Endogenous public amenities*

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Abstract

This paper examines how local public amenities are distributed across neighbourhoods within cities. Using comprehensive data on libraries, parks, pools, leisure centres, and infrastructure investments in England (2005–2024), I document a striking U-shaped relationship between neighbourhood affluence and public amenity access: the poorest and wealthiest neighbourhoods have the best access, while middle-income areas are systematically underserved. To address endogeneity from household sorting and amenity capitalisation, I exploit quasi-experimental variation from the 2014 Stamp Duty Land Tax reform, which generated discontinuous changes in transaction costs across the house price distribution. Instrumental variable estimates confirm the U-shaped pattern. Investigating mechanisms, I show that poor neighbourhoods exhibit high demand for public amenities, while rich neighbourhoods have greater political power. In contrast, private amenities like restaurants or bars concentrate exclusively in affluent areas. A quantitative spatial model with endogenous public amenity provision rationalises these patterns through political economy: local governments balance redistribution toward needy neighbourhoods and capture by politically powerful wealthy neighbourhoods, leaving the middle class behind. The findings reveal a novel form of spatial inequality within cities and have implications for local public finance, urban policy, and quantitative spatial models.

Keywords: Public amenities, local public goods, political economy, neighbourhood inequality, quantitative spatial models, urban economics
JEL Codes: D72, H41, H72, R23, R31, R51

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1 Introduction

Local public amenities such as libraries, parks, and leisure centres shape where people live, how children grow up, and which neighborhoods thrive (Roback, 1982). A large body of research documents that households value proximity to public amenities and are willing to pay substantial premiums to live near parks (Brueckner, Thiesse, and Zenou, 1999; Koster, 2023; Minano-Manero, 2025; Puente-Beccar, 2025), libraries (Gilpin, Karger, and Nencka, 2024; Hanzl and Gilpin, 2025; Karger, 2021), hospitals (Castanheira, Mariani, and Tricaud, 2025), and schools (Bayer, Ferreira, and McMillan, 2007; Steve Gibbons and Machin, 2003; Stephen Gibbons, Machin, and Silva, 2013). At the same time, a parallel literature in political economy shows that the allocation of public resources is often shaped by favoritism and targeted redistribution, with politicians disproportionately directing resources toward swing districts, co-ethnic regions, or politically connected constituencies (Baskaran and Lopes Da Fonseca, 2021; Franck and Rainer, 2012; Grossman and Helpman, 1996; Hodler and Raschky, 2014; Larcinese, Rizzo, and Testa, 2006; Solé-Ollé and Sorribas-Navarro, 2008; Olson, 1965; Weingast, Shepsle, and Johnsen, 1981). Yet despite the importance of amenities for residential sorting and the well-documented role of political economy in shaping public spending, much less is known about how these forces operate *within* cities: which neighborhoods – poor, middle-income, or rich – actually receive public amenities, and what role do political distortions play in generating spatial inequality at the neighborhood level? This paper addresses this gap by asking: *Who gets access to local public amenities within a city, and why?*

This question is important for three reasons. First, it is *a priori* unclear whether public amenities should serve some neighborhoods more than others at all. One might expect that, as public goods funded by general taxation, amenities should be distributed equitably across all neighborhoods regardless of income. This would imply that there is no systematic relationship between affluence and access. However, if such a relationship exists, its direction is theoretically ambiguous. On the one hand, neighborhood affluence could translate into political power, enabling wealthy residents to capture public resources through voter participation, campaign contributions, or influence over local officials—implying a positive relationship between affluence and amenity provision. On the other hand, public policy may prioritize equity and target deprived neighborhoods for upgrading through investments in libraries, parks, and community facilities—implying a negative relationship. Without empirical evidence, theory alone cannot settle whether amenities are distributed equitably, skewed toward the rich, or directed toward the poor.

