The Amenity Value of Bicycle Infrastructure: A Hedonic Application to Greater Manchester, UK

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Abstract

Using hedonic and spatial regressions, this paper estimates a significantly larger association between proximity to bicycle networks and property prices than previously reported. As cities face increasing challenges of congestion and pollution, many are implementing policies to integrate bicycle facilities and other active modes of transport. However, policymakers are slow to support these initiatives and remain skeptical due to the investment costs required and appropriation of limited land. Drawing on a large dataset of approximately 253,000 transactions in Greater Manchester, over a 9-year period, we find clear evidenced that a 1 km reduction in distance to the nearest bicycle network is associated with property values being around 2.8% higher, on average, and 7.7% 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 and a discussion on the property tax system.

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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 2.8%-7.7% 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 panel regressions with multiple imputation to derive new estimates of the amenity value of bicycle networks for local neighborhoods. We provide robust evidence that households have internalized the benefits of bicycling amenities, reflected by significantly higher property value in closer proximity to the network than previously thought. In the United Kingdom (UK), this suggests an unmet demand for bicycling infrastructure: one that property developers and policymakers are not yet aware of.

We build upon a modest literature that uses hedonic models to quantify the impact of bicycling facilities on local house prices. We contribute to this literature in several important ways. Compared to previous studies, we use a much larger sample of over 253K observations and are the first to report on a European country. Another contribution lies in the use of spatial panel models alongside multiple imputation to ensure a balanced panel. We confirm and extend on findings from the North American literature, but we report significantly larger positive estimate of amenity value. This should not be entirely surprising: the *network effects* of bicycle networks, discussed by Ohler and Blanco (2017), are likely to already be present in our data, given the existing cycle network. Moreover, cities in the USA are generally less dense than their European counterparts and vehicle use is higher (both things that might imply lower levels of amenity for cycle lanes).

We find that across Greater Manchester (GM), properties gain 2.8% in value (compared to properties 1 km away) with some regional disparities, e.g., in the borough of Manchester, it is as high as 7.7%. In comparison, in the USA, Liu and Shi (2017); Welch et al. (2016) in Portland, Oregon, Krizek (2006) in Minneapolis, Minnesota and Ohler and Blanco (2017) in Bloomington, Illinois, use much smaller datasets of 8K to 35K observations and older by a decade. These find that properties close to a bicycle network gained 0.6%-1% in value compared to similar properties 1 km away, whilst Ohler and Blanco (2017) 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). In a recent paper, Conrow et al. (2021) collects data on 5200 homes in Tempe, Arizona-USA, and finds that improvements in the density of bicycle facilities had a significant positive impact on house prices. We instead focus on distance from the network rather than the density thereof.

We also test several alternative measures and network definitions, but find that our core findings are preserved. Furthermore, we are concerned with possible collinearity between some bicycle lanes and major roads adjacent to them. As a robustness check, to attempt to counter this, we repeated the regressions excluding these lanes (i.e., only traffic-free routes not adjacent to roads), but continue to find much stronger amenity value compared to previous studies. On average across GM, even in this more conservative case, properties gain 1.4% in value (compared to properties 1 km away), while in Manchester alone, the gain is as as high as 3.5%. Our findings support the claim that bicycling potentially delivers a much higher level of amenity than previously thought.

Finally, another major issue is the usual endogeneity problem due to omitted variable bias, which because of our geographical setup, could be magnified several times over by spatial autocorrelation (Pace and LeSage, 2010). Indeed, we test and find evidence of residual spatial correlation in house prices, and therefore use various computationally intensive spatial panel models to ameliorate the issue. We report no major change from our overall findings.

The paper concludes with two discussions: First, we add an application to demonstrate how local authorities and property developers could integrate our approach to rank investments alongside traditional transportation cost-benefit analysis. We obtain location and investment cost data for a new bicycle lane and compute the overall change in property value around its vicinity. Second, we end with a debate that highlights the current inefficient property tax system in the UK and propose changes to the system that could improve the way local authorities invest in public services.

Our empirical findings are important because bicycling has the potential to generate vibrant and interconnected neighborhoods and encourages a sense of community interaction (Kim et al., 2017; Goodman et al., 2013). Active transport can enable communities to foster an environment that promotes physical and mental well-being, reduces emissions and noise pollution, 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). 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, a number of governments in Europe and elsewhere have sought to improve active transport infrastructure, enable people to choose cycling and walking for their daily commutes and short journeys, and help achieve their net-zero targets. Regrettably, in the UK, there has been minimal observable government action, despite the commitment made in July 2020 to budget £2 billion (bl) for dedicated bicycle lanes, storage, and walking infrastructure over an unspecified number of years (GOV.UK, 2020c,a) - a small investment compared to the UK government's funding towards motorized infrastructure on average of £5 bl per year (ONS, 2022). Recently, however, for political reasons, this cycling budget commitment has been halved in anticipation of the upcoming UK election (Walker, 2023).[3]

This paper unequivocally demonstrates the link between bicycling infrastructure and its amenity value internalized by property prices. We therefore strongly urge local and central level policymakers and property developers to integrate bicycling infrastructure from the initial stages of design. Doing so will address unmet demands, foster better quality neighborhoods, and yield improved sustainable environmental outcomes.

In the following, Section 2 presents our methodological approach, Section 3 presents our data and Section 4 the results. Section 5 provides an extension with application and debate on the local tax system, and Section 6 concludes.

2 Methodology

The most well-known method for assessing the value of bicycling infrastructure is Cost-Benefit Analysis (CBA) that has included diverse and competing transport modes, e.g., CBAs with 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

[3] Similar issues, linked to political affiliation and polarized views, are found at local levels, e.g., see news items in Birmingham and London.

maintenance cost, traffic noise, CO_2 and other 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).[4] Thus, CBA might not effectively quantify the value of bicycling infrastructure, might seem ad hoc and incorrectly quantify the non-marketed value.

