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Do Bicycle Networks Have Economic Value? A Hedonic Application to Greater Manchester

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Abstract

Using hedonic and spatial regressions, this paper estimates much larger association between proximity to bicycle networks and house prices than previously reported. Given the challenges of congestion and pollution, many cities across the world are implementing policies to improve bicycling facilities and other active modes of transport. Bicycle lanes are a solution that could potentially provide significant amenities to residents, but they require investment and the appropriation of limited land. Drawing on a large dataset of approximately 253,000 transactions in Greater Manchester, over a 9-year period, we find that a 1 km reduction in distance to the nearest bicycle network is associated with property values being around 3.2% higher, on average, and 7.3% higher in the central borough of Manchester. We also provide an applied example to rank new bicycle routes by comparing their benefit-to-cost ratios.

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Highlights

- Hedonic pricing is used to quantify the association between house prices and bicycle lanes in Greater Manchester.
- The dataset contains 253,000 property sale observations over a 9-year period.
- Property value rises by 3.2%-7.3% when close to bicycle lane compared to properties 1km away.
- Spatial hedonic regressions and other alternative models and sub-samples arrive at a similar result.

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1 Introduction

This paper uses hedonic and spatial regressions to derive new estimates of the amenity value of bicycle networks for local neighborhoods. Our findings show that households have internalized the benefits of bicycling amenities, reflected by much higher property value in closer proximity to the network than previously thought. In the UK, this suggests an unmet demand for bicycling infrastructure.

Bicycling, as an active mode of travel enables communities to foster an environment that promotes physical and mental well-being, reduces emissions, alleviates traffic congestion and saves scarce resources. Healthier, happier, people lower the burden on health services and increase economic output (Lamu et al., 2021; Ma et al., 2021; Hafner et al., 2020; Brown et al., 2016). Bicycling generates vibrant and interconnected neighborhoods and encourages a sense of community interaction (Kim et al., 2017). In a natural experimental study in England, Goodman et al. (2013) show that incorporating town-wide cycling into urban planning raises its prevalence, with similar evidence from Barcelona in Spain (Cole-Hunter et al., 2015). These benefits vastly outweigh the risks from traffic injuries that would fall as bicycling numbers increase (Pucher et al., 2010) - a form of network effect (Ohler and Blanco, 2017).

Recognizing these benefits, in July 2020, the United Kingdom (UK) Government announced the "Cycling and Walking Revolution" as part of the government's efforts to improve infrastructure, enable people to choose cycling and walking for their daily commutes and short journeys, and help achieve the net-zero 2050 targets (GOV.UK, 2020c,a). £2 billion (bln) - over an unspecified number of years - was promised for dedicated bicycle lanes, storage, and walking infrastructure. Regrettably, little visible government action has taken place, and pales in comparison to the government investment in motorized infrastructure of £5 bln per year (on average) (ONS, 2022). More recently, the current UK government has halved previous cycling and walking budget commitments (Walker, 2023).

Arguments against bicycle infrastructure investment claim that cycling would not yield substantial returns compared to other transportation modes that have a broader reach and potentially greater benefits (e.g., including public transportation). Bicycle infrastructure may be underutilized because of its seasonal nature, commuters may not know how to ride a bike, have physical limitations, not feel safe on roads, and may need to carry heavy cargo not suitable for cycling. Other arguments are that cyclists are exposed to vehicle pollution that lowers health benefits, businesses reliant on automobile traffic may be negatively affected, and ongoing maintenance costs and potential disruptions to existing traffic patterns would further strain resources.[1]

Nonetheless, these arguments lack robust evidence and often appear intertwined with the prevailing polarized political climate surrounding climate change. Specifically, the financial justification against cycling infrastructure is not evidenced, even though financial assessments have been used. The most well-known method is Cost-Benefit Analysis (CBA) that has included diverse (and competing) transport modes, e.g., they evaluate bicycling as a potential substitute for car use. (See Krizec, 2007 as an early literature review that generally finds positive benefits from cycling.) More recently, CBAs have also included the health benefits and fuel saving from bicycling (Chapman et al., 2018; Fishman et al., 2015; Gotschi, 2011) and compare bicycle and car traffic by incorporating parameters such as: travel times, health, accidents, operation and maintenance cost, traffic noise, CO_2 and other

[1] See also https://www.cyclistshub.com/disadvantages-of-cycling/.

pollutant emissions. These studies generally agree that cycling is considerably less costly per-km-traveled than cars (Gössling and Choi, 2015) and may even generates external net-benefits (Gössling et al., 2019a; Meschik, 2012; Rabl and de Nazelle, 2012).

CBAs, however, have some weaknesses, primarily stemming from the subjective choice of model inputs and parameter calibration. Furthermore, they might vastly underestimate or omit non-market value, and struggle with time-horizon and equity issues. Other issues involve double counting effects and assuming that individuals have fixed preference (Parks and Gowdy, 2013; Gössling et al., 2019a).[2] Thus, CBA might not effectively quantify the value of bicycling infrastructure, might seem ad hoc and incorrectly quantify the non-marketed value.

Hence, some studies have instead used indirect methods to value bicycling infrastructure. One popular approach is Contingent Valuating Method (CVM) whereby consumers are asked specific questions to impute their Willingness to Pay (WTP) for a product, or Willingness to Accept (WTA) product removal, in a hypothetical market setup. For example, Gössling et al. (2019b) elicit estimates of the private cost that cyclist place on avoiding traffic risks, harmful emissions and noise pollution. CVMs, however, also have significant weaknesses including: irrational choice, higher WTP estimates without considering realistic budget constraints, individuals' lack of understanding of the policy or program, inconsistency between WTP and WTA (because loss matters more than gains), and arbitrariness of the estimation (e.g., "protest vote") (Parks and Gowdy, 2013).

In this paper, we use yet another indirect method - hedonic pricing with spatial regressions. This is an attractive approach because it uses observable market data on ordinary commodities (e.g., property market) as a proxy for inferring the monetary value of non-marketed objects such as bicycle networks. Many studies have already employed variants of Rosen (1974)'s hedonic pricing framework to test factors that influence property value. Common to most, they consider: (i) internal factors (e.g., size, age, quality of the property), (ii) external factors (e.g., location, surrounding amenities, transportation network, school quality and crime in the neighborhood), and (iii) other macro-economic factors.

We thus draw upon a very large body of related hedonic literature including, for example, proximity of property to subways and trains networks (Wang, 2017; McMillen and McDonald, 2004; Bajic, 1983), to canals, lakes and water bodies (Gibbons et al., 2021; Abbott and Allen Klaiber, 2013), and various types of open space and recreational facilities (Gibbons et al., 2014; Abbott and Klaiber, 2010; Asabere and Huffman, 2009; Cho et al., 2008; Crompton, 2001). Not all necessarily find a positive link, e.g., proximity to wind farms or neighborhood crime attracts negative value to property (Sunak and Madlener, 2017; Gibbons, 2015; Lynch and Rasmussen, 2001).

To our knowledge, only four studies have attempted to use hedonic methods to value bicycle networks: Liu and Shi (2017) and Welch et al. (2016) in Portland, Oregon, Krizek (2006) in Minneapolis, Minnesota and Ohler and Blanco (2017) in Bloomington, Illinois (all in the USA). These used a limited dataset of 8K to 35K observations. The first three find that properties close to a bicycle network gained 0.6%-1% in value compared to similar properties 1 km away, whilst the latter posits a rather more complex time sensitive relationship (i.e., an implied initial drop of almost 3% compared to similar properties 1 km away, but with value becoming positive over time due to network effect).

Our study uses a much larger sample of over 253K observations in a European country and finds a significantly larger positive estimate of amenity value than previous estimates. For example, across

[2]For example, cases where car ownership once symbolized social status are no longer the same as income increased, and a heightened environmental and health awareness spur greater demand for cycling as an alternative mode of transportation.

Greater Manchester (GM), properties gain 3.2% in value (compared to properties 1 km away) with some regional disparities. For example, in the borough of Manchester, it is as high as 7.3%. This should not be entirely surprising: the network effects identified by Ohler and Blanco (2017) are likely to already be present in our data, given the existing cycle network. Moreover, US cities tend to be less dense than their European counterparts and vehicle use is higher (both things that might imply, *ceteris paribus*, lower levels of amenity for cycle lanes).

Unfortunately, our data are limited in their ability to verify causality because we cannot be confident about when the cycle networks were created or substantially upgraded. This means that we cannot use natural experiments (e.g., Difference-in-Difference) to test whether the new bicycle infrastructure is the cause of a property value increase. One concern in this regard is that the results might be capturing the value of major roads adjacent to the bicycle network. To attempt to counter this, we performed various robustness checks that assess different models and subsets of the data, for example, applying spatial regressions find similar results. When we test bicycle networks with only traffic-free routes not adjacent to roads, we continue to find much stronger amenity value compared to previous studies. On average across GM, even in this more conservative case, properties gain 2.1% in value (compared to properties 1 km away), while in Manchester alone, the gain is as as high as 4.7%. Our findings support the claim that bicycling potentially delivers a much higher level of amenity than previously thought. We urge policymakers and property developers to integrate this infrastructure at the initial stages of design and fill the unmet demands.

In the following, Section 2 presents our methodological approach, Section 3 presents our data, and Section 4 the results. Finally, Section 5 provides an extension with application, to show how our results could be used by local policy makers to rank investment benefits.