Second, quantitative spatial models (QSMs) that are increasingly used to study urban policy typically treat amenities as exogenous or abstract from the functional form of their provision altogether (Gabriel M. Ahlfeldt, Stephen J. Redding, et al., 2015; Stephen J Redding and Rossi-Hansberg, 2017). Recent work has begun to model amenity supply explicitly (Almagro and Domínguez-Iino, 2025; Bordeu, 2025; Fajgelbaum et al., 2024), but the supply side – how local governments allocate public amenities across neighborhoods – remains largely unexplored. Understanding the empirical relationship between neighborhood characteristics and public amenity provision is a necessary first step toward building realistic models of endogenous local public goods.

Third, the distributional consequences of amenity allocation have direct implications for urban inequality: if middle- or low-income neighborhoods systematically receive fewer public amenities than the rich, this could reinforce spatial sorting, deepen neighborhood stratification, and undermine social cohesion.

The answer I find is surprising. Using high-resolution data on roughly 34,000 neighborhoods in England between 2005 and 2024, I document a robust U-shaped relationship between neighborhood affluence – measured primarily by average property transaction prices – and access to local public amenities: the poorest and the richest neighborhoods have the best access, while middle-income neighborhoods lose out. Poor neighborhoods tend to be close to public libraries and other amenities, and so do the wealthiest neighborhoods; it is the "middle" of the house price distribution that is physically furthest away and least well served. This pattern holds across different measures of access (distance to the nearest amenity, presence within the neighborhood, presence within 1 km) and for an aggregate amenity index constructed from multiple amenity types, as well as for different amenity types.

Establishing this U-shaped pattern is challenging because neighborhood affluence and amenity provision are jointly determined. Amenities capitalize into house prices, and households sort into neighborhoods partly based on amenity availability, generating severe endogeneity concerns. To account for that, I exploit quasi-experimental variation from the 2014 reform of the UK Stamp Duty Land Tax (SDLT), which discretely changed transaction tax rates at different price thresholds. By constructing neighborhood-level exposure measures to the reform and using them as instruments for average transaction prices, the paper isolates plausibly exogenous variation in neighborhood affluence and shows that the U-shaped relationship persists in instrumental variable specifications.

The analysis proceeds in three steps. First, I assemble a new dataset that combines stock and flow measures of local public amenities for the whole of England. On the stock side, I collect novel information on the universe of public libraries, public pools, and leisure centres from 2005 to 2024 via Freedom of Information requests to all 317 local authorities, complemented with administrative Points of Interest (POI) data for libraries, parks, museums, community centres, and related amenities. On the flow side, I build a new measure of local infrastructure investments by classifying public procurement tenders into infrastructure versus non-infrastructure contracts using a large language model and geolocating them via postcodes. These data are matched to neighborhood-level measures of affluence based on the universe of property transactions, as well as measures of education, income estimates, and demographic composition.

Second, I quantify the relationship between neighborhood affluence and both the presence and quality of public amenities. I show that public amenity access is U-shaped in neighborhood affluence: compared to middle-income neighborhoods, both the poorest and the richest neighborhoods have shorter distances to the nearest library and higher values of an aggregate public amenity index. Instrumental variable estimates using exposure to the SDLT reform as an instrument for neighborhood house prices confirm that this U-shape is not driven by sorting or omitted variables and indicate that the response of amenity access to affluence is even stronger for neighborhoods whose prices are most affected by the reform. I further distinguish extensive and intensive margins: while the stock of amenities exhibits the U-shaped pattern, over time, neighborhoods that grow richer gain more infrastructure investments and see larger improvements in amenity quality than neighborhoods that do not.

Third, I explore mechanisms. Using survey data on library usage, I show that children from low-income households use public libraries much more frequently than children from high-income households, consistent with high demand for publicly provided amenities in poor neighborhoods. At the same time, poor and rich neighborhoods both receive more public amenities than middle-income neighborhoods, whereas private amenities such as bars, cafés, and restaurants concentrate almost exclusively in affluent areas. Combining information on age composition and homeownership from the census with the amenity data, I show that public amenities are disproportionately located in neighborhoods with high political power (older residents and homeowners), whereas private amenities follow purely market-driven patterns. Taken together, these patterns suggest that public amenity allocation reflects both redistribution toward needy neighborhoods and capture by politically powerful, affluent neighborhoods, leaving the urban middle class relatively underserved.