Instead, some studies have 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 hedonic studies have 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, energy efficiency in commercial properties (Fuerst and McAllister, 2011), the rent premium associated with smoking (Gedikli et al., 2023), proximity of property to subways and trains networks (Keeler and Stephens, 2023; Wang, 2017; McMillen and McDonald, 2004), 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).

[4]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.

2.1 Hedonic pricing in the context of bicycle networks

Utility is assumed strictly concave, with x defined as all other goods consumed with price set to unity[5]

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

Following Rosen (1974), 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 property type, environmental performance, floor area, number of rooms, new/old build and others. $N(\cdot)$ neighborhood location desirability attributes such as school quality, green space, crime, socio-economic metrics, and locality specific features (e.g., neighborhood "charm", which may not be measurable), and time attribute T. Finally, $D(\cdot)$ distance to bicycle networks is

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

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.[6]

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,

[5]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).

[6]For example, house prices fall by less when distance rises from 5250 meters (m) and 5500 m compared to 250 m and 500 m.

$\frac{\partial^2 B}{\partial^2 d} > 0$. 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. A specific concern for us is that d could be correlated with unobservable characteristics within N. 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 might lead to significant omitted variable bias, and the literature therefore uses extensive control variables and spatial fixed effects to approximate neighborhood indicators (Abbott and Klaiber, 2011). Unfortunately, confounding effects due to omitted variable bias remains even after including multiple controls. Also, as spatial fixed effects become increasingly fine-grained they also become collinear with distance from the cycle network (as the areas themselves shrink, i.e., within-area variation falls towards zero). Data limitations make the use of quasi-natural experiments (e.g., Difference-in-Difference) infeasible because we cannot be confident about when the cycle networks were created or substantially upgraded.

Arguably, the major challenge in estimation lies in seeking to mitigate these. We thus also employ computationally heavy spatial regressions to support our findings.

2.2 The basic estimation strategy

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:

$$P_i = \beta_0 + \psi_1 d_i + \psi_2 d_i^2 + \boldsymbol{\beta' Q_i} + \boldsymbol{\gamma' N_j} + \tau' T_i + \epsilon_i \tag{7}$$

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;

Q_i = vector of house specific attributes, e.g., brand-new, number of rooms, floor area, property type, environmental performance certificate (EPC);

N_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, green space, 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. Heteroskedasticity is a minor concern given that we use Huber-White robust standard errors (White, 1980).

The principal empirical concern here lies in the presence of unobserved neighborhood effects, which violate the strict exogeneity assumption. Three strategies are adopted which lend robustness to the results in the face of this. 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 green space, local school quality, 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. Third, below, we estimate several variants of spatial panel models, and find that they deliver very similar estimates to our core (OLS) hedonic model. These give additional confidence in our overall findings.

2.3 Spatial regression

The inclusion of spatial panels is particularly important given that, as shown by Pace and LeSage (2010), models that include a spatial error covariance structure can significantly outperform simple OLS in the presence of spatially correlated omitted variables. The intuition for this is that if an omitted variable, e.g., z_j, is even weakly correlated with an explanatory variable d_j, the strength of that correlation (and hence the size of the bias and inconsistency in OLS) is magnified by the fact that both the independent variable and the error term are correlated with their values in adjacent locations. This undesirable situation emerges because - unlike temporal autocorrelation (in which a shock in the past can affect the future, but a future shock cannot change the past) - spatial autocorrelation is *not* unidirectional. As a result, the correlation between the explanatory variable and the error term has both a direct component (the actual correlation between z_j and d_j) and an indirect component (caused by their correlation with the values in adjacent neighbourhoods). Explicitly accounting for the spatial nature of the data generating process can reduce (or ideally eliminate) the indirect component of any bias.

Moreover, OLS is also inconsistent in the presence of spatial autocorrelation in the dependent variable (Anselin, 1988). The intuition is similar: if house prices in one location affect those in an adjacent location and *vice-versa*, then they will themselves be further affected by the price change induced in the neighbouring location. In other words, failure to explicitly model this means that any independent variables will necessarily be correlated with the error term (thus violating conditions for consistency of OLS). Finally, these two issues can interact such that the overall bias can be several times larger than its "direct" component, particularly when the independent variable is also spatially autocorrelated (Pace and LeSage, 2010).

We therefore 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 many datapoints remain. We adopt a static spatially pooled panel specification with time-specific dummies (necessary because the bicycle networks themselves are one of the spatially-invariant fixed effects that we seek to recover). Spatially lagged dependent variables and errors are included. 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 cannot rule out a priori that these might be jointly determined and thus also include a spatial lag of neighborhood house prices. Extending the hedonic model (7), we hence estimate a static spatial panel model of the form:

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

In this case, $\bar{p}_{jt}$ is the average price of sold properties in neighbourhood j in year t. Similarly, $\bar{\boldsymbol{Q}}_{jt}$ is a vector of average property characteristics of neighborhood j in year t. The remaining variables are as before, with the addition of $\lambda \boldsymbol{W \bar{p}_t}$ 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).

3 Description of the data

Greater Manchester (GM) is a large metropolitan area in the United Kingdom (UK) with a population of 2.87 million (ml) people. It spans over 1,277 km^2 and is the third most populous urban area in the UK. Much of the local transport policy is devolved to the area's mayoral authority. Transport for Greater Manchester (TfGM), a sub-body tasked with implementation, has cataloged bicycle routes (TfGM, 2021), offering a rich source of data that we exploit.

3.1 Bicycle networks

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. Next, we overlay the bicycle network onto the GM's 10 boroughs, 221 Localities, 1673 lower layer super output areas (LSOA) and 8684 output areas (OA), which were set by the 2011 Census (ONS, 2021). Of these, 8573 output areas had at least one house sale during the period of our dataset.

