure starts having significant effects only beyond the 50 m. This may indicate a trade-off between costs and benefits of the infrastructure. On one hand, immediate access to the infrastructure may improve accessibility and induce an urban transformation at the street level. On the other hand, the redistribution of public space away from driving towards cycling may imply reduced parking availability and congestion or traffic displacement. While the amenity value generated by an urban transformation is very localized, accessibility, parking space and traffic displacement have broader spatial implications. Moreover, the last two factors depend on the space trade-off. As cycle lanes require more space redistribution than Bicing stations, their effect on parking space and traffic displacement is likely higher. This trade-off will be more or less relevant to residents, depending on their car and bike usage as modal share. In terms of magnitude, doubling the number of Bicing stations in close proximity induces a 0.23% increase in rents and a 0.75% increase in sales. Doubling the length of cycle lanes translates into 0.66% and 0.54% higher rents and sales, respectively.

The mere presence of cycling infrastructure does not fully reflect the intensity with which it is used. To better understand whether its impact depends on network connectivity and bike-friendliness, we estimate bike traffic across the entire cycling network using origin-destination data from the bike-sharing service. This approach provides a more comprehensive indicator of infrastructure relevance, encompassing both cycle lanes and Bicing stations.

Our findings indicate that doubling bike traffic in the immediate vicinity—equivalent to an increase of approximately 130 bikes—leads to a 3.53% increase in property sale prices. Notably, the magnitude of this effect grows with distance. However, we find no statistically significant effect on rental prices. The estimated effect of bike traffic is substantially larger than that of the infrastructure's physical presence. We interpret this difference as evidence that bike traffic serves as a more holistic measure of infrastructure potential. It emphasizes streets with high usage and may also signal to prospective buyers that the cycling environment is both functional and attractive. Additionally, the modal share of urban cycling increased substantially over the sample period. Given that our estimation focuses on the final year of the dataset, it is plausible that the valuation of the infrastructure at that time exceeds the average over the full period.

When compared to previous studies examining the capitalization of urban cycling infrastructure into housing prices, our estimates for the infrastructure effect are in line with what is estimated in Shr et al. (2022), but lower than those reported in Shang (2024), and Daniele et al. (2022). In contrast, our results for bike traffic are more in line with their findings. We attribute these differences to variations in the type and layout of the infrastructure examined. In our case, much of the cycling infrastructure had a relatively modest impact on the streetscape. Although it involved reallocating space from cars to bicycles, it did not entail major structural changes to the street itself. If the infrastructure assessed in other studies included more substantial street transformations, this could explain the higher estimated effects.

Furthermore, infrastructure implemented alongside broader urban interventions is generally more permanent. In Barcelona, the typical design of bike lanes is relatively minimal, relying on painted markings and simple physical separators that can be installed in a single day. While this approach is highly cost-effective, it also makes the infrastructure easier to remove. Compared to other forms of transportation infrastructure examined in the literature—such as metro rail stations (Gupta et al., 2022, Ahlfeldt et al., 2019, Gibbons and Machin, 2005), bus stops (Fan et al., 2021), and tramways (Garcia-López and Gómez-Hernández, 2024)—our capitalization estimates are naturally lower.

The policy implication of this paper is that the cycling infrastructure is overall positively valued by residents. However, there is a trade-off in the distribution of public space across modal shares which create costs and benefits which may vary with heterogeneous preferences. As the spatial distributions of benefits and costs is not homogeneous across distances, the net capitalization is complex. This once again shows that urban policies can have vaster effects than what may initially be anticipated. Moreover, the capitalization in housing prices does not seem sufficiently high to motivate the concerns of gentrification created by this kind of infrastructure. Therefore, cycling, as a sustainable transport mode, may help improving urban environments without generating a displacements of residents due to a gentrification process.

References

Ahlfeldt, G. M., Nitsch, V., and Wendland, N. (2019). Ease vs. noise: Long-run changes in the value of transport (dis)amenities. *Journal of Environmental Economics and Management*, 98:102268.

Albalate, D. and Gragera, A. (2020). The impact of curbside parking regulations on car ownership. *Regional Science and Urban Economics*, 81.

Baum-Snow, N. (2007). Did Highways Cause Suburbanization? *The Quarterly Journal of Economics*, 122(2):775–805.

Baum-Snow, N. (2026). Transport infrastructure and urban spatial structure. *Regional Science and Urban Economics*. Forthcoming.

Bernard, L. A. (2022). The impact of cycling segregated lanes on road users. *Processed, London School of Economics*.

Bhuyan, P., McCoy, E. J., Li, H., and Graham, D. J. (2021). Analysing the causal effect of London cycle superhighways on traffic congestion. *Processed, Imperial College London*.

Dahir, A. and Le, H. T. (2025). Impacts of bicycle facilities on residential property values in 11 us cities. *Journal of Transport Geography*, 123.

Daniele, F., Segu, M., Bounie, D., and Camara, Y. (2022). Bike-friendly cities: An opportunity for local businesses? Evidence from the city of Paris. *THEMA Working Paper 2022-09*.