To provide a structural interpretation of these findings, I develop a quantitative spatial equilibrium model with endogenous public amenity provision. Households with heterogeneous income and preferences choose residential locations based on wages, housing costs, commuting access, and the availability of both public and private amenities. Local politicians allocate public amenities across neighborhoods by maximizing a weighted combination of overall welfare and political power of the two groups. The model nests two competing mechanisms: politicians may favor affluent neighborhoods due to their disproportionate political influence, or they may target poor neighborhoods to address social needs and maximize aggregate welfare gains from public investment. By calibrating the model to match the reduced-form estimates from the instrumental variable analysis, I can quantify the relative importance of these mechanisms and simulate counterfactual policies. For instance, redistributing amenities toward middle-income neighborhoods—thereby flattening the U-shape—would affect household sorting, housing prices, and welfare in equilibrium. The model provides a framework for evaluating such policies and understanding the general equilibrium implications of alternative amenity allocation rules.

This paper contributes to four strands of literature. First, it adds to the emerging literature on endogenous amenities in spatial models. While quantitative spatial models have traditionally treated amenities as exogenous location fundamentals or modeled them as a distance-weighted function of the mass of people living nearby (Gabriel M. Ahlfeldt, Stephen J. Redding, et al., 2015; Stephen J Redding and Rossi-Hansberg, 2017), recent work has begun to unpack the determinants of amenity provision and model amenities as endogenous outcomes of economic activity (Ang, Angel, and Parkhomenko, 2024). Almagro and Domínguez-Iino (2025) and Leonardi and Moretti, 2023 develop frameworks where private amenities (restaurants, bars, retail) respond to local demand and income. Bagagli (2025), Bordeu (2025), and Fajgelbaum et al., 2024 incorporate political economy mechanisms such as segregation, coordination, and voting into the provision of public transport infrastructure. My paper extends this literature by focusing explicitly on *local* public amenities—such as libraries, parks, and leisure centres—and modelling their supply through political economy mechanisms at the neighbourhood level rather than market forces. This distinction is important because public amenities are provided by local governments facing political incentives rather than profit-maximising firms, leading to different spatial allocation patterns.

Second, I contribute to research on public goods within cities. Recent studies have examined the spatial distribution of various public goods and services: Asher et al. (2025) study infrastructure provision in Indian cities, showing that schools and hospitals are regressively distributed with respect to caste. Castanheira, Mariani, and Tricaud (2025) analyse hospital and school accessibility in Belgium and show that public goods favour rich neighbourhoods. Similarly, Fabre (2023) confirms this finding for higher education opportunities in France. Harari (2020) examines urban service provision in developing countries and provides evidence that segregation affects provision patterns. My paper adds to this literature by documenting a U-shaped relationship between neighbourhood affluence and public amenity provision and by developing a model with explicit political economy microfoundations for local amenity allocation decisions.

Third, the paper intersects with the political economy literature on local public goods provision. A large body of work shows that political incentives—including favouritism towards co-ethnics (Franck and Rainer, 2012; Hodler and Raschky, 2014), pork barrel spending in swing districts (Larcinese, Rizzo, and Testa, 2006; Solé-Ollé and Sorribas-Navarro, 2008), and the influence of special interest groups (Grossman and Helpman, 1996; Olson, 1965; Weingast, Shepsle, and Johnsen, 1981)—shape the spatial allocation of public resources at regional and national scales. Baskaran and Lopes Da Fonseca (2021) provide comprehensive evidence on political targeting in public employment. My contribution is to bring these political economy insights into urban economics by documenting how political power operates within cities at the neighbourhood level. By showing that public amenities concentrate in both poor (high-need) and rich (high-political-power) neighbourhoods while middle-income areas lose out, the paper reveals a novel form of spatial inequality driven by the intersection of redistributive motives and political capture.