We omit (type 3) on-road routes without physical segregation due to evidence that cyclists prefer separated or traffic free bicycle lanes to on-road routes with no physical separation (Mitra et al., 2021). In addition, 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 are excluded, as are other unsurfaced routes unsuitable for commuting or recreation on a road-biased bicycle (although unsurfaced routes may be favored by non-road recreation cycling). Canals would pose severe challenges for estimation given that they provide amenity value in their own right. Moreover, they are

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.

shared with pedestrians, generally unpaved, and much narrower than a bicycle lane. Finally, we filter out lanes shorter than 100 m, a peculiar feature of English roads,[7] leaving 620 that remain.

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. For our main analysis, we remove all networks shorter than 1000 m because a typical urban cyclist could be expected to traverse these in under 4 minutes, limiting their usefulness. We calculate that the mean length of excluded networks is less than 500 m, representing a 2-minute bicycle ride. We thus end up with 88 bicycle networks. Table 1 summarizes their descriptive statistics: the shortest network is 1.03 km and the longest stretches to 22.1 km. (For robustness, we also test scenarios with the full set of networks. Full analysis reported in the online supplementary appendix.)

3.2 Property Attributes and proximity to bicycle networks

The cleaned 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 official Land Registry Price Paid Data with property information from the official Domestic Energy Performance Certificates (Chi et al., 2021), which includes information on property type,[8] 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

[7]Very short cycle lanes are a peculiar feature of English roads, whereby roads without dedicated bicycle lanes suddenly introduce very short sections of cycle markings, often near junctions, vehicle lane merges, curves, or in seemingly arbitrary locations. These types of lanes are not integrated into any cohesive cycling network, and are typically around 20 m, or as short as 3 m. (Two telling anecdotal news items are here and here). Reasons may stem from local initiatives, poor road design, or even past efforts to access 'Green' funding (by artificially inflating the council's total cycle lane length). However, from a cyclist's perspective, such lanes do not contribute to a functional cycling network, and therefore filtered out. As a robustness check, we tested regressions without this minimum length and find the results to be extremely close. (All results are provided in the online supplementary appendix).

[8]The UK defines five property types: (1) Bungalows are single-story houses, often popular with retirees to avoid stairs. (2) Detached homes are houses that do not share any walls with neighboring properties. (3) Semi-detached houses share one wall with a neighboring house, while (4) Terraced houses are part of a row of homes that share both side walls with adjacent properties. Finally, (5) flats (apartments) are individual units within a larger building.

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

District	Number of sales	Average property value, £2019	Median property value, £2019	Median distance to nearest bicycle network (km)	Number of primary schools	Number 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.

sales transactions between 2011-2019.

Table 2 provides the average sales price and number of sales to bicycle network by the ten metropolitan boroughs in GM and Table 3 summarizes the descriptive statistics. 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 Euclidean (straight-line) 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 whilst postcodes cover a considerably smaller number of properties, they 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.[9] Perhaps a more significant limitation is the fact that we lack reliable data on road network distance to the nearest bicycle network.[10] As such, our results should be correctly interpreted as the *ceteris paribus* association

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

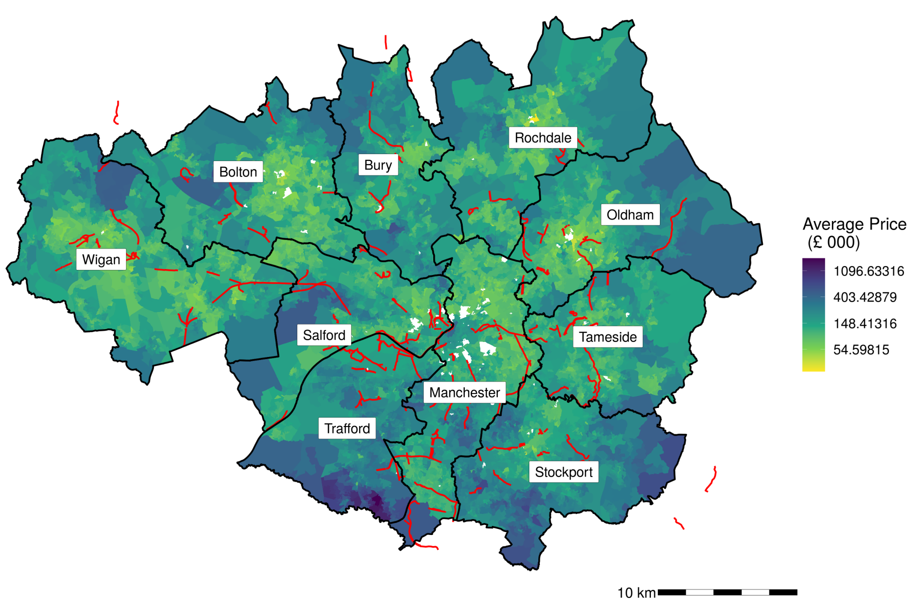
[10]One concern is the presence of an obstruction (e.g., motorway roads or bodies of water) that would necessitate a cyclist finding a - potentially circuitous - route around them. By far, the largest of these is the orbital road (M60) around the center that accounts for half of the total freeway network. Fortunately, only 3.1% of all property purchases have their nearest cycle network on the other side of this motorway, and bodies of water are predominantly located in the periphery. This gives a degree

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 italics. *Totals may not sum to 100% due to rounding.