2 Methodology

Whilst the primary justification for the estimation strategies adopted here is empirical, Rosen (1974) and subsequent works have developed a theoretical framework justifying our focus on hedonic prices and implicit markets, in which capitalization works through constrained utility maximization. Utility is assumed strictly concave, with x defined as all other goods consumed with price set to unity[3]

$$U(x, H) \tag{1}$$

A house H has a quoted market price and is associated by a vector of several physical and location attributes

$$H = H(Q, N, T, D) \tag{2}$$

whereby $Q(\cdot)$ is a function of house-specific quality attributes such as house type, environmental performance, floor area, number of rooms, new/old build and others. $N(\cdot)$ neighborhood location desirability attributes such as school quality, crime, socio-economic metrics, and locality specific features (e.g., neighborhood "charm", which may not be measurable or green space), and T time attribute. Finally, $D(\cdot)$ distance to bicycle networks is

[3]Due to Hicks, as long as the relative prices of all other consumption goods remain constant throughout the analysis, we can treat the entire bundle of all other consumption goods as a single numeraire composite commodity, x. Thus, since we are primarily interested in the trade-off between houses and all other goods, the only price variation that we focus on will be the house price (Gravelle and Rees, 2004).

$$D = D(d) \tag{3}$$

where d represents distance in meters to a bicycle network. House prices are expected to fall when the distance d is larger from a bicycle network $D_d < 0$, but at a marginally decreasing rate $D_{dd} > 0$ because, as distance rises, accessing a bicycle network gets harder overall. For example, house prices fall by less when distance rises from 5250 meters (m) and 5500 m compared to 250 m and 500 m.

Consumers' utility will be reflected by their revealed preferences and by their income level y_0, defined in terms of units of x. Furthermore, it is possible that a range of financial benefits/savings S may accrue to the consumer by cycling rather than driving. Savings will depend upon uncertain assumptions about future transportation cost inflation, behavioral patterns and appropriate discount rates. So, the individual's budget constraint can be written as $B + x - S = y$, with bid-rent

$$B(H; u, y_0) \tag{4}$$

the expenditure a consumer is willing to pay for H, at a given utility index and income, defined implicitly by

$$U(H, (y + S - B)) = u \tag{5}$$

Our question of interest is how much is a consumer willing to pay for a house with specific attributes, namely distance d from a bicycle network? Using any attribute of $H()$, the shape of the bid-rent function (4) is then represented by the partial derivatives of the house attributes. For example,

$$B_D = \frac{U_D}{U_x},\ B_u = -1/U_x,\ \text{and } B_y = 1 \tag{6}$$

with the slope B_D interpreted as the price a consumer is willing to pay for an incremental decrease in the distance of a house to a bicycle network. Assuming a strictly diminishing marginal rate of substitution, B will increase with a decrease in d, $B_d < 0$ because $D_d < 0$, but at a decreasing rate, $\frac{\partial^2 B}{\partial^2 d} > 0$. Thus, (4) can be estimated using regression techniques whereby our focus is on coefficient of each parameter from (6).

The problem is that there are several possible sources of bias that may impede the ability to estimate (4) consistently, i.e., subjective unobservable attributes correlated with the observed ones. A specific concern for us is that d could be correlated with N, including those factors that are not observable. For example, bicycle networks might be located near areas with more green space which is known to increase market desirability (Cho et al., 2008), or major roads which also have positive (or negative) amenity value. This unobserved heterogeneity has the potential to lead to significant omitted variable bias and is an issue to which we repeatedly return to later in the paper.

The end result of such unobserved neighborhood variation is a bias of indeterminate sign and magnitude. This problem is well recognized (Abbott and Klaiber, 2011), and has been dealt with in the literature primarily through the use of extensive control variables and spatial fixed effects to approximate neighborhood indicators. Unfortunately, whilst the inclusion of extensive control variables is a sensible strategy (and one which this paper pursues), it is possible that confounding due to omitted variable bias remains an issue even after the inclusion of multiple controls. Worse still, as spatial fixed effects become increasingly fine-grained they also become more collinear with distance from the cycle network (as the areas themselves shrink, within-area variation falls towards zero). Arguably the major challenge in estimation lies in seeking to mitigate this.

2.1 Estimation strategy and robustness

Assuming sufficient variability and liquidity in the housing market and well-behaved preferences among the population, house prices will be bid up or down according to these characteristics and will therefore capitalize into the value of the property. In this paper, we estimate (4) using a partially-linear, semi-log hedonic price function as a function of (i) distance to a bicycle network, (ii) house attributes, (iii) neighborhood attributes, and (iv) other attributes:

$$P_i = \beta_0 + \psi_1 d_i + \psi_2 d_i^2 + \boldsymbol{\beta' x_i} + \boldsymbol{\gamma' y_j} + \tau' t_i + \epsilon_i \tag{7}$$

where

P_i = natural logarithm of the sale price of house i;

d_i = the distance of each individual house i to its nearest bicycle network. Utility is expected to fall as bicycle networks are further away from a house, but at a decreasing rate, i.e., $\psi_1 < 0$ and $\psi_2 > 0$. The quadratic form works well empirically and can be conceptualised as a second-order Taylor expansion of a more flexible functional form;

x_i = vector of house specific attributes, e.g., new/old build, number of rooms, floor area, house type, environmental performance certificate (EPC);

y_j = a vector of neighborhood-attributes, indexed by j (i.e., a larger scale than individual houses). For example, we control for neighborhood school performance metrics, poverty index, crime, and National Statistics Socio-economic Classification (NS-SEC) as a proxy for income levels. In addition, we compute the 1999 average house prices of output areas (OA) to capture pre-bicycle lanes attributes that change more slowly over time, such as historical amenity value.

t_i = a dummy variable for the year of sale (equal to unity if the house was sold in that year and zero otherwise) to account for non-linear house price growth over the period. This also acts as a good proxy for wider macro-economic effects (e.g., interest rate variation). Finally, ϵ_i is a strictly exogenous stochastic error term.

The semi-log functional form is widely used in the literature and is preferred due to evidence that such simple functional forms tend to outperform more complex specifications in recovering marginal welfare effects when the hedonic price function is misspecified (Cropper et al., 1988) alongside the ease of interpretation of marginal effects within the framework. The principal empirical concern here lies in the presence of unobserved neighborhood effects, which violate the strict exogeneity assumption, non-spherical errors, or at least heteroskedastic ones that are a much more minor concern given that we use Huber-White robust standard errors (White, 1980).

Three strategies are adopted which lend some credibility and robustness to the results in the face of these concerns. Firstly, the vector of neighborhood-specific attributes is specifically designed to include variables that are widely believed to be closely linked to area desirability. Hence, multiple measures of local school quality are constructed, alongside average property prices for each neighborhood in 1999 (prior to the construction or upgrading of most cycle networks). The latter should be an effective proxy for unobserved variables linked to neighborhood desirability because these typically change slowly over time. Secondly, we ascertain whether our results change significantly following the inclusion of moderately coarse-grained spatial fixed effects. Finally, we derive and estimate several spatial panel models, which deliver very similar estimates to our core (OLS) hedonic model.

The latter is particularly important in light of evidence that models that include a spatial error covariance structure outperform simple OLS in the presence of spatially correlated omitted variables (Pace and LeSage, 2010; Conway et al., 2010). Since GIS coordinates for individual properties are unavailable, we construct a spatial panel by neighborhood based on the characteristics of the average property sold in that neighborhood in that year. Whilst this entails some loss of information, the large number of neighborhoods means that a large number of datapoints remain (a total of 67,941). We adopt a static panel specification, in which results are fully pooled (due to the fact that the bicycle networks themselves are one of the spatially-invariant fixed effects that we seek to recover) with time-specific effects and a spatially lagged dependent variables and errors (akin to the widely-used SAC model (Lesage, 2009). The intuition here is that unobserved location-specific variables are likely to cause house prices to be highly correlated with prices in nearby locations. Whilst this is expected to manifest via correlation through the error term (Elhorst, 2014), we also include a spatial lag of neighborhood house prices because we do not wish to rule out a prior that these might be - at least to a certain extent - jointly determined. Extending the hedonic model (7), we estimate a static spatial panel model of the form:

$$\begin{aligned}\bar{p}_{jt} &= \beta_0 + \psi_1 d_j + \psi_2 d_j^2 + \boldsymbol{\beta'} \boldsymbol{\bar{x}_{jt}} + \boldsymbol{\gamma'} \boldsymbol{y_j} + \tau' t_j + \lambda \boldsymbol{W} \boldsymbol{\bar{p}_t} + \epsilon_{it} \\ \epsilon_{jt} &= \rho \boldsymbol{W} \boldsymbol{\epsilon_t}\end{aligned} \tag{8}$$

In this case, $\bar{p}_{jt}$ is the average price of sold properties in neighbourhood j in year t. Similarly, $\bar{\boldsymbol{x}}_{jt}$ is a vector of average property characteristics (e.g., mean floor area, proportion of properties with each energy efficienty rating etc.) of neighbourhood j in year t. The remaining variables are as before, with the addition of $\lambda \boldsymbol{W} \boldsymbol{\bar{p}_t}$ the weighted spatially lagged dependent variables, λ is the spatial lag parameter, ρ is the spatial moving error term and W the spatial weighting matrix that characterize the relationship between output areas. In the absence of empirical evidence favouring an alternative specification, the same spatial weighting matrix was used for both the autoregressive and moving average components of the model. Errors are of the form suggested by Baltagi et al. (2003).

An attractive alternative would be to use Difference-in-Difference (DiD) estimation, which has been already used to link new infrastructure investments and property prices. For example, Kanasugi and Ushijima (2018) distinguish between the annoucement of the project in 2011 and the implementation in 2017 of a high speed train in Japan. Unfortunately, this is infeasible with the present dataset because of limited information about how cycle lanes were changed over time and when these changes occurred, as well as announcements around potential upgrades. This we plan to attempt in future work, if data become available.