Finally, this paper contributes by constructing a comprehensive dataset on local public amenities covering an entire country over two decades. The combination of administrative data on amenities, procurement tenders, property transactions, and census demographics provides fruitful ground for future studies on public amenity provision in England. The quantitative spatial model I develop integrates these empirical patterns and allows for counterfactual policy evaluation, building a bridge between reduced-form causal inference and structural general equilibrium analysis.

The rest of the paper is organized as follows. Section 2 describes the institutional context of local government finance and political organization in England. Section 3 introduces the data and the construction of amenity and affluence measures. Section 4 presents the empirical analysis of amenity presence and quality, including the instrumental variable strategy based on the SDLT reform. Section 5 discusses mechanisms related to demand and political economy. Section 6 outlines a quantitative urban model that embeds the empirical patterns in a spatial equilibrium framework. Section 7 concludes.

2 Context

I examine the effect of neighborhood affluence on public amenity availability in England between 2005 and 2024. My focus is on amenities provided by local government rather than national government. Large-scale infrastructure projects—such as building a new rail line between London and Manchester—are unlikely to respond to neighborhood-level socioeconomic characteristics. Instead, I focus on local government decisions about where to locate libraries, leisure centres, and parks within cities, where the spatial allocation of resources can reflect neighborhood characteristics.

England comprises 317 Local Authority Districts (LADs) of various types, including county councils, district councils, London boroughs, metropolitan boroughs, and unitary authorities. These Local Authorities are responsible for providing public services including waste collection, social care, fire and police services, education, highways, and the provision of public amenities such as public libraries, swimming pools and leisure centres, transport infrastructure, and parks[1]. To understand why England is an ideal setting for this research, it is important to examine how councils allocate their resources.

Local Authority spending Understanding the composition of Local Authority spending is essential to comprehend why England provides an excellent setting for studying public amenity allocation. The largest portion of council spending is on statutory services like social care and fire and police services, with around three-quarters of overall spending. In contrast, cultural amenities—including libraries, museums, galleries, theatres, community centres, leisure centres, and parks account for only 5% of total council spending. This stark difference reflects the distinction between statutory and discretionary services. While councils face legal obligations to provide social care, education, and emergency services, most cultural amenities are provided on a discretionary basis. Although libraries are technically mandatory under the Public Libraries and Museums Act 1964, councils retain substantial discretion in determining what constitutes 'comprehensive and efficient' service provision. This discretion extends to most other cultural amenities, which are provided on a purely discretionary basis.

This institutional structure creates a fiscal environment where public amenities serve as the primary margin of adjustment when Local Authorities face financial pressure. Between 2010-11 and 2023-24, while total service expenditure increased in nominal terms, spending on cultural services declined by £472 million (30%) as councils protected statutory services amid rising demand and constrained revenues. The discretionary nature of most public amenities, combined with growing statutory obligations, makes England an ideal setting for examining how neighborhood-level political economy factors influence the spatial allocation of scarce public resources.

Local Authority revenue Local government in England operates within a centralized fiscal system with limited local revenue autonomy. National government grants comprise approximately 70% of Local Authority revenue, making them the largest revenue source. The remaining portion

[1] Unitary authorities are responsible for all services while in two-tier councils, the county and district councils divide the services between them. In my empirical analysis, I control for the relevant authority and cluster standard errors at that level.

comes from retention of business taxes, local fees, and council taxes. Council tax, the primary source of locally-controlled revenue, is levied annually on residential properties based on their 1991 property values. Properties are assigned to one of eight bands (A through H) based on these historical valuations. Critically for this analysis, property valuations for tax purposes remain frozen at 1991 levels. Increases or decreases in property values due to housing market changes do not alter the council tax band, meaning neighborhoods that have gentrified experience no increase in their local tax base, nor do deteriorating neighborhoods see tax reductions. This is important for my analysis as this makes it unlikely that councils locate amenities in response to the council tax revenue of some neighborhoods.