Figure 1: House prices and bicycle networks in Greater Manchester



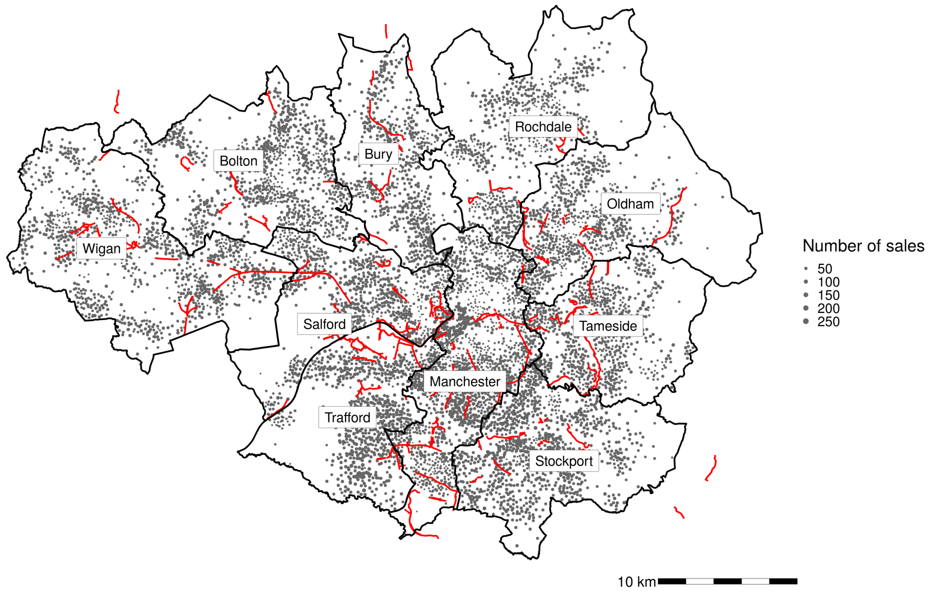
Note: Colours are on a logarithmic scale provided in the map legend.

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



between house prices and the straight-line distance to the nearest bicycle network.

3.3 Neighborhood attributes

3.3.1 Green Space

It is well documented that property prices are positively correlated with higher density of green space (e.g., Gibbons et al., 2014; Conway et al., 2010; Cho et al., 2008). Furthermore, it is more likely that bicycle lanes are built near neighborhoods that have a higher density of public green space. To control for this, we use LSOA level data of access to public parks, public gardens, and playing fields (ONS Green Space, 2020). Two measures are included: (i) Average combined size of public parks, gardens, or playing fields (hectare, ha) within 1 km radius of the OA (see Figure 3), and (ii) the Average distance of the OA to nearest public park, garden, or playing field (km). Figure 3 shows that bicycle networks in GM are not specifically located around areas with public green space, with the exception of South East Wigan.

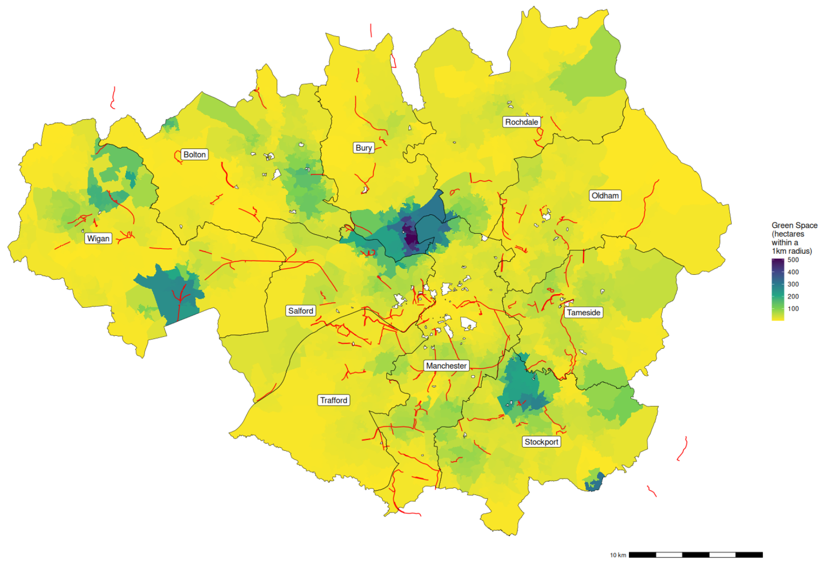
3.3.2 School quality as a proxy for neighborhood characteristics

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)[11]. Furthermore, we remove small, specialized,

of reassurance that Euclidean and road network distance are directly proportional in the vast majority of cases.

[11] 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

Figure 3: Green space and bicycle networks in Greater Manchester



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 of the two scores.[12] (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, 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, 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). These elements capture pupil characteristics and school desirability.

3.3.3 Socio-economic clasifications and crime

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

school's test scores into their average. They also accord with anecdotal parental perceptions.

[12] 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.

bands are aggregated into all others.[13] 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. In addition, we used data that specifies which decile of the *Index of Multiple Deprivation* each of the LSOA is in (GOV.UK, 2024).[14]

Finally, we assemble LSOA 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.[15]

3.3.4 1999 house prices and central business district

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 post-codes 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 also compute a distance of each OA to the central business district (City Centre Ward in Manchester) to capture employment opportunities.

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 Euclidean distance from the bicycle networks - our main variable of interest, (ii) house attributes (whether brand-new, 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 (Public green space, Primary and Secondary school results, National Statistics Socio-Economic Clasifications (NS-SEC), multiple deprivation decile, 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%.

[13]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.

[14]The Index of Multiple Deprivation (Deprivation decile) is comprised of seven distinct domains of deprivation, combined and appropriately weighted, covering: Income, Employment, Health Deprivation and Disability, Education, Skills Training, Crime, Barriers to Housing and Services, and Living Environment (GOV.UK, 2024). The index is available from the ONS Green Space (2020).

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

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 dis-amenity) value of significant roads.[16] These traffic-free networks make up 49.2% of the total bicycle network length in Greater Manchester (GM).[17]

We begin with general observations and end with the main variables of interest. Focusing on property attributes, in Model 1, brand-new properties - referred to as *New Build* in the UK - increase in value by 13.4% compared to *Old Build*, holding all else equal. With each additional *room*, 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.[18] Detailed results for *Property type* and *EPC* are not shown here, but are provided in the online supplementary appendix. Consistent with general trends in the UK, we find that *Property type* significantly influences premiums, with bungalows and detached homes attract the highest, followed by Semi-detached, Terraced homes, and finally Flats.[19] Lastly, as expected, higher *EPC* rating has a positive relationship with sale price, consistent with findings by Cajias and Piazolo (2013) for Germany and Fuerst et al. (2015) for the UK.