3 Description of the data

3.1 A background to cycling in Greater Manchester

Greater Manchester (GM) is a substantial metropolitan area in the United Kingdom (UK) with a population of 2.87 million (mln) people. It spans over 1,277 km^2 and is the third most populous urban area in the UK after London and the West Midlands metropolitan area. Whilst direct comparisons are difficult, it is roughly similar in population to Chicago in the US or the Hamburg metropolitan area in Germany. Much of the local transport policy is devolved to the area's mayoral authority, which is tasked with setting policy, approving finances and implementing investments. Recent traffic growth has coincided with an effort to improve active transport to counteract this whilst concomitantly improving quality of life and hitting environmental targets. Thus, starting from 2008, Transport for Greater Manchester (TfGM - a sub-body tasked with implementation) began cataloging new and upgraded bicycle routes (TfGM, 2021). Between 2013 and 2018 some £9.5 million (mln) was invested into cycling infrastructure). The largest part of the investment centered on a 4.8 km stretch along the busiest corridor into Manchester that passes through the university area (GOV.UK, 2020b).[4]

A post-intervention count in 2018 assessed changes to bicycle volumes relative to a 2015 baseline and found that bicycle volumes between 0-3.2 km from the city center increased around 85%-175%, while journeys between 3.2-4.0 km from the center increased by around 104%-128%. Overall, in 2018, more than 1 million journeys were counted on the busiest route, with up to 5,000 trips daily. This equates to around 621 thousand of car journeys saved, and a potential reduction of up to 1.9 tonnes of nitrogen dioxide and 873.5 tonnes of carbon dioxide (GOV.UK, 2020b).

In 2018, GM announced their *Bee Network* vision for walking and cycling. This promises a £1.5 bln investment in cycling infrastructure, over 10 years, to create 1,800 miles cycling routes and 2,400 new crossings, in theory, connecting all neighborhoods, schools, high streets and public transport hubs in the region (TfGM, 2021, 2018).

3.2 Bicycle networks

We overlaid a GIS layer of bicycle networks onto the GM 10 boroughs, 221 Localities, 1673 lower layer super output areas (LSOA) and 8684 output areas (OA), set by the 2011 Census (ONS, 2021). Of these, 8573 output areas had at least one house sale during the period of our dataset.

TfGM provide GIS shapefiles with 3306 known bicycle lanes, characterized by eleven types (TfGM, 2021). Of these, we keep only those lanes which are physically segregated from motor vehicles: (type 4) segregated bicycle lanes and shared use footways adjacent to the carriageway, (type 5) traffic-free routes (not adjacent to road), e.g., converted railway line, and (type 11) on-road routes with physical segregation.

We omit on-road routes without physical segregation (type 3) due to evidence that finds cyclists prefer separated or traffic free bicycle lanes to on-road routes with no physical separation (Mitra et al., 2021). This is perhaps unsurprising in light of the BBC Panorama Report (2022) survey of 12,545 of UK drivers that finds that one in three drivers thought that cyclists should not be allowed to share public roads and should be restricted to bicycle paths only. Aldred (2013) studies the stigmatized

[4] £6 mln came from the UK central government's *Bicycle Cities Ambition Fund* and £3.5 mln from TfGM itself. GM was one of eight cities receiving this government fund from a small pot of £191 mln countrywide.

Table 1: Network Statistics

Network length	**No. of networks**	**Average network length (km)***
<0.5 km	118	0.23 km
0.5 - 0.75 km	35	0.63 km
0.75 - 1 km	19	0.88 km
Total removed	**172**	**0.39 km**
Bicycle networks in our sample		
1 - 2 km	42	1.44 km
2 - 5 km	32	3.17 km
>5	14	9.74 km
Total included	**88**	**3.39 km**
Total overall	260	1.40 km

* Bicycle networks are a collection of individual separated lanes. Within a network, the average gaps without a cycle lane is less than 2.5% on average.

dichotomous views British people have on bicyclists, i.e., either being the "competent" professionals (that use specialized gear), or the "incompetent" (those ignorantly commuting on the road, illegally, or unconcerned with their own or others' safety). With appropriate infrastructure, cycling would rise and channeled away from the most direct route to take advantage of these amenities, which are safer, healthier or more scenic (Gössling et al., 2019b; Liu and Shi, 2017; Welch et al., 2016; Krizek, 2006). Finally, (type 3) on-road cycle lanes are frequently located on major roads, which would act as a confounding variable, further strengthening the rationale for omitting them.

Canal towpaths, other unsurfaced cycle lanes and planned future lanes are also excluded. None of these meet a strict definition of cycle lanes that are likely to be suitable for commuting or recreation on a road-biased bicycle (although unsurfaced routes may be favored by non-road recreation cycling). Canals in particular would pose challenges for estimation given that they provide amenity value in their own right. They are shared with pedestrians, generally unpaved, and much narrower than a bicycle lane, thus limiting drastically the speed of the ride.

Imposing these conditions leads to 901 separate bicycle lanes. Many of these lanes are short and discontinuous, and hence bicycle lanes shorter than 100 m are removed, leaving 620 cycle lanes to be included.[5] We then define a "bicycle network" as a collection of bicycle lanes whereby a lane is included if it is within 100 m of the nearest cycle lane in that network. This leaves a series of 260 unique independent bicycle networks. We calculate that within a network, the average gaps without a bicycle lane are less than 2.5% on average. Finally, we remove all networks shorter than 1000 m because a typical urban cyclist could be expected to traverse these in under 4 minutes. We calculate that the mean length of these networks is less than 500 m, representing a 2-minute bicycle ride. We therefore end up with 88 bicycle networks. Table 1 summarizes their descriptive statistics: the shortest network is 1.03 km and the longest stretches 22.1 km.

3.3 House Attributes and proximity to bicycle networks

The bicycle network dataset is then merged with a novel dataset of residential housing transactions in England and Wales, comprising approximately 80% of all transactions from 2011 to 2019 (Chi et al., 2021). This rich dataset combines Land Registry Price Paid Data with property information from

[5]For example, in England, roads with no bicycle lanes might unexpectedly (randomly) have bicycle markings at a junction of around 20 m. We want to avoid including these types of lanes because they do form part of a "real" bicycle network.

Table 2: Greater Manchester descriptive statistics: price, sales and schools (2019)*

District	# of sales	Average property value, £2019	Median property value, £2019	Median distance to nearest bicycle network (km)	# of primary schools	# of secondary schools
Bolton	25,833	140,318	133,000	1.76	88	17
Bury	19,493	165,708	172,500	1.16	59	12
Manchester	39,503	169,824	170,000	0.53	123	25
Oldham	18,220	134,646	130,000	0.84	80	12
Rochdale	16,582	133,964	130,000	2.00	68	12
Salford	22,403	151,093	158,000	0.66	74	13
Stockport	34,719	219,230	225,000	0.95	76	13
Tameside	19,936	135,683	143,000	0.86	66	15
Trafford	26,249	281,109	285,000	1.09	53	19
Wigan	29,633	129,542	129,000	1.07	92	19
Total	252,571	170,871	163,000	0.95	779	157

* Results are provided for 2019 as this is the most recent year that our 2011-2019 data set covers.

the official Domestic Energy Performance Certificates (Chi et al., 2021), which includes information on property size (total floor area), number of rooms, and other important property-specific attributes likely to have a significant impact on transaction prices. The comprehensiveness and size of these data enable us to overcome a number of limitations that otherwise would have made calculation of these effects infeasible. For each property, the data includes sales price, sale date (2011-2019), postcode (the UK equivalent of a zip code) and output area details. Overall, the data for GM includes a total of 252,571 sales transactions between 2011-2019.

Table 2 provides the average sales price and number of sales by the ten metropolitan boroughs in GM and Table 3 summarizes the descriptive statistics. For example, the mean sale price for the combined 2011-2019 data is approximately £170 thousand (k). Most properties have between 3 to 7 rooms, with an average size of 89 square meters (m^2). Flats are more common in the city of Manchester compared to other locations.

Figure 1 shows the location of the 88 bicycle networks (in red) within the 10 boroughs (outlined in black). Output areas (OA) vary by color, proportional to average sale prices. The highest average prices are in the borough of Trafford (south-west of the metropolitan area). Figure 2 shows the location pattern of transactions and number of sales. As expected, more densely populated areas (towards the center of the urban area) saw higher sales compared to rural suburbs. Notwithstanding this, the data are relatively evenly clustered, with no obvious pattern between sales and bicycle network.

Unfortunately, our data do not include precise GPS coordinates and we cannot measure proximity of individual properties to the bicycle network. Our main results therefore use the GPS position of the centroid of each OA to calculate its shortest distance to a bicycle network. This means that we will be quantifying the amenity value of bicycle networks in terms of their proximity to neighborhoods j rather than specific properties as defined by (7). Table 4 reports that OA centroids are, on average, less than 218m from their edge (i.e., a radius with an area of 0.15 km^2), and that 75% of them have a radius smaller than 178m. These are very short distance for a cyclist to traverse. We also calculate that only 1.8% of all OAs have areas larger than $1km^2$ (i.e., a radius larger than 564m) and are located in the rural areas.