Political system The spatial allocation of discretionary resources reflects both fiscal constraints and political incentives. The political system governing Local Authorities is structured as follows: Local Authorities in England are governed by elected councils operating under either a Leader and Cabinet model or a committee system. Under the Leader and Cabinet model—adopted by most councils between 2000 and 2011—the political party or coalition with the most seats forms a cabinet that makes executive decisions, with a council leader elected by fellow councillors. The Localism Act 2011 gave councils the option to return to committee systems, and some have done so. 27 councils have directly elected mayors who perform the leader's role but are elected by residents rather than councillors.

Approximately 17,000 councillors serve on England's 317 Local Authorities, elected on four-year terms to represent single or multi-member wards using first-past-the-post voting. Local elections are staggered across the country rather than held simultaneously, unlike national elections. Two-thirds of councils (67%) hold elections for all seats every four years. Just under one-third (31%) hold elections annually, with one-third of seats contested each year (meaning all seats are renewed every three years). The remaining 2% hold elections every two years, with half the seats contested at each election. As a result, in any given year, only a subset of councils hold elections, and the specific councils holding elections differ from year to year.

3 Data

Unit of observation Before I start outlining the different data sources, it is important to clarify the unit of observation that I use in my analyses. As I am interested in differences in accessibility of public amenities within cities, my unit of observation will be neighborhoods. I define lower layer super output areas (LSOAs) as a neighborhood. This is a statistical unit in the UK aggregated from census blocks (also called output areas) and constructed to have, on average, a comparable size in terms of population. LSOAs have an average population of 1500 people or 650 households. Within cities, they can be understood as neighborhoods, while in rural parts, the area is significantly larger. I will control in all my analyses for urban versus rural neighborhoods and for neighborhood population density. Throughout this paper, I will refer to these units as "neighborhoods".

3.1 Data on public amenities

To analyze the effect of neighborhood affluence on the availability of public amenities, I collect a novel and comprehensive dataset on public amenity accessibility for England. The dataset covers the period from 2005 to 2024 and includes both stock measures (the presence of physical amenities) and flow measures (investments in amenity quality and local infrastructure). The reason to include both the stock and the flow of local public goods is that it usually takes a fair amount of time to build, for instance, a new library. A flow measure of money being directed towards a library gives information on the quality improvements of a physical stock of a given public amenity. In the following two paragraphs, I will explain these two kinds of public amenities.

Stock of public amenities The information on the physical stock of public amenities comes from two main sources. First, I collect novel data on public libraries, public pools, and public leisure centres in England by sending out Freedom of Information (FOI) requests to all English local authorities. In these requests, I ask for the following information for the period 2005 – 2024: For each facility (library, pool, or leisure centre) that was open during that period, I request the current or historical address, year of opening, year of closing (if applicable), and average weekly opening hours in each year.

In the United Kingdom (UK), FOI requests are a powerful tool to ask for recorded information held by public bodies. Under the Freedom of Information Act of 2000, these bodies are obliged to reply to the request. They can refuse the request on different grounds, among others, if the information asked for is publicly available, if the information is classified, or if providing the information asked for would result in unreasonably high costs to the public body asked. The FOI requests resulted in an 80% success rate of retrieving answers and collecting data from local authorities (see Appendix Figure A1). I supplement the information on libraries with data from the Chartered Institute of Public Finance and Accountancy (CIPFA), an association of public accountants in the UK that provides reports and data on local government finances and services. For the years 2016, 2021 – 2024 they provide official data on each public library in the UK with the same information that I collected and additional variables such as the staffed hours. This allows me to validate the FOI data and obtain information from authorities that did not respond to FOI requests.