At the neighborhood level, school attainment, crime, and other control variables have the expected signs. Furthermore, a 1 km rise in distance to green space lowers property value by 1.7%, while the size of the green area within a 1 km radius has minor impact on property value. Interestingly, this effect is somewhat sensitive to the choice of model specification and sub-data because green spaces might systematically differ depending on whether the neighborhood is near the urban center, as well as the fact that locality is likely somewhat collinear with the quantity of green space.

Turning to our main variables of interest, Table 5 reports a statistically significant reduction in property price as distance increases but - as expected - at a marginally nonlinear decreasing rate (see distance^2). Models 3 and 7 (which only include Manchester) are exceptions with weaker significant 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 0.53 km compared to 0.95 km across the whole of GM (see statistics in Table 2).

Computing the combined effect of distance, on average in GM, the property value of homes adjacent to a bicycle network is 2.8% higher than those 1 km away (see Table 6 for other distances).[20] There are regional disparities, for example, in Manchester Only (model 3), the affect is highest at 7.7%, 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, in rural areas, properties near a bicycle network attract a positive and significant premium (model 4).

[16] 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 3.1

[17] We provide the full set of results for Table 5 and for all other model variations and robustness checks in the online supplementary appendix, e.g., postcodes instead of OA centroids, no minimum lane length, etc.

[18] Note that the (Pearson) correlation between *Number of rooms* and *Floor Area*, in the full dataset, is 0.77, which is acceptable given the large number of observations (>250K).

[19] Recall description of Property types in footnote 8.

[20] 2.8% is obtained by: $-0.02847 = -0.03371 \cdot 1km + 0.00524 \cdot (1km)^2$

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	Full	Full with locality	Only Manchester	Exclud. Manchester
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	5.76286***	5.17562***	1.20088 ***	6.96854***	5.71219 ***	5.15377***	0.29898	6.90003***
	0.06869	*0.08742*	*0.22877*	*0.07345*	*0.06981*	*0.08793*	*0.2265*	*0.07398*
distance	0.03371***	0.04060***	0.08184***	0.01205***	0.01688***	0.02949***	0.03139***	0.00489***
	0.00134	*0.00163*	*0.00614*	*0.0014*	*0.00078*	*0.00096*	*0.0052*	*0.0008*
distance^2	0.00524***	0.00583***	0.00531*	0.00207***	0.00256***	0.00345***	-0.00361*	0.00116***
	0.00031	*0.00041*	*-0.00215*	*0.00031*	*0.0001*	*0.00011*	*0.00172*	*0.0001*
1. Property attributes								
Old build	Base	Base	Base	Base	Base	Base	Base	Base
New build	0.13371***	0.13622***	0.05450***	0.20603***	0.13394***	0.13517***	0.04942***	0.20671***
	0.00639	*0.00631*	*0.01008*	*0.00834*	*0.00639*	*0.00631*	*0.01013*	*0.00834*
No. of rooms	0.10914***	0.11076***	0.13997***	0.10288***	0.10945***	0.11123***	0.13856***	0.10302***
	0.00183	*0.00181*	*0.00492*	*0.00194*	*0.00183*	*0.00181*	*0.00494*	*0.00194*
No. of rooms^2	-0.00604***	-0.00621***	-0.00965***	-0.00531***	-0.00606***	-0.00625***	-0.00950***	-0.00532***
	0.00016	*0.00016*	*0.00046*	*0.00017*	*0.00016*	*0.00016*	*0.00046*	*0.00017*
Floor area (m^2)	0.00616***	0.00618***	0.00767***	0.00597***	0.00615***	0.00618***	0.00771***	0.00597***
	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*
Property type	YES	YES	YES	YES	YES	YES	YES	YES
EPC	YES	YES	YES	YES	YES	YES	YES	YES
2. Neighborhood attributes								
Distance to green area (km)	-0.01666***	-0.00959**	0.03208***	-0.00993***	-0.01448***	-0.00233	0.03280***	-0.00979 **
	0.00288	*0.00307*	*0.00913*	*0.00301*	*0.00289*	*0.00307*	*0.00919*	*0.00301*
Size of green areas (m^2)	0.00000	-0.00017***	0.00010*	0.00005***	<-0.0000**	<-0.0000***	<0.00000	<0.00000**
	0.00001	*0.00001*	*0.00004*	*0.00001*	*<0.00000*	*<0.00000*	*<0.00000*	*<0.00000*
Secondary: Attainment 8 score	0.00697***	0.00773***	0.01092***	0.00564 ***	0.00643***	0.00728 ***	0.01061***	0.00535***
	0.00023	*0.00036*	*0.00087*	*0.00024*	*0.00023*	*0.00036*	*0.00088*	*0.00023*
Primary: KS2 score	0.03031***	0.03642***	0.07070***	0.02043 ***	0.03093***	0.03671***	0.07853***	0.02127***
	0.00068	*0.00088*	*0.00237*	*0.00071*	*0.00069*	*0.00089*	*0.00235*	*0.00072*
Disadvantaged pupils	-0.13279***	-0.12341***	-0.07469***	-0.15039***	-0.12860***	-0.12211***	-0.07032***	-0.14705***
	0.00404	*-0.00414*	*0.00969*	*0.00443*	*0.00404*	*0.00414*	*0.00976*	*0.00443*
NS-Sec (bands 1+2)	0.91962 ***	0.89334 ***	0.90898***	0.82556 ***	0.91666***	0.89185***	0.91338***	0.82245***
	0.00603	*0.00628*	*0.01391*	*0.00687*	*0.00604*	*0.00629*	*0.01399*	*0.00687*
Locality	NO	YES	NO	NO	NO	YES	NO	NO
Distance to CBD	YES	YES	YES	YES	YES	YES	YES	YES
Deprivation decile	YES	YES	YES	YES	YES	YES	YES	YES
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	0.82258	0.82773	0.79258	0.83474	0.82241	0.82779	0.79041	0.83481
Adj. R^2	0.82254	0.82754	0.79237	0.8347	0.82237	0.8276	0.7902	0.83477
Num. obs.	252571	252571	39503	213068	252571	252571	39503	213068

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. Property type: Bugalow, Detached, Semi-detached, Terraced, Flat; EPC bands A to G. Crime: anti-social, damage, theft, vehicle theft, violence and sex offense, other crime; 221 Localities, 10 Boroughs.