Dippel, C., Gold, R., Heblich, S., and Pinto, R. (2021). The Effect of Trade on Workers and Voters. *The Economic Journal*, 132(641):199–217.

Estruch-Garcia, C., Solé-Ollé, A., Tassinari, F., and Viladecans-Marsal, E. (2025). The electoral effects of banning cars from the streets: Evidence from Barcelona's Superblocks. CEPR Discussion Paper 19925, Centre for Economic Policy Research.

Fan, Y., Teo, H. P., and Wan, W. X. (2021). Public transport, noise complaints, and housing: Evidence from sentiment analysis in Singapore. *Journal of Regional Science*, 61(3):570–596.

Garcia-López, M.-À. and Gómez-Hernández, L. Y. (2024). Housing prices, buses and trams in medellín (colombia). *Research in Transportation Economics*, 106:101464.

Garcia-López, M.-À., Sanchis-Guarner, R., and Viladecans-Marsal, E. (2026). Transportation and housing markets in cities. *Regional Science and Urban Economics*. In Press, Corrected Proof.

Gibbons, S. and Machin, S. (2005). Valuing rail access using transport innovations. *Journal of Urban Economics*, 57:148–169.

Gupta, A., Nieuwerburgh, S. V., and Kontokosta, C. (2022). Take the q train: Value capture of public infrastructure projects. *Journal of Urban Economics*, 129:103422.

Hendrich, T., Loumeau, N., Koster, H., Ommeren, J. V., and Koster, H. R. A. (2025). Cycling cities: Mode choice, car congestion, and urban structure. *CPB Discussion Paper*.

Idealista.com (2023). Housing demand survey - spain 2023.

Mekuria, M., Furth, P., and Nixon, H. (2012). Low-stress bicycling and network connectivity. Technical report, Mineta Transport Insitute.

Moovit (2019). Informe Moovit Global de Transporte Público 2019. Technical report, Moovit.

Pereira, R. H. M., Saraiva, M., Herszenhut, D., Braga, C. K. V., and Conway, M. W. (2021). r5r: Rapid realistic routing on multimodal transport networks with R^5 in r. *Findings*. Publisher: Network Design Lab.

Schrauth, P. (2022). The causal effect of cycling infrastructure on traffic and accidents: Evidence from pop-up bike lanes in berlin. *CEPA Discussion Paper*, DP No. 48.

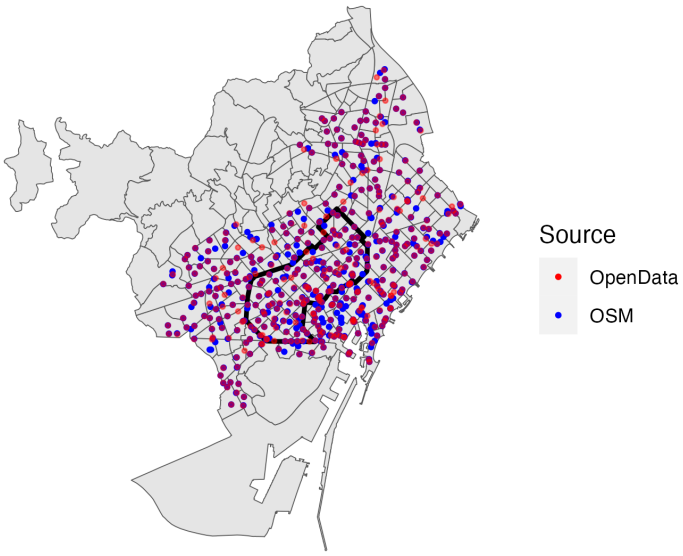
Shang, Z. (2024). Infrastructure or amenity: The role of bike lanes. *Working Paper*.

Shr, Y.-H. J., Yang, F.-A., and Chen, Y.-S. (2022). The housing market impacts of bicycle-sharing systems. *Regional Science and Urban Economics*, 98:103849.

Thorne, V. (2022). Cycling towards cleaner cities? evidence from new york city's bike share program. *Processed, Trinity College*.

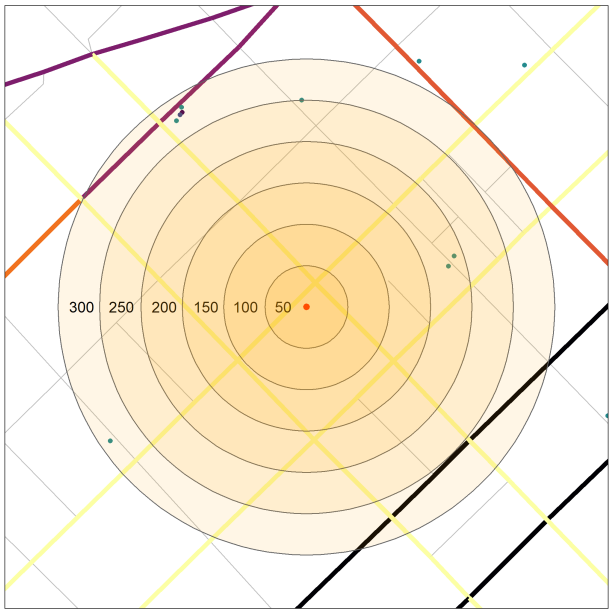
Appendix A. Figures

Figure A.1: Comparison of Bicing stations across data sources in 2019



Note: This maps compares the Bicing stations as reported by OpenStreetMap (OSM) and by the City Council of Barcelona (OpenData) in 2019. The Eixample district is highlighted in black. As the figure shows, the overlap between the two sources appear satisfactory. Our preferred source is OpenStreetMap, as it offers higher temporal coverage.