The second source is the Points of Interest (POI) data provided by Ordnance Survey. This dataset contains all public and private businesses, as well as education and leisure services. I have access to the data for the years 2014 – 2024. I filter the dataset to get information on public libraries, parks, museums, community centres, Wi-Fi hotspots, and public toilets, as well as public "bads" such as recycling centres. This administrative dataset provides me with the universe of points of interest in the UK. This means that for all available years I know the stock of all public amenities mentioned above. The POI data span only 2014–2024, limiting longitudinal analysis. In particular, this period does not align with the 2011 and 2021 census years, which provide the only years with detailed demographic data at the neighborhood level. Furthermore, in these variables, I only know the extensive margin of public amenity presence. The data from the FOI requests enhances this information by providing intensive margin measures via the opening hours.

Flow of public amenities Both the POI data and the data from the FOI requests give me extensive margin measures of the physical presence of a public amenity like a library or a pool. Building a new library or pool is a large-scale programme that can take a long time and comes with several bureaucratic hurdles, like getting approval for your planning application. Thus, there is very likely not much variation over time in the accessibility of these amenities. To overcome this issue, I rely on a measure of infrastructure investments using public procurement tender data from the EU's TED database (2009–2024). The data are at the procurement tender level and provide information on the tender, like title, description, type, or price, as well as buyer and supplier information. Each tender represents a contract that local authorities have announced. I first filter the data on whether the buyer of the tender is a local authority, and then on whether there is a postcode of implementation available. Postcodes of implementation are not available for every tender but only for a subsample of 70%. Tenders don't have a postcode of implementation if there is no clear location identifiable. This is the case, for instance, if a local council hires a new officer or if they are buying new vehicles for their waste disposal department. This leaves me with a subset of procurement tenders for the UK of 5731 tenders. Not all tenders are infrastructure investments; many involve service contracts, vehicle purchases, or administrative hires. While there is a broad categorization of tenders into Supplies, Services, and Works provided in the data, I use a local large language model to classify the tenders into infrastructure investments and other tenders. The prompt I run is the following, where the text is composed of the title and the description of the tender. I provide an example of a tender text that was classified in appendix section C.

> *"I am giving you the extracted title and description from a UK procurement tender. The buyer of the tender is a UK local authority. Your task is to classify whether the tender represents an investment into local infrastructure.*
>
> *Local infrastructure investments can either be physical investment in the form of repairs, newly built infrastructure or investments into services that likely affect the quality of public goods or public services.*
>
> *Please classify the tender into whether it is an infrastructure investment or not. If it is an investment into local infrastructure, extract the type of investment. Lastly, please flag if this is an investment into a library.*
>
> *Please return the output in structured JSON format with three keys: d_investment, investment_type, d_library.*
>
> *Here is the document text:*
>
> *[Followed by title and description]*

I refine the prompt in an iterative manner, giving examples of misclassified tenders to avoid errors. The resulting subset of classified infrastructure investments is 5298 tenders. These include investments like the repair of a library's roof or the building of a new playground in a park. I manually cross-validate a 10% sample of the classified tenders.

To give more context on the procurement data, Panel A of Figure 1 shows the number of tenders in the data for which I know the postcode of implementation by year and type of tender. The tender types are given by the data as explained above. There is variation over time in the number of tenders, with up to 3000 tenders in a given year. Panel B of the figure shows how these types translate into infrastructure investments as classified by the LLM. The figure shows that among tenders labeled as Works, virtually all are classified as infrastructure investments. For Supplies and Services, the share classified as infrastructure investments is lower but still high, with around 70%.

Access to public amenities For each neighborhood in my dataset, I construct different measures of access to each public amenity and infrastructure investment. I first create a population-weighted centroid of each neighborhood and then create three types of access measures: distance of each centroid to the closest amenity/infrastructure investment, presence of an amenity/infrastructure investment within a neighborhood, and presence of an amenity/infrastructure investment within a radius of 1 km of the centroid. I subdivide the last two measures into a discrete and continuous variable. To provide some information on these measures, Table 1 shows summary statistics for each type of access measure and each type of amenity.