Table 6: The reduction in value of property by distance to bicycle network

	All bike lane types				Only traffic-free (TF) bike lanes			
Distance from network	Full	Full with locality	Only Manch.	Exclud. Manch.	Traffic-free routes	Traffic-free with locality	TF: only Manch.	TF exclud. Manch.
km	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.25	-0.8%	-1.0%	-2.0%	-0.3%	-0.4%	-0.7%	-0.8%	-0.12%
0.5	-1.6%	-1.9%	-4.0%	-0.6%	-0.8%	-1.4%	-1.7%	-0.23%
0.75	-2.2%	-2.7%	-5.8%	-0.8%	-1.1%	-2.0%	-2.6%	-0.30%
1.0	-2.8%	-3.5%	-7.7%	-1.0%	-1.4%	-2.6%	-3.5%	-0.37%
1.25	-3.4%	-4.2%	-9.4%	-1.2%	-1.7%	-3.1%	-4.5%	-0.43%
1.5	-3.9%	-4.8%	-11.1%	-1.3%	-2.0%	-3.6%	-5.5%	-0.47%
1.75	-4.3%	-5.3%	-12.7%	-1.5%	-2.2%	-4.1%	-6.6%	-0.50%
2.0	-4.6%	-5.8%	-14.2%	-1.6%	-2.4%	-4.5%	-7.7%	-0.51%

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.

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 removal of 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 estimated amenity value slightly.[21]

How plausible are these findings? For a median property in 2019 of £163K, model 1 implies an approximated value of £4,640 (compared to properties 1 km away). As a back-of-the-envelope estimate, this is a willingeness-to-pay (WTP) of at least £312 per year (using the annuity formula with interest rate of $r = 3\%$ over 20 years). English commuters are 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.[22]

Testing with the traffic free bicycle networks leads to smaller results, implying that major roads have a positive amenity (see Table 6 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 1.4% (relative to 1 km away), which is a WTP of £157. 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 public green space, 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 that distance from a bicycle network is also spatially correlated by design, we have

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

[22] 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 in GM, 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.

some concern over omitted variable bias. In Section 2.3, we warned that the overall combined bias can be several times larger.

We therefore 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 do not apply (Robinson, 1950) (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 was employed (Honaker et al., 2011). 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. Note that convergence issues meant that data on the combined size of green spaces (but not the distance to them) needed to be excluded from the "listwise deletion" panel.

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 7, model 1) which suggests that bicycle networks generate an amenity premium of around 3.6% per 1 km.[23] 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

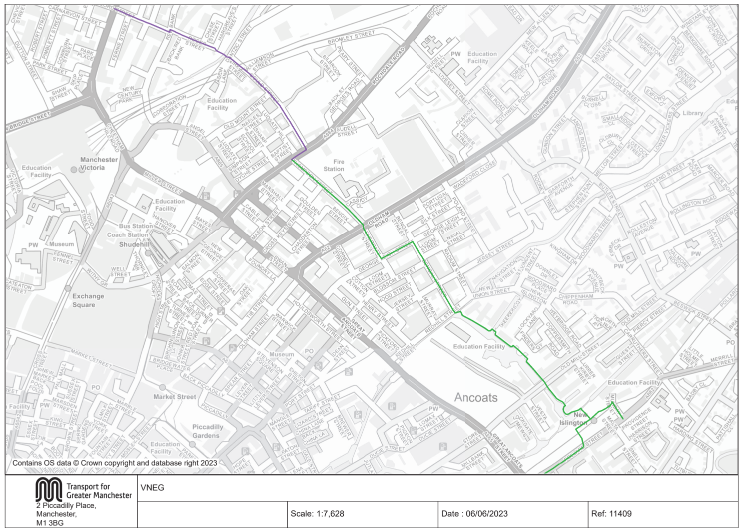
[23] $-0.03586 = -0.04208 \cdot 1km + 0.00623 \cdot (1km)^2$

Table 7: Results for spatial regressions (dependent variable: log of price)

	Multiple imputation		Listwise Deletion
Weighting	Row-standardized	Unstandardized	Row-standardized
	(1)	(2)	(3)
Intercept	5.32818***	5.28040 ***	5.36957***
	0.22128	*0.19023*	*0.14869*
Distance (1 km), ψ_1	-0.04208***	-0.04430***	-0.03123***
	0.00426	*0.00364*	*0.00308*
Distance^2, ψ_2	0.00623***	0.00600***	0.00384***
	0.00100	*0.00084*	*0.00071*
1. Property attributes			
Old build	Base	Base	Base
New build	0.16508***	0.15679***	0.17396***
	0.02368	*0.02444*	*0.02320*
No. of rooms	0.11234***	0.11160***	0.11051***
	0.00502	*0.00511*	*0.00499*
No. of rooms^2	--0.00540***	-0.00530***	-0.00632***
	0.00045	*0.00046*	*0.00044*
Floor area (m^2)	0.00552***	0.00555***	0.00652***
	0.00013	*0.00013*	*0.00010*
Floor area (m^2)^2	--0.000005***	-0.000005***	-0.00001***
	<0.000000	*<0.000000*	*<0.00000*
Bungalow	Base	Base	Base
Detached	0.09513***	0.08861***	-0.02990***
	0.00714	*0.00700*	*0.00555*
Semi-detached	--0.04384***	-0.04361***	-0.15062***
	0.00632	*0.00636*	*0.00445*
Terraced	-0.20720***	-0.20860***	-0.34533***
	0.00591	*0.00588*	*0.00447*
Flat	-0.24014***	-0.23351***	-0.38465***
	0.00824	*0.00799*	*0.00643*
EPC	YES	YES	YES
2. Neighborhood attributes			
Distance to nearest green space (km)	-0.01530*	-0.02068***	-0.01049
	0.00713	*0.00648*	*0.00595*
Size of green areas (m^2)	0.00005	0.00006*	NO
	0.00003	0.00002	
Secondary: Attainment 8 score	0.00799***	0.00717***	0.00450***
	0.00079	*0.00065*	*0.00052*
Primary: KS2 score	0.03842***	0.03498***	0.03453***
	0.00230	*0.00188*	*0.00147*
Disadvantaged pupils	-0.13626***	-0.13566***	-0.13824***
	0.00998	*0.00878*	*0.00820*
Index of multiple deprivation	0.01605***	0.01586***	0.01361***
	0.00073	*0.00066*	*0.00058*
NS-Sec (bands 1+2)	0.78738***	0.82140***	0.75378***
	0.01199	*0.01186*	*0.01164*
Log price 1999, Missing data for 1999, Crime, Borough, Major conurbation	YES	YES	YES
3. Other attributes			
Year	NO	NO	YES
Dummies for imputed observations	YES	YES	
Spatial Auto-Correlation	-0.03725***	0.00006 **	0.00359***
	0.00981	*0.00002*	*0.00045*
Spatial Moving Average	0.62964***	0.09412***	0.32662***
	0.00793	*0.00065*	*0.00551*
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 4: Manchester Victoria Northern/Eastern Gateway (VNEG) route