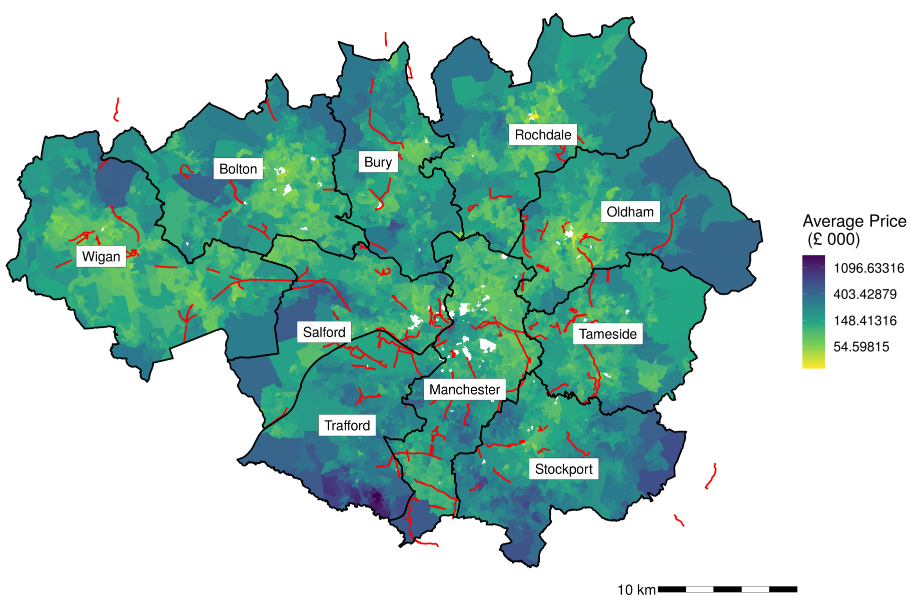
An alternative option that we also tested was to use postcodes. However, we found postcodes to be inferior to OA based measure because postcodes cover a considerably smaller number of properties,

Table 3: Greater Manchester descriptive statistics (2011-2019)

Variable	**Full Sample**	**Only Manchester**	**Excluding Manchester**
Average sales price, £	170,872	169,826	171,065
s.e.	*(126,511)*	*(110,227)*	*(129,304)*
Average area, m^2	89.2	83.1	90.3
s.e.	*(37.7)*	*(33.1)*	*(38.4)*
Average # of Rooms	4.6	4.2	4.7
s.e.	*(1.42)*	*(1.44)*	*(1.40)*
Property Type, % of total*			
Bungalow	8%	1%	9%
Detached house	11%	4%	13%
Semi-detached house	33%	28%	34%
Terraced house	36%	36%	36%
Flat	12%	32%	9%
Energy Performance Certificate (EPC), % of total*			
A/B	2%	5%	1%
C	24%	31%	23%
D	51%	44%	52%
E	19%	17%	19%
F/G	4%	4%	5%
Total	**252,571**	**39,503**	**213,068**

Standard error (s.e.) are in parenthesis. * Totals may not sum to 100% due to rounding.

Figure 1: House prices and bicycle networks in Greater Manchester



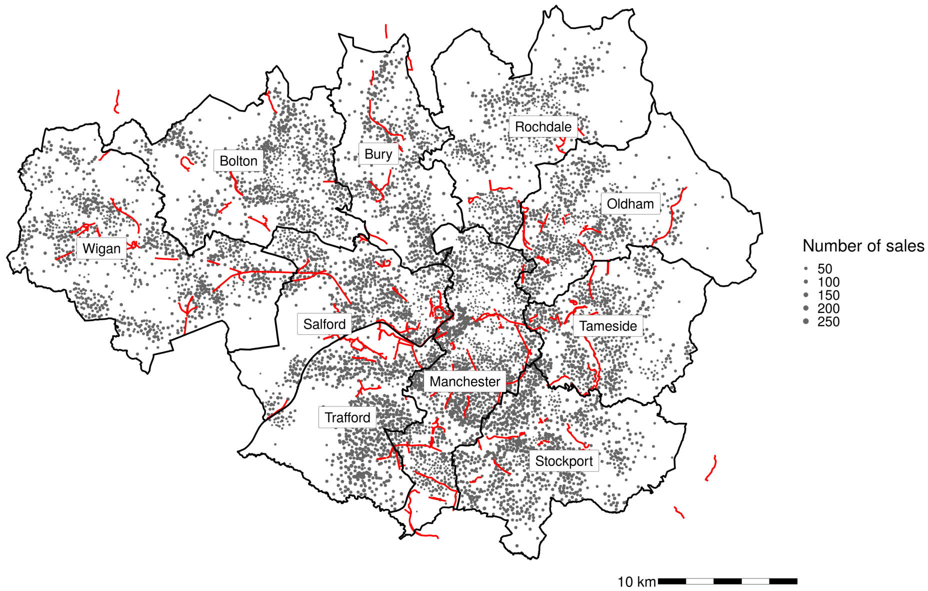
Note: Colours are on a logarithmic scale provided in the map legend.

Table 4: Size of an output area

	Min	Median	Mean	75% Quartile	Max
Radius m	20	138	218	178	2,821
Area km^2	0.0013	0.06	0.15	0.1	25

Note: The table summarizes the area (km^2) and centroid radius (m) of 8,573 output areas.

Figure 2: House sales and bicycle networks in Greater Manchester



do not necessarily represent a midpoint of an area, and postcode areas are often discontinuous. Finally, using postcodes made no appreciable difference to the results and, moreover, an OA measure is comparable to the spatial results introduced later in the paper.[6]

3.4 Neighborhood attributes

Next, we link additional neighborhood characteristics into the main dataset.

3.4.1 School quality as a proxy for neighborhood characteristics

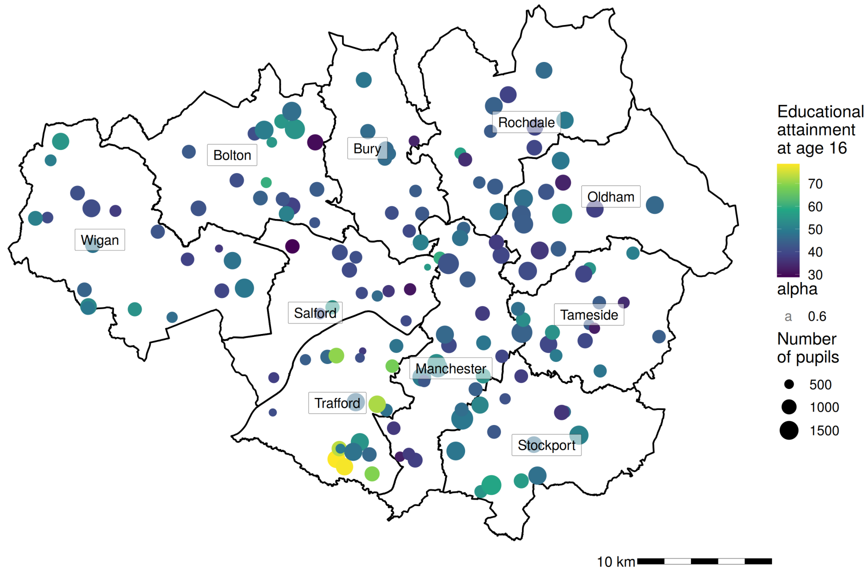
The quality of the school catchment area strongly correlates with neighborhood specific characteristics (Davidoff and Leigh, 2008; Downes and Zabel, 2002; Crone, 1998; GOV.UK, 2017). Schools can directly affect house prices because parents are willing to pay more to be in better school catchment areas. To capture these neighborhood-specific school characteristics, we compute an average of the schools' standardized test scores within a 2.5 km radius for primary schools (serving pupils aged 4-11), and 4.5 km for secondary schools (serving pupils aged 11-16)[7]. Furthermore, we remove small, specialized, schools (e.g., independent or community special schools) that do not reflect the local community of pupils, and keep only state-funded mainstream schools. Table 2 reports a total of 779 primary schools and 157 secondary schools in the Greater Manchester area.

To ensure an accurate comparison of school performance over time, the English education system assesses pupils at two main junction points: (i) At the end of primary school (typically aged 11), pupils take *Key Stage 2* (KS2) national curriculum tests in mathematics and English. We take the average

[6]Results based on postcodes are available in the online supplementary appendix.

[7]In the case where schools have greater demand than places available, distance is frequently used as a criterion to allocate places. Although there is no accepted customary radius used (as these vary from school-to-school and year-to-year depending on demand), these distances are the minimum (to the nearest 0.5 km) that ensure that all output areas incorporate at least one school's test scores into their average. They also accord with anecdotal parental perceptions.

Figure 3: Educational attainment scores in Greater Manchester's secondary schools



The figure shows all mainstream secondary schools in GM, with color reflecting the Attainment 8 score and size of circle proportional to the number of pupils per school.

of the two scores.[8] (ii) At the end of secondary school (typically aged 16), pupils are scored based on how well they perform in eight government approved qualifications, and the overall mark is provided by the *Attainment 8 score*.

Finally, to capture a measure of deprivation that might confound with schools catchment area quality, we control for the proportion of *Disadvantaged Pupils* among primary schools. Disadvantaged pupils are those who are either eligible for Free School Meals in the last 6 years (i.e., the biggest proportion), or have been looked after by the local authority in the past 6 months, or who have been adopted-from-care. Data for KS2, Attainment 8, and Disadvantaged Pupils is assembled for 2019 from GOV.UK (2023a).

3.4.2 National Statistics Socio-Economic Clasifications (NS-SEC)

From the 2011 census data, we incorporate the National Statistics Socio-Economic classification (NS-SEC) which has been constructed to measure the employment relations and conditions of occupations positions in modern societies, to explain variations in social behavior and other social phenomena. Collected every ten years, it measures the proportion of an output area's population in terms eight bands (ONS, 2022). To simplify, we aggregated these bands into two groups: (i) the top two bands make up white collar high-skilled jobs (e.g., lawyers, accountants and managers). (ii) The lower six bands are aggregated into all others.[9] By design, NS-SEC strongly correlates these two groups into different socio-economic characteristics such as income levels, education attainment, etc., and should be correlated with neighborhood variations across GM.