Creation of a public amenity index Different amenities are likely distributed in different ways within a city. In addition, I want to provide an average figure of amenity access for neighborhoods. To that end, I create an amenity index in two ways. The first way is to standardize each access measure for each type of public amenity and average them, i.e., given for each measure of access the K amenities $X_1, X_2, ..., X_K$, I compute the standardized values of the access measure to each amenity $\hat{X}_{itk}$, like standardized distance to the closest public library in year t. The simple average amenity index is then:

$$\text{AmenityIndex}_{it} = \frac{1}{K} \sum_{k=1}^{K} \hat{X}_{itk}$$

where K is the number of amenities. This index represents the mean standardized accessibility across all amenity types. This results in five averages of amenity access, one for each type of access measure.

The second way follows Cook, Currier, and Glaeser (2023) and Diamond (2016), who use the first principal component of a principal component analysis (PCA) and interpret it as an amenity index. This first component is defined as

$$\text{PC1}_{it} = \sum_{k=1}^{K} w_k \hat{X}_{itk}$$

where $\hat{X}_{ikt}$ are standardized values of a given access measure of neighborhood i to amenity k in year t. w_k are loadings of this variable on the first primary component, which satisfy $\sum_k w_k^2 = 1$ and are chosen to maximize the variance among all possible weighted averages.

Again, I do this for every type of access measure, which results in five amenity indices. The simple average index assumes all individuals value amenities equally, a limitation recognized in the literature on heterogeneous amenity preferences (Gabriel M Ahlfeldt, Mulalic, et al., 2025; Albouy and Faberman, 2025; Almagro and Domínguez-Iino, 2025; Cook, 2025; Couture et al., 2024; Deffebach et al., 2025; Diamond and Gaubert, 2022). The PCA index identifies a common latent factor driving joint amenity distributions without imposing explicit preference weights. Appendix Figure A2 shows that these two indices are highly correlated, suggesting they capture the same underlying amenity access variation despite different conceptual approaches. While most literature uses PCA indices as explanatory variables, I use the first principal component as a dependent variable to test whether neighborhood affluence predicts overall amenity access. Although the PCA coefficients lack direct economic interpretation (representing a latent amenity index rather than a specific amenity type), this approach provides a parsimonious test of the overall amenity-affluence relationship before examining specific amenity types.

Additionally, I leverage the POI data to get information on private amenities, specifically bars, cafés, and restaurants, to contrast them with the findings for public amenities. I create the same amenity indices for private amenities as for public amenities.

3.2 Measures of neighborhood affluence

I use the term "neighborhood affluence" descriptively to refer to variables measuring a neighborhood's economic well-being, without normative implications.

Transaction prices As the main measure, I use average property transaction price from the HM Land Registry, which provides comprehensive transaction data and has become standard in UK spatial economics research (Gabriel M. Ahlfeldt, Szumilo, and Tripathy, 2024; Kleven, Landais, and Saez, 2013; Koster, 2023). The data is at the address level, covers the period 2005 – 2022, and records the price for which the property was sold. To bring the data to my unit of analysis, a neighborhood, I calculate the average transaction price of all transactions that happened in a given year and neighborhood pair. The benefit of using this measure as the main one in my analysis is the granularity and coverage of the data. Furthermore, property transaction prices should capture neighborhood deprivation and affluence quite well, being correlated with other measures such as wealth or income. The obvious drawback of using property transaction prices as the independent variable in a regression with access to amenities on the left-hand side is that amenities capitalize into house prices because households sort based on them. This introduces an endogeneity issue in my regressions. I will use an instrumental variable strategy to overcome this issue, leveraging a national transaction tax reform, which I will discuss in further detail in section 4.

Further measures of neighborhood affluence An alternative measure of neighborhood socioeconomic status is the share of residents with a university degree from the UK census. However, census data are available only for 2011 and 2021, limiting analysis of changes over time to only one difference. The last measure to capture how well off or deprived a neighborhood is, is estimated household income from the small area income estimates provided by the ONS. I use as the main variable from this dataset net weekly household income. Household income is not directly observed at the neighborhood level. Instead, the Office for National Statistics estimates income using correlated variables such as benefit receipt and council tax band. These estimates are available only at the coarser MSOA level (rather than the LSOA level used in this analysis), limiting their utility for within-city comparisons.