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

Table 8 (for row-standardized weights).

5 Ranking Investments and Inefficient Local UK Property Tax

We end with two comments: First, our results could generate a Cost-Benefit Analysis (CBA) to rank investments and assist local authorities and property developers. Second, we question the current UK local property tax and suggest a future research agenda.

5.1 Ranking Investments

In 2018, GM announced their *Bee Network* vision for walking and cycling. This promises a £1.5 bl 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). Given limited budgets, we propose a simple method to rank investments based on property value, to be used alongside the transportation CBAs traditionally used.

We examine the recently approved £8.9 million (ml) investment by the Manchester Council for a new off-road bicycle route known as the Manchester Victoria Northern/Eastern Gateway (VNEG) scheme. Its route and costing was provided by TfGM. The VNEG 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 4 sketches the route.)

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 7, 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 £16.6 ml, which compared with a total cost of £8.9 ml, is a benefit-to-cost ratio of 1.9, i.e., a positive benefit. Having additional planned bicycle routes, developers could compare and rank investments from highest to lowest ratio.[24]

5.2 Inefficiency in local UK property tax

Finally, ranking investments based on CBAs alone does not mean that projects are "fairly" funded because it does not account for those baring the cost of the investment and those benefiting from it. Though the new cycle network is a public good, only those within a practical radius will utilize it.

In the UK, *Council Tax* - a tax on domestic property - is the main source of *locally* raised income, giving them a wide discretion over this element of their budget (but limited discretion from the central government's allocation). The payable, flat-rate, amount depends on Tax Bands A to G to which a property is allocated, based on a valuation made in April 1991. In Wales, the bands were re-set on April 2005. For each band, the payable council tax increases by inflation and ad hoc amendments, but properties remain in the same band unless formally challenged (e.g., demolished, split into multiple properties, merged, change of used, etc.) (GOV.UK, 2023b).

One important social policy idiosyncrasy is that council tax is highly regressive in nature whereby the lowest income households pay a higher proportion of their income, and a strict ceiling protects the wealthiest - lowering their proportional payment as property value increases (Orton, 2023, 2002). Furthermore, the bands no longer reflect the true property value compared with 1991 because many properties have been refurbished and extensions made that raise their value, and neighborhoods gentrification (or decline) has changed property values overall.

The current arrangement, therefore, struggles to fairly allocate costs and benefits, and weakens local community powers to make choices. One suggestion would be to introduce a property tax linked directly to the property value. This is a simple matter to achieve because all data is already publicly available online from the UK Price Paid Data, since 2000. The data includes the sale price, date of sale, property type, and other relevant information. It provides transparency and helps individuals and professionals to research property prices and trends in specific areas. For example, UK's two most popular property search websites, Zoopla and Rightmove, already predict individual property value that are updated monthly.

The political will to change the current local tax system is out of the scope of this paper, but has been implemented in other countries, e.g., biannual updates in Denmark, annual in the Netherlands, and every third year in Sweden (Slack and Bird, 2014). Under this type of property tax framework,

[24] A limitation of this approach is that it does not capture network effect of bicycling infrastructure (as infrastructure becomes more dense, a greater range of destinations are feasible even for existing users).

investments that improve local amenities would be reflected intrinsically by the rise in property value. Ranking investments based on property value CBAs would be meaningful, and it would even be possible for local councils to re-coop (or raise) investment and maintenance cost based on expected tax revenue, similar to central government bonds.

6 Conclusion

Amid the polarized political environment, arguments against bicycle infrastructure investment often surface but lack robust empirical evidence. This paper uses observable property market data in Greater Manchester to measure the link between property value and proximity to bicycle networks. We find a much larger positive link than previously thought, which policymakers and developers are unaware of. Testing a variety of alternative models and specifications including spatial regressions, we conclude that bicycle infrastructure provides benefits of around 2.8% of property value (compared to properties 1 km away), and that the benefits could be substantially higher in congested urban centers at around 7.7%. These findings are much higher than previously reported.

The primary limitation of this study is the challenge of identifying causal relationships, given the likely presence of unobserved factors. Future research should focus on collecting additional data to harness the advantages of a difference-in-difference approach, despite the inherent difficulties. Moreover, future studies should employ road network distances where possible, rather than straight-line measures, to account for obstacles such as motorways or bodies of water. Nevertheless, the findings highlight the benefits of well-designed and implemented cycling networks, reinforcing the importance of integrating such infrastructure into urban planning. This not only promotes sustainable living, reduces emissions, and fosters healthier, more connected communities, but also has significant implications for policymakers and property developers, particularly in addressing the climate crisis and creating more livable urban environments.