[8] Pupils obtain a scaled score between 80 to 120 which ensures an accurate comparisons of performance over time, per pupil and per school. Scores above 100 mean pupils have met expected standards, and above 110 have exceed expectations.

[9] The first group are the higher (band 1) and lower (band 2) of managerial, administrative and professional occupations. The second group (bands 3 to 8) are intermediate occupations, small employers, lower supervisory, semi-routine, routine and never worked.

3.4.3 1999 house prices and crime data

To capture additional unobserved long-run specific neighborhood characteristics (e.g., historically significant, exclusive) we include the average logarithm sales prices in 1999 per OA (GOV.UK, 2023c), which is before bicycle lanes were introduced to GM, and hence acts as an effective proxy for (non-cycling related) historical amenity value. Though these data are available back to 1995, they lack the detailed hedonic information we required and were not used further. Note that 6.7% of our post-2011 OA data could not be linked to this 1999 average house price data because some of the OA and postcodes have changed and/or no sales were recorded in 1999. In these cases, to avoid losing observations, a dummy variable for missing 1999 was coded.

Finally, we assemble data on crime in 2015 from the Police UK data archive (Police.UK, 2022). The raw data is provided monthly by type of crime: Anti-social behavior, Criminal damage and arson, Other theft, Vehicle crime, Violence and sexual offenses and Other crime.[10] The data includes location at the lower super output area (LSOA) with which we link to our main housing data set.

4 Results

We begin by fitting a standard hedonic model to the full set of observations and sub-samples following (7). We then provide additional robustness checks using a variety of different spatial regressions.

4.1 Main hedonic results

The results are presented in Table 5. The log of house price is explained as a function of (i) the distance from the bicycle networks - our main variable of interest, (ii) house attributes (whether a new build, house type, energy performance certificate (EPC), number of bedrooms and floor area, as well as the square of the latter two to capture nonlinearities), (iii) neighborhood attributes (Primary and Secondary school results, National Statistics Socio-Economic Clasifications (NS-SEC), Borough and Locality fixed effects, conurbation, log 1999 average output area house prices, a dummy for OAs missing data for 1999, and various crime attributes) and (iv) yearly time fixed effects. Using a semi-log functional form, the coefficients can be interpreted as the percent change of house prices while holding all others fixed. All coefficients have the expected signs and nearly all are statistically significant at less than 1%.[11]

The following eight model variations are reported in Table 5: (1) our main specification, (2) the main specification with 221 additional locality dummies, (3) only properties in Manchester, and (4) all other boroughs excluding Manchester. Models 5-8 reprise these (in the same order), but using only those bicycle lanes that are traffic-free routes to attempt to avoid the potential confounding amenity (or disamenity) value of significant roads[12]. These traffic-free networks make up 49.2% of the total bicycle network length in Greater Manchester (GM).

We begin with general observations and end with the main variables of interest. Focusing, for example, on model 1, it shows that being a *New Build* home raises property value by 13.5% - holding

[10]Other crimes include bicycle theft, burglary, drugs, possession of weapons, public order, robbery, shoplifting, theft from the person, and any other crime.

[11]We provide the full set of results for Table 5 and for all other model variations in the online supplementary appendix, e.g., postcodes instead of OA centroids.

[12]In the nomenclature of the dataset, we keep only type 5 lanes that are away from roads, and removed type 4 and type 11 - see Section 3.2

all else equal. With each additional *Bedroom*, property value rises by 11% but at a decreasing marginal rate (captured by the second polynomial). Similarly, *Floor Area* also raises property price, but at a decreasing marginal rate. As expected, bungalows (set as base) and detached homes are known to attract higher premiums, followed by Semi-detached, then Terraced and finally Flats. Finally, *EPC rating* shows a positive relationship with sale price (see full detail in the online appendix) - similar to findings by Cajias and Piazolo (2013) for Germany and Fuerst et al. (2015) for the UK.

At the neighbourhood level, school attainment has a significant positive association with property prices and these effects are powerful. To capture poverty in the local neighborhoods, we control for the proportion of pupils receiving free school meals. As might be anticipated, property prices are considerably lower near to schools with higher proportions of disadvantaged pupils. Second, at the level of output areas[13], the coefficient for NC-SEC shows a large statistically significant positive link between the socio-economic class and property price (i.e., a 1 percentage point increase in the proportion of the population in bands 1+2 raises property prices by 1.03%). We also control for log of 1999 average property price in output areas (plus a dummy for a modest number of output areas where these data are unavailable), which is statistically significant below 1% with the expected sign. These capture a large proportion of the neighborhood level specific characteristics. In models 2 and 6, we also include 221 dummy variables for each locality.

At the level of lower super output area, we control for various crime attributes, which are all statistically significant, whilst dummies for each borough indicate that Manchester, Stockport and Trafford attract the highest relative property prices, which is as expected. Finally, year dummies are included that capture inflation. For example, property prices in Greater Manchester rose on average by around 4% per year.

We now turn to our main variables of interest, property value as a function of its distance to a bicycle network. Holding all else equal, Table 5 reports a statistically significant reduction in property price as distance increases (see distance) but - as expected - at a marginally decreasing rate (see distance^2). Figure 4 illustrates the nonlinearity of this effect. Models 3 and 7 (which only include Manchester) are exceptions with an insignificant quadratic term, likely due to the reduced variation in distance to a cycle lane near the city centre. The median distance of the Manchester neighborhoods to the nearest cycle lane is only 0.53km compared to 0.95 km across the whole of GM (see statistics in Table 2).

For convenience, Appendix Table 7 calculates the impact that distance has on property value. Across GM (model 1), the property value of homes adjacent to a bicycle network is 3.2% higher than those 1 km away[14] - *ceteris paribus,* with some regional disparities. In Manchester Only (model 3), for example, the affect is highest at 7.3%, which we hypothesize is due to cycle networks being closer to major employment centers and therefore more valuable in a traffic congested environment. Note, however, that even outside this area, properties near a bicycle network attract a positive and significant premium (model 4).

These results are robust to specification changes, including distance from postcodes rather than output area centroids, removal of the minimum bicycle lane length criteria, and/or removed the minimum cycle network limitation of 1 km. In all cases estimates remain virtually the same. However, as might be expected, removing all bicycle networks shorter than 2 km (rather than 1 km) lowers the

[13]The ONS designates output areas and super output areas to roughly maintain a similar population density. Note that these do not correspond with the radius approach we used for schools.

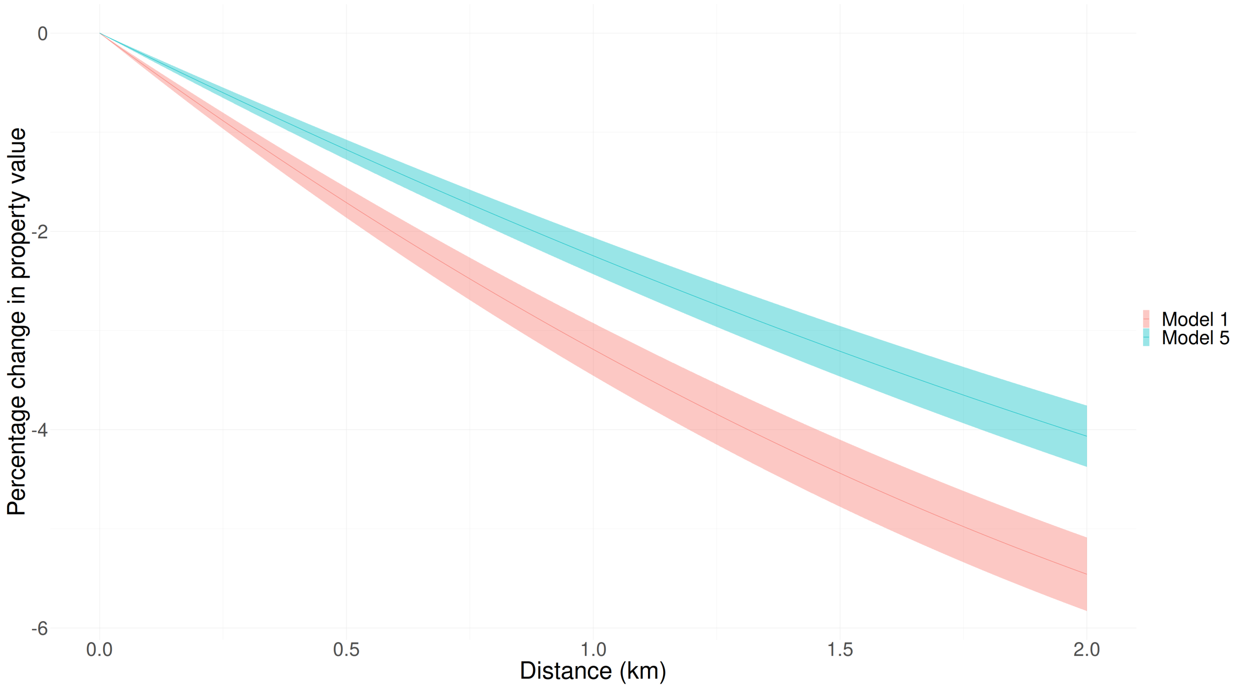
[14]i.e., $-0.0319 = -0.03651 \cdot 1km + 0.00461 \cdot (1km)^2$

Table 5: Results for the hedonic regressions (dependent variable: log of price)