Figure A.2: Rings estimation



Note: This map illustrates the ring approach we follow. The red dot at the center of the map is a randomly chosen flat listed on Idealista. The colored lines in the background represent cycle lanes and the color indicates the year of construction. The gray lines are the streets without cycle lanes. The dots are the Bicing stations, colored by their opening year.

Appendix B. Tables

Table B.1: Descriptive statistics of rings (I): Cycling infrastructure

	2011	2015	2019	Full sample
Number of Bicing stations				
0-50 m	0.01	0.04	0.12	0.05
	(0.12)	(0.20)	(0.35)	(0.22)
50-100 m	0.04	0.12	0.34	0.15
	(0.20)	(0.36)	(0.56)	(0.40)
100-150 m	0.07	0.19	0.63	0.27
	(0.27)	(0.48)	(0.78)	(0.58)
150-200 m	0.10	0.28	0.83	0.37
	(0.35)	(0.57)	(0.88)	(0.69)
200-250 m	0.15	0.48	1.31	0.58
	(0.43)	(0.79)	(1.19)	(0.93)
250-300 m	0.11	0.41	1.13	0.49
	(0.38)	(0.75)	(1.14)	(0.85)
Length of Cycle lanes (m)				
0-50 m	30.91	35.12	45.00	36.90
	(46.33)	(48.14)	(55.60)	(50.20)
50-100 m	79.86	90.98	129.00	97.90
	(89.43)	(90.79)	(112.19)	(97.22)
100-150 m	150.06	167.36	215.08	177.06
	(129.34)	(128.45)	(137.34)	(132.87)
150-200 m	202.28	222.66	291.44	241.59
	(157.03)	(151.96)	(162.64)	(159.98)
200-250 m	294.34	337.59	450.35	361.72
	(193.26)	(197.88)	(213.90)	(207.76)
250-300 m	265.98	290.43	365.99	311.82
	(172.87)	(168.92)	(178.37)	(176.40)

Table B.2: Descriptive statistics of rings (II): 2019 Estimated Bike traffic

	Traffic	Origin-Destination pairs
Number		
0-50 m	131.78	2982.59
	(176.08)	(4225.60)
50-100 m	132.38	2788.22
	(175.23)	(3946.82)
100-150 m	133.38	2752.65
	(163.86)	(3857.15)
150-200 m	131.00	2731.57
	(159.32)	(3678.51)
200-250 m	155.24	3020.75
	(160.06)	(3734.96)
250-300 m	106.04	2105.28
	(126.61)	(2944.44)
Share (%)		
0-50 m	1.43	2.20
	(1.91)	(3.12)
50-100 m	1.44	2.06
	(1.90)	(2.91)
100-150 m	1.45	2.03
	(1.78)	(2.85)
150-200 m	1.42	2.02
	(1.73)	(2.71)
200-250 m	1.69	2.23
	(1.74)	(2.76)
250-300 m	1.15	1.55
	(1.38)	(2.17)

Note: This table reports descriptive statistics of the estimated bike traffic and distinct origin-destination (OD) pairs crossing each ring on an average working day (Wednesday) of 2019, during morning hours (7-10 am). The first panel reports absolute numbers. The second panel reports the share relative to the sum of all trips and distinct OD pairs travelled across the whole city during the same time period. Mean values and standard deviations are included in parenthesis. Source: OpenStreetMap, Pereira et al. (2021).

Table B.3: Open Street Map highway classifications

Motorway	A restricted access major divided highway, normally with 2 or more running lanes plus emergency hard shoulder.
Trunk	The next most important roads in a country's system that aren't motorways.
Primary	The next most important roads in a country's system (often link larger towns.)
Secondary	The next most important roads in a country's system (often link towns).
Tertiary	The next most important reads in a country's system (often link smaller towns and villages).
Unclassified	The least important through roads in a country's system; i.e. minor roads of a lower classification than tertiary, but which serve a purpose other than access to properties (often link villages and hamlets).
Residential	Roads which serve as an access to housing, without function of connecting settlements. Often lined with housing.
Living street	For residential streets where pedestrians have legal priority over cars, speeds are kept very low and where children are allowed to play on the street.
Service	For access roads to, or within an industrial estate, camp sit, business park, car park, alleys, etc.
Pedestrian	For roads used mainly/exclusively for pedestrians in shopping and some residential areas which may allow access by motorized vehicles only for very limited periods of the day.
Track	Roads for mostly agricultural or forestry uses.
Busway	A dedicated roadway for bus rapid transit systems.
Footway	For designated footpaths; i.e. mainly/exclusively for pedestrians.
Path	A non-specific path.
Cycleway	For designated cycleways.