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A Appendix

Table 8: Cross-sectional year-by-year spatial regressions (Row-standardized weights)

	2011	2012	2013	2014	2015	2016	2017	2018	2019
(Intercept)	-0.00522***	-0.00433***	-0.0021	-0.00661***	-0.00868***	-0.00572***	-0.00722***	-0.00622***	-0.00796***
	0.0012	*0.00097*	*0.00115*	*0.00103*	*0.00105*	*0.00112*	*0.00115*	*0.00077*	*0.00096*
distance	-0.03592	-0.07449*	-0.05338	-0.07380*	-0.11253***	-0.09611***	-0.04849*	-0.07580**	-0.03812
	0.028	*0.02956*	*0.03138*	*0.02887*	*0.02511*	*0.02362*	*0.02387*	*0.0244*	*0.02337*
distance^2	0.22611***	0.24442***	0.26274***	0.36974***	0.43213***	0.47636***	0.45482***	0.46847***	0.42799***
	0.01692	*0.01676*	*0.01673*	*0.01563*	*0.01473*	*0.01406*	*0.01441*	*0.01407*	*0.0145*
1. Property attributes									
% New build	-0.00003	-0.00004**	-0.00002	-0.00004*	-0.00003	-0.00001	-0.00002	-0.00001	-0.00002
	0.00002	*0.00002*	*0.00002*	*0.00002*	*0.00001*	*0.00002*	*0.00001*	*0.00002*	*0.00002*
Average # rooms	0.00559***	0.00639***	0.00665***	0.00645***	0.00579***	0.00697***	0.00581***	0.00625***	0.00632***
	0.00025	*0.0003*	*0.00032*	*0.00024*	*0.00025*	*0.00027*	*0.00026*	*0.00024*	*0.00023*
Average # rooms^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
Average floor area	-0.34336***	-0.35782***	-0.37078***	-0.40309***	-0.42170***	-0.40009***	-0.41661***	-0.42712***	-0.46277***
	0.0178	*0.01689*	*0.01696*	*0.01582*	*0.01509*	*0.01511*	*0.01485*	*0.01479*	*0.01463*
Average floor area^2	-0.34960***	-0.37395***	-0.33437***	-0.34360***	-0.33531***	-0.31743***	-0.36128***	-0.34048***	-0.35884***
	0.01322	*0.01245*	*0.01247*	*0.01147*	*0.0112*	*0.0112*	*0.01112*	*0.01141*	*0.01072*
% of property type	YES	YES	YES	YES	YES	YES	YES	YES	YES
% of EPC	YES	YES	YES	YES	YES	YES	YES	YES	YES
2. Neighborhood attributes									
Distance to nearest green space (km)	0.00391	0.01633***	0.02421***	0.01978***	0.01343**	0.01622***	0.01284**	0.00617	0.0203 ***
	0.00395	*0.00416*	*0.00498*	*0.00528*	*0.0047*	*0.00459*	*0.00485*	*0.00431*	*0.00334*
Secondary: Attainment 8 score	-0.13375***	-0.12692***	-0.17572***	-0.13972***	-0.13069***	-0.14298***	-0.14215***	-0.11780***	-0.13114***
	0.02377	*0.02249*	*0.02201*	*0.02068*	*0.02028*	*0.0201*	*0.02011*	*0.02015*	*0.02117*
Primary: KS2 score	-0.02787**	-0.03610***	-0.03989***	-0.04129***	-0.04521***	-0.04077***	-0.04920***	-0.04360***	-0.04026***
	0.00858	*0.00800*	*0.00802*	*0.0081*	*0.00815*	*0.00849*	*0.00828*	*0.00839*	*0.00861*
Disadvantaged pupils	0.91626***	0.88861***	0.85673***	0.85402***	0.80767***	0.84175***	0.78136***	0.76003***	0.77054***
	0.03464	*0.03233*	*0.03204*	*0.02906*	*0.02785*	*0.02743*	*0.02777*	*0.02739*	*0.02929*
NSSec.AB	-0.08061**	-0.10631***	-0.09848**	-0.12561***	-0.14435***	-0.12004***	-0.08370***	-0.09388***	-0.07565**
	0.02791	*0.02957*	*0.03137*	*0.02879*	*0.02511*	*0.02343*	*0.02374*	*-0.02413*	*0.02323*
Borough, Log price 1999, Missing 1999, Major conurbation, Crime, Deprivation decile	YES	YES	YES	YES	YES	YES	YES	YES	YES
Auto-correlation	6.74311***	6.12108***	6.25728***	5.71107***	5.42163***	5.42332***	5.48299***	5.87576***	6.15929***
	0.42452	*0.40074*	*0.39956*	*0.39368*	*0.39823*	*0.40935*	*0.40175*	*0.40832*	*0.41261*
Moving average	0.11621***	0.10092***	0.07221***	0.10551***	0.13614***	0.10191***	0.12428 ***	0.11350***	0.13261***
	0.01313	*0.01115*	*0.01303*	*0.0113*	*0.01135*	*0.01228*	*0.01223*	*0.00926*	*0.01071*
Num. obs.	7146	7085	7459	7768	7706	7808	7828	7810	7340
Parameters	43	43	43	43	43	43	43	43	43
Log Likelihood	1112.77217	1638.01773	1700.89059	2553.04989	2986.00949	3142.18843	3100.00835	3116.34751	2642.671
AIC (Linear model)	-1964.63681	-2939.70762	-3000.08283	-4452.67755	-5128.22821	-5210.13709	-5226.46352	-5208.7911	-4352.86186
AIC (Spatial model)	-2139.54434	-3190.03545	-3315.78117	-5020.09977	-5886.01897	-6198.37686	-6114.01671	-6146.69501	-5199.342
LR test: statistic	178.90753	254.32783	319.69834	571.42222	761.79076	992.23977	891.55318	941.90391	850.48014
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.