	All networks				Only traffic-free (TF) networks			
	Full	Full with locality	Only Manchester	Exclud. Manchester	Traffic-free	Traffic-free locality	TF: Only Manchester	TF exclud. Manchester
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	6.07024***	5.30501***	2.88497***	7.02792***	6.24220***	5.36407 ***	1.87726 ***	7.15436 ***
	(0.06755)	*(0.08741)*	*(0.22636)*	*(0.07209)*	*(0.06765)*	*(0.08746)*	*(0.22309)*	*(0.07151)*
Distance (km)	-0.03651***	-0.04414***	-0.07554***	-0.01593***	-0.02280***	-0.03367***	-0.04493***	-0.00967***
	(0.00134)	*(0.00164)*	*(0.00624)*	*(0.00140)*	*(0.00077)*	*(0.00095)*	*(0.00523)*	*(0.00079)*
Distance^2 (km)	0.00461***	0.00597***	0.00225	0.00185***	0.00205***	0.00299 ***	-0.00236	0.00073 ***
	(0.00031)	*(0.00042)*	*(0.00214)*	*(0.00032)*	*(0.00010)*	*(0.00011)*	*(0.00170)*	*(0.00010)*
1. House attributes								
Old build	Base	Base	Base	Base	Base	Base	Base	Base
New build	0.13547***	0.13754***	0.05188***	0.21283***	0.13465***	0.13573***	0.04749***	0.21213***
	(0.00645)	*(0.00636)*	*(0.01029)*	*(0.00842)*	*(0.00646)*	*(0.00636)*	*(0.01031)*	*(0.00842)*
No. of rooms	0.10935***	0.11073***	0.13216***	0.10348***	0.10956***	0.11123***	0.13193 ***	0.10349 ***
	(0.00185)	*(0.00182)*	*(0.00502)*	*(0.00195)*	*(0.00185)*	*(0.00182)*	*(0.00503)*	*(0.00195)*
No. of rooms ^2	-0.00605***	-0.00618***	-0.00875***	-0.00537***	-0.00606***	-0.00622***	-0.00871***	-0.00537***
	(0.00016)	*(0.00016)*	*-0.00046*	*-0.00017*	*(0.00016)*	*(0.00016)*	*(0.00047)*	*(0.00017)*
Floor area (m^2)	0.00616***	0.00616***	0.00786***	0.00595***	0.00615***	0.00616***	0.00786***	0.00594***
	(0.00004)	*(0.00004)*	*(0.00012)*	*(0.00004)*	*(0.00004)*	*(0.00004)*	*(0.00012)*	*(0.00004)*
Floor area ^2	-0.00001***	-0.00001***	-0.00001***	-0.00001***	-0.00001***	-0.00001***	-0.00001***	-0.00001***
	<(0.00000)	*<(0.00000)*	*<(0.00000)*	*<(0.00000)*	*<(0.00000)*	*<(0.00000)*	*<(0.00000)*	*<(0.00000)*
Bungalow	Base	Base	Base	Base	Base	Base	Base	Base
Detached	-0.01933***	-0.01658***	0.02333	-0.00868***	-0.01954***	-0.01727***	0.02000	-0.00874***
	(0.00242)	*(0.00240)*	*(0.01542)*	*(0.00241)*	*(0.00242)*	*(0.00240)*	*(0.01545)*	*(0.00241)*
Semi-detached	-0.15892***	-0.16549***	-0.10027***	-0.15888***	-0.15848***	-0.16544***	-0.10779***	-0.15892***
	(0.00199)	*(0.00199)*	*(0.01387)*	*(0.00198)*	*(0.00199)*	*(0.00199)*	*(0.01391)*	*(0.00198)*
Terraced	-0.33692***	-0.34055***	-0.23426***	-0.34262***	-0.33629***	-0.34042***	-0.24105***	-0.34255***
	(0.00201)	*(0.00201)*	*(0.01379)*	*(0.00201)*	*(0.00201)*	*(0.00201)*	*(0.01383)*	*(0.00201)*
Flat	-0.40106***	-0.41470***	-0.2681 ***	-0.42958***	-0.40114***	-0.41590***	-0.27568***	-0.42983***
	(0.00267)	*(0.00266)*	*(0.01412)*	*(0.00284)*	*(0.00267)*	*(0.00266)*	*(0.01416)*	*(0.00284)*
EPC	YES	YES	YES	YES	YES	YES	YES	YES
2. Neighborhood attributes								
Secondary: Attainment 8 score	0.00561***	0.00505***	0.00913***	0.00469***	0.00514***	0.00500 ***	0.00842***	0.00444***
	(0.00023)	*(0.00035)*	*(0.00087)*	*(0.00024)*	*(0.00023)*	*(0.00035)*	*(0.00087)*	*(0.00023)*
Primary: KS2 score	0.02685***	0.03475***	0.05547***	0.01925***	0.02485 ***	0.03367***	0.06413***	0.01770***
	(0.00067)	*(0.00089)*	*(0.00237)*	*(0.00070)*	*(0.00067)*	*(0.00089)*	*(0.00234)*	*(0.00070)*
Disadvantaged pupils	-0.17896***	-0.16204***	-0.11654***	-0.20303***	-0.17867***	-0.16303***	-0.11597***	-0.20370***
	(0.00396)	*(0.00407)*	*(0.00965)*	*(0.00431)*	*(0.00396)*	*(0.00408)*	*(0.00970)*	*(0.00432)*
NS-Sec (bands 1+2)	1.03347***	1.01637***	1.14604 ***	0.93675***	1.03424***	1.01679***	1.14239***	0.93791***
	(0.00575)	*(0.00595)*	*(0.01190)*	*(0.00661)*	*(0.00575)*	*(0.00595)*	*(0.01192)*	*(0.00661)*
Locality	NO	YES	NO	NO	NO	YES	NO	NO
Log price 1999	YES	YES	YES	YES	YES	YES	YES	YES
Missing data for 1999	YES	YES	YES	YES	YES	YES	YES	YES
Crime	YES	YES	YES	YES	YES	YES	YES	YES
Borough	YES	YES	YES	YES	YES	YES	YES	YES
Major conurbation	YES	YES	YES	YES	YES	YES	YES	YES
3. Other attributes								
Year	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.81908	0.82504	0.78347	0.83156	0.81880	0.82508	0.78257	0.83151
Adj. R^2	0.81905	0.82485	0.78328	0.83152	0.81877	0.82490	0.78238	0.83148
Num. obs.	252,571	252,571	39,503	213,068	252,571	252,571	39,503	213,068

Standard errors (s.e.) are marked in italics. $*\ p < 5\%,\ **\ p < 1\%,\ ***\ p < 0.1\%$. Columns 1-4 include all types of bicycle lanes (types 4,5 and 11). Columns 5-8 are traffic free routes that exclude type 4 and 11.

Figure 4: Fall in house prices as distance from the cycle network rises



Note: The figure shows results for model 1 and model 5, based on Table 7. The percentage reduction in property value is non-linear as distance rises. Colors indicate the 99% confidence interval around the point estimate.

estimated amenity value slightly.[15]

How plausible are these findings? For a median property in 2019, a logarithmic approximation of model 1 implies a value of £5,200 (compared to properties 1 km away). As a back-of-the-envelope estimate, this is a willingeness-to-pay (WTP) of at least £350 per year (using the annuity formula with interest rate of $r = 3\%$ over 20 years). English commuters are, however, already prepared to pay at least £900 per year for an equivalent drive to a car park, or at least £500 for a local bus ride.[16]

Using the traffic free bicycle networks leads to smaller results (see Table 7 model 5). This is a conservative sub-sample aimed to minimize potential confounding effects of significant roads. Overall in GM, this sub-sample implies a property value gain of 2.1% (relative to 1 km away), which is a WTP of £227. These WTP seem therefore plausible and an undervaluation.

4.2 Spatial regressions

As noted, we have some concern around the possibility of unobserved neighborhood effects. Whilst this is undoubtedly mitigated by the presence of various census variables alongside our measures of school quality and crime (plus locality dummies), it is unlikely that these capture the entirety of what makes a neighborhood "desirable" or otherwise. Given that the desirability of neighborhoods is spatially correlated (i.e., more expensive locales tend to be clustered together and vice versa) and

[15] Full set of results and checks are provided in the online supplementary appendix.

[16] The annuity formula is $PMT = PV \frac{r}{1-1/(1+r)^n}$ with PV the present value of the amenity. We "roughly" assume an inexpensive car park fee of £7 per day, plus a bare minimum of £2 in fuel, over 100 days per year. Depending on location, a car park in Manchester could be as high as £30. An inexpensive local bus fair would be £5 per day (return) x 100 days.

that distance from a bicycle network is also spatially correlated by design, we have some concern over omitted variable bias.

We calculate Moran's I on the mean of all residuals (from the hedonic regression) for each output area. A Moran's I of 0.35 is statistically significantly different from the expected value, suggesting spatial autocorrelation amongst the residuals remains. This is also true for the model including 221 locality dummies (Moran's I of 0.29) reinforcing our concerns over unobserved spatial factors (notwithstanding the location-specific variables and our use of past log house prices). In an attempt to mitigate this, we test variants of spatial lag models (Pace and LeSage, 2010).

First, we calculate the mean (log) sale price for each output area, for each year, and do the same for property-specific independent variables that are measurable (e.g., total floor area, number of rooms, etc.). For categorical variables, whether ordered or unordered (e.g., property-type or energy efficiency) the proportion of total sales in each category within the output area, in each year, is included as a regressor. We are left with 67,941 observations, implying an average of around 4 sales in each output-area-by-year combination. Given this high level of granularity, many of the concerns over ecological regression (Robinson, 1950) do not apply (all the more so because we are interested in the impact of neighbourhood-specific effects on area averages rather than individual-specific effects). Since the panel is unbalanced (i.e., not all output area had a sale in each year), we performed multiple imputation and listwise deletion of missing values. For the imputation itself, the "Amelia" software package (Honaker et al., 2011) was employed. This uses a multivariate normal approximation to missing observations. Evidence shows that this is robust in a number of settings (Kropko et al., 2014) and far less computationally burdensome than conditional multiple imputation.

Several specifications were tested to assess the robustness of the results. The multiple imputation regression was re-run with a dummy for imputed observations and this was interacted with all temporally-varying effects so as to further minimise the impact of imputations on our estimates. This produced more reasonable results for certain house-specific variables (notably EPC and property type) but had minimal impact on our central results. Similarly, the results were calculated using listwise deletion in which output areas with any missing observations were completely removed. Naturally, this is inefficient relative to multiple imputation because a single year in which an output area lacks a sale entails removal of that output area for all years (even if sales are observed in all other years) to guarantee a balanced panel. With 9 years of data, 42,183 observations remained. The core results remained remarkably stable (and close to the hedonic regression results), giving us confidence in the sign and magnitude of the effects found.

The spatial error takes the form proposed by Baltagi et al. (2003) and our preferred model is multiple imputation approach with row-standardised weights (Table 6, model 1) which suggests that bicycle networks generate an amenity premium of around 3.7% per 1 km.[17] Note further that Row-standardized weights and unstandardised neighbour weights give very similar results (see models 1 and 2), which although unsurprising given the evidence of LeSage and Pace (2014) is nevertheless reassuring. As an additional robustness check, we run a series of cross-sectional spatial regressions on each year of the panel data (with around 7500 observations per year). Again, all results are statistically significant and of the same sign and similar magnitude. The results are shown in Appendix Table 8 (for row-standardized weights).

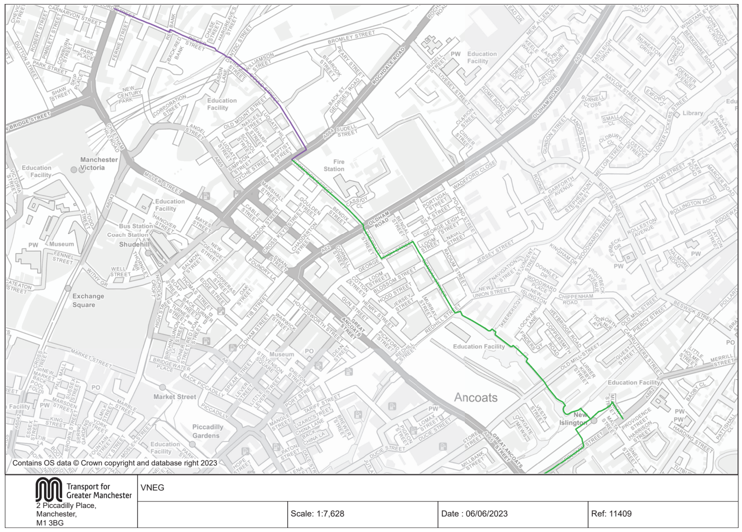
[17] $-0.03735 = -0.04302 \cdot 1km + 0.00567 \cdot (1km)^2$

Table 6: Results for spatial regressions (dependent variable: log of price)

	Multiple imputation		Listwise Deletion
Weighting	Row-standardized	Unstandardized	Row-standardized
	(1)	(2)	(3)
Intercept	5.17638***	5.18466 ***	4.99181***
	0.12826	0.13234	*0.15015*
Distance (1 km), ψ_1	-0.04302***	-0.04139***	-0.03060***
	0.00254	0.00276	*0.00312*
Distance^2, ψ_2	0.00567***	0.00537***	0.00373***
	0.00060	0.00066	*0.00073*
1. House attributes			
Old build	Base	Base	Base
New build	0.18005***	0.18624***	0.17567***
	0.02198	0.02197	*0.02331*
No. of rooms	0.11325***	0.11240***	0.11312***
	0.00410	0.00413	*0.00501*
No. of rooms^2	-0.00601***	-0.00600***	-0.00653***
	0.00037	0.00037	*0.00044*
Floor area (m^2)	0.00606***	0.00602***	0.00645***
	0.00009	0.00010	*0.00010*
Floor area (m^2)^2	--0.00001***	-0.00001***	-0.00001***
	<0.00000	0.0000002	*<0.00000*
Bungalow	Base	Base	Base
Detached	-0.03055***	-0.01746***	-0.03118***
	0.00525	0.00549	*0.00558*
Semi-detached	-0.16348***	-0.15780***	-0.15678***
	0.00417	0.00419	*0.00447*
Terraced	-0.33902***	-0.33699***	-0.35657***
	0.00414	0.00425	*0.00447*
Flat	-0.37876***	-0.37375***	-0.39437***
	0.00556	0.00556	*0.00645*
EPC	YES	YES	YES
2. Neighborhood attributes			
Secondary: Attainment 8 score	0.00630***	0.00725***	0.00513***
	0.00045	0.00048	*0.00053*
Primary: KS2 score	0.02545***	0.03599***	0.03781***
	0.00124	0.00132	*0.00149*
Disadvantaged pupils	-0.13316***	-0.17747***	-0.17625***
	0.00760	0.00742	*0.00810*
NS-Sec (bands 1+2)	0.89989***	0.96207***	0.82476***
	0.01039	0.01038	*0.01127*
Log price 1999, Missing data for 1999, Crime, Borough, Major conurbation	YES	YES	YES
3. Other attributes			
Year	YES	YES	YES
Dummies for imputed observations	YES	YES	
Spatial Auto-Correlation	0.10609***	0.00010 ***	0.00413***
	0.00547	0.00002	*0.00055*
Spatial Moving Average	0.25529***	0.05786 ***	0.33328***
	0.00950	0.00124	*0.00555*
Num. obs.	77148 (of which: 9207 imputed)	77148 (of which: 9207 imputed)	42183

Standard errors (s.e.) are marked in italics. $*\ p < 5\%,\ **\ p < 1\%,\ ***\ p < 0.1\%$. Listwise uses row-standardized weights.

Figure 5: Manchester Victoria Northern/Eastern Gateway (VNEG) scheme



Source: TfGM Active Travel Network Development and Design Assurance team with permission.

5 Policy implication, discussion and limitation

To illustrate some potential policy implications of our findings, we demonstrate how local authorities could apply Cost-Benefit Analysis (CBA) to rank investments. For instance, in the case of Manchester, we examine the recently approved £8.85 million investment by the Manchester Council for a new bicycle route known as the Manchester Victoria Northern/Eastern Gateway (VNEG) scheme. This new off-road bicycle lane runs from Roger Street in the Green Quarter, passing Islington Marina and through the Ancoats conservation area, to Pollard Street's junction with Great Ancoats Street. (Figure 5 sketches the route.)[18]

We estimate the project's total benefit by

$$= \sum_j V_j \cdot v_j \tag{9}$$

which is the sum-product of the total current property value V_j, in neighborhood j, with its corresponding percent change in property value v_j due to the VNEG investment.

V_j is computed by multiplying the average property value in each output area, sourced from the most recent year in our dataset (2019), by the number of private households in that neighborhood (which correlates extremely closely with the total dwelling stock) provided by the census (ONS, 2020).

From Table 6, column 1, we estimate the expected average percent change in property value for each output area by

$$v_j = \left(\psi_1 d_{1j} + \psi_2 d_{1j}^2\right) - \left(\psi_1 d_{0j} + \psi_2 d_{0j}^2\right) \tag{10}$$

with ψ_1 and ψ_2 the estimated coefficients for distance and distance^2, respectively, and d_{0j} and d_{1j} are the pre and post-VNEG distance of neighborhood j's centroid to its nearest bicycle network, respectively. Using (9) and (10), the total benefit comes out at £15.1 mln. When compared with a total

[18]This planned route and costing was provided to us by the Transport for Greater Manchester, Active Travel Network Development and Design Assurance team.

cost of £8.85 mln, the benefit-to-cost ratio is 1.72, clearly indicating that this is a beneficial project to its surrounding area. With additional data on other planned bicycle routes, we could rank them from highest to lowest ratio.

Note that a limitation of this approach is that it does not capture any network effect of bicycling infrastructure (as infrastructure becomes more dense, a greater range of destinations are feasible even for existing users). Finally, ranking investments based on CBA alone does not mean that projects are "fairly" funded because the beneficiaries do not bear most of the costs of the investment. Unlike many other parts of Europe, local governments in the UK (and particularly in England) have only very limited tax-raising powers. Since funding ultimately relies upon the central government, it is likely that local assets such as cycle networks will continue to be underfunded in the future. Our findings suggest that this lack of funding is a missed opportunity. Indeed, looking forward, Bigazzi and Wong (2020) note that electric bicycles displace a variety of other transport modes, increasingly including automotive trips which suggests that the amenity value of bicycle networks is likely to grow further.

6 Conclusion

Using a variety of hedonic regressions to estimate the potential amenity value of bicycle networks for local neighborhoods, this paper suggests that supporting such infrastructure is likely to be financially justified. Amid the polarized political environment, arguments against bicycle infrastructure investment often surface but lack robust empirical evidence. This paper uses observable market data in Greater Manchester to proxy the monetary value of being close to bicycle networks. Testing a variety of alternative models and specifications, including spatial regressions, we conclude that bicycle infrastructure provides benefits ranging from 2.2% to 3.8% of property value (compared to properties 1 km away), but that the benefits could be substantially higher in congested urban centres.

The principal limitation of this work lies in the difficulty of disentangling what causal relationships might exist given the probable presence of (unknown) unobservables. Future research will want to attempt to collect additional data in order to leverage the power of a difference-in-difference approach, notwithstanding the inevitable challenges of doing so. Nevertheless, these findings do suggest that appropriately designed and implemented cycle networks are of value and underscore the importance of integrating such infrastructure into urban planning, thereby also promoting sustainable living, reducing emissions, and fostering healthier and interconnected communities. They thus have critical implications for policymakers and property developers, particularly in the context of addressing the climate crisis and creating more livable urban environments.

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A Appendix

Table 7: The reduction in value of property by distance to bicycle network

	All networks				Only traffic-free (TF) networks			
Distance from network km	Full (1)	Full with locality (2)	Only Manch. (3)	Exclud. Manch. (4)	Traffic-free routes (5)	Traffic-free with locality (6)	TF: only Manch. (7)	TF exclud. Manch. (8)
0	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.25	-0.9%	-1.1%	-1.9%	-0.4%	-0.6%	-0.8%	-1.1%	-0.2%
0.5	-1.7%	-2.1%	-3.7%	-0.8%	-1.1%	-1.6%	-2.3%	-0.5%
0.75	-2.5%	-3.0%	-5.5%	-1.1%	-1.6%	-2.4%	-3.5%	-0.7%
1.0	-3.2%	-3.8%	-7.3%	-1.4%	-2.1%	-3.1%	-4.7%	-0.9%
1.25	-3.8%	-4.6%	-9.1%	-1.7%	-2.5%	-3.7%	-6.0%	-1.1%
1.5	-4.4%	-5.3%	-10.8%	-2.0%	-3.0%	-4.4%	-7.3%	-1.3%
1.75	-5.0%	-5.9%	-12.5%	-2.2%	-3.4%	-5.0%	-8.6%	-1.5%
2.0	-5.5%	-6.4%	-14.2%	-2.4%	-3.7%	-5.5%	-9.9%	-1.6%

The table summarizes the fall in property price by its corresponding increase in distance from the bicycle network. Columns 1-4 include all types of bicycle lanes (types 4,5 and 11). Columns 5-8 are traffic free routes that exclude type 4 and 11.

Table 8: Cross-sectional year-by-year spatial regressions (dependent variable: log of price, Row-standardized weights)

Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Intercept	6.25137***	5.67903***	5.77870***	5.29094***	4.91728***	4.94530***	5.04951 ***	5.38360 ***	5.71890 ***
	(0.42500)	(0.40193)	(0.39923)	(0.39316)	(0.39925)	(0.41021)	(0.40321)	(0.40884)	(0.41449)
Distance (1 km)	-0.02697**	-0.03529***	-0.03913***	-0.04029***	-0.04405***	-0.04012***	-0.04827 ***	-0.04329 ***	-0.03963 ***
	(0.00867)	(0.00810)	(0.00810)	(0.00816)	(0.00824)	(0.00858)	(0.00838)	(0.00847)	(0.00873)
Distance ^2	0.00435*	0.00568**	0.00589**	0.00552**	0.00635***	0.00525**	0.00701 ***	0.00660 ***	0.00499 *
	(0.00206)	(0.00189)	(0.00190)	(0.00193)	(0.00192)	(0.00201)	(0.00196)	(0.00198)	(0.00205)
1. House attributes									
Old build	Base	Base	Base	Base	Base	Base	Base	Base	Base
% Newbuild sales	0.23319***	0.19911***	0.13657*	0.16563***	0.15219**	0.26217***	-0.05598	0.20897	-0.07346
	(0.05545)	(0.04812)	(0.05576)	(0.04444)	(0.05437)	(0.07768)	(0.14363)	(0.23897)	(0.15266)
Average # of rooms	0.11917***	0.10433***	0.07345***	0.10684***	0.14018***	0.10239***	0.12544 ***	0.11551 ***	0.13704 ***
	(0.01321)	(0.01122)	(0.01311)	(0.01136)	(0.01142)	(0.01234)	(0.01229)	(0.00931)	(0.01074)
Average # of rooms ^2	-0.00549***	-0.00459***	-0.00218	-0.00670***	-0.00891***	-0.00575***	-0.00731 ***	-0.00632 ***	-0.00832 ***
	(0.00120)	(0.00097)	(0.00116)	(0.00103)	(0.00105)	(0.00113)	(0.00115)	(0.00077)	(0.00097)
Average floor area	0.00551***	0.00630***	0.00661***	0.00640***	0.00571***	0.00693***	0.00578 ***	0.00619 ***	0.00624 ***
	(0.00026)	(0.00030)	(0.00032)	(0.00024)	(0.00025)	(0.00027)	(0.00026)	(0.00024)	(0.00023)
Average floor area ^2	-0.00000***	-0.00001***	-0.00001***	-0.00001***	-0.00000***	-0.00001***	-0.00000 ***	-0.00001 ***	-0.00001 ***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Bungalow	Base	Base	Base	Base	Base	Base	Base	Base	Base
% Detached	-0.04292**	-0.06143***	-0.03417*	-0.02723	-0.00601	0.00435	-0.03264 *	-0.01763	-0.02257
	(0.01664)	(0.01561)	(0.01584)	(0.01441)	(0.01407)	(0.01401)	(0.01394)	(0.01439)	(0.01366)
% Semi-detached	-0.19306 ***	-0.20931***	-0.18162***	-0.18035***	-0.16123***	-0.14438***	-0.17768 ***	-0.17337 ***	-0.17555 ***
	(0.01312)	(0.01232)	(0.01251)	(0.01161)	(0.01137)	(0.01130)	(0.01114)	(0.01148)	(0.01073)
% Terraced	-0.36411***	-0.38529***	-0.34827***	-0.35344***	-0.34742***	-0.33026 ***	-0.37048 ***	-0.35452 ***	-0.36703 ***
	(0.01319)	(0.01245)	(0.01242)	(0.01147)	(0.01121)	(0.01117)	(0.01112)	(0.01137)	(0.01072)
% Flats	-0.35941***	-0.36846***	-0.38425***	-0.41195***	-0.43305***	-0.41376***	-0.42662 ***	-0.43992 ***	-0.47073 ***
	(0.01783)	(0.01696)	(0.01698)	(0.01588)	(0.01516)	(0.01512)	(0.01489)	(0.01482)	(0.01468)
% with each EPC	YES	YES	YES	YES	YES	YES	YES	YES	YES
2. Neighborhood attributes									
Secondary:	0.00560***	0.00553***	0.00624***	0.00626***	0.00744***	0.00864***	0.00764 ***	0.00678 ***	0.00650 ***
Attainment 8 score	(0.00151)	(0.00142)	(0.00142)	(0.00143)	(0.00144)	(0.00150)	(0.00148)	(0.00149)	(0.00151)
Primary: KS2 score	0.02623 ***	0.03065***	0.02793***	0.03444***	0.03907***	0.03977***	0.03967 ***	0.03886 ***	0.03528 ***
	(0.00426)	(0.00403)	(0.00399)	(0.00397)	(0.00403)	(0.00413)	(0.00406)	(0.00411)	(0.00415)
Disadvantaged pupils	-0.18106***	-0.17121***	-0.21564***	-0.17485***	-0.16732***	-0.17350***	-0.17451 ***	-0.15173 ***	-0.16489 ***
	(0.02344)	(0.02221)	(0.02177)	(0.02046)	(0.02015)	(0.01999)	(0.01996)	(0.01999)	(0.02100)
NS-Sec (bands 1+2)	1.01886 ***	0.98271***	0.95014***	0.93417***	0.89297***	0.91533***	0.85405 ***	0.83577 ***	0.84753 ***
	(0.03314)	(0.03098)	(0.03062)	(0.02788)	(0.02678)	(0.02641)	(0.02670)	(0.02637)	(0.02805)
Log price 1999	YES	YES	YES	YES	YES	YES	YES	YES	YES
Missing data for 1999	YES	YES	YES	YES	YES	YES	YES	YES	YES
Crime	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borough	YES	YES	YES	YES	YES	YES	YES	YES	YES
Major conurbation	YES	YES	YES	YES	YES	YES	YES	YES	YES
Auto-Correlation	0.00591	0.01830***	0.02758***	0.02258***	0.01675***	0.01929***	0.01519 **	0.00880 *	0.02141 ***
	(0.00397)	(0.00418)	(0.00499)	(0.00530)	(0.00473)	(0.00460)	(0.00487)	(0.00432)	(0.00336)
Moving Average	0.23077***	0.24995***	0.26673***	0.37188***	0.43608***	0.48073***	0.46071 ***	0.47178 ***	0.43484 ***
	(0.01688)	(0.01671)	(0.01669)	(0.01561)	(0.01468)	(0.01400)	(0.01433)	(0.01403)	(0.01441)
Num. obs.	7146	7085	7459	7768	7706	7808	7828	7810	7340
Parameters	41	41	41	41	41	41	41	41	41
Log Likelihood	1066.97459	1590.20093	1656.66315	2508.08703	2930.69431	3097.08937	3057.05393	3069.22482	2603.44791
AIC (Linear model)	-1866.27608	-2833.00590	-2895.98223	-4353.01790	-5005.67764	-5105.37999	-5122.71637	-5107.63600	-4252.44064
AIC (Spatial model)	-2051.94919	-3098.40187	-3231.32630	-4934.17405	-5779.38862	-6112.17875	-6032.10785	-6056.44965	-5124.89582
LR test: statistic	189.67310	269.39597	339.34408	585.15615	777.71098	1010.79876	913.39148	952.81365	876.45518
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Standard errors (s.e.) are marked in italics. $* p < 5\%$, $** \ p < 1\%$, $*** p < 0.1\%$.

Supplementary online appendix

The supplementary online appendix is an Excel file that has a full set of results of all covariates and of various combinations of bicycle network lengths, usage of postcodes, etc.