Table 1 shows summary statistics for the measures of neighborhood affluence described: on average, house prices are £292000, which is in line with the micro-geographic house price index from Gabriel M Ahlfeldt, Carozzi, and Makovsky (2023). The average share of people with a university degree is 30%, and the mean net weekly household income is £631, both of which are in line with official statistics. The average neighborhood observes 0.35 libraries and 0.28 infrastructure investments over the period of observation. Interestingly, there is significant variation in the opening hours of public libraries in my data, hinting at the fact that even if a neighborhood has access to a public library, the quality of that library might significantly differ from that of other libraries.

3.3 Other data

Age composition (share age 65+) and homeownership rates serve as proxies for political participation, based on evidence that older voters and homeowners are more politically engaged (Gabriel M. Ahlfeldt and Maennig, 2015; Gabriel M. Ahlfeldt, Moeller, et al., 2017; Barilari, Mastrorocco, and Paradisi, 2025). These are detailed below in Section 5 on mechanisms. Additionally, Distance to central business district (CBD)[2], distance to town halls, and buildings' age control for spatial and historical heterogeneity within local authorities. I include an urban/rural indicator to account for differences in amenity provision between city and rural areas.

4 Empirical analysis

4.1 Amenity presence

I begin the empirical analysis by examining the relationship between neighborhood affluence and public amenity access. The data reveal a striking U-shaped pattern: both the poorest and wealthiest neighborhoods have significantly better amenity access than middle-income neighborhoods. Panels A and B of Figure 2 illustrate this relationship. Panel A shows average distance to the closest library by house price decile, with the first decile representing the poorest neighborhoods, the fifth the median, and the tenth the wealthiest. The shortest distances occur at the extremes (deciles 1 and 10), while the longest distances are in the median decile (decile 5). Panel B demonstrates that this U-shaped pattern extends beyond libraries to the overall amenity index, suggesting it is a general feature of public amenity allocation rather than specific to one amenity type.

[2] Measured as the coordinates on Google Maps when googling a local authority, except for the case of London, where I define the centroid of the City of London as the CBD.

Panels C and D show the same relationship in binned scatter plots, controlling for local authority fixed effects and neighborhood characteristics (distance to CBD, distance to townhouse, population density, age of properties, and urban–rural location). Even after accounting for these spatial and historical characteristics, the U-shaped relationship persists.

To test this relationship more formally, I run the following OLS regressions

$$y_{ilt} = \delta_{lt} + \beta_1 \log(\text{ price }_{ilt}) + \mathbf{X}'_{ilt}\theta + \varepsilon_{ilt} \tag{1}$$

$$y_{ilt} = \delta_{lt} + \beta_1 \log(\text{ price }_{ilt}) + \beta_2 \log(\text{ price }_{ilt})^2 + \mathbf{X}'_{ilt}\theta + \eta_{ilt} \tag{2}$$

where y_{ilt} measures the amenity access of neighborhood i, located in local authority l in year t. I run different regressions across the access measures and the types of amenities, as well as the amenity indices. Price$_{ilt}$ is the average transaction price of properties sold in neighborhood i, located in local authority l, in year t – my variable of interest. In equation 6 I add a square term of the neighborhood affluence measure to capture the inverted U-shape seen in the raw data. $\mathbf{X}_{ilt}$ is a vector of controls including population density, distance to CBD, distance to town halls, property age, and an urban dummy. Additionally, I control for LAD by year fixed effects (δ_{lt}) so that I isolate purely cross-sectional variation in the relationship of public amenity access and neighborhood affluence. ε_{ilt} and η_{ilt} represent idiosyncratic errors. I cluster standard errors at the local authority district level, which is the unit supplying public amenities in England.

Table 2 presents the results for public libraries as an example of public amenities, and Table 3 presents the results for the amenity index. In each table, the access measure varies across columns, where in columns (1) and (2) it is distance to the closest, in columns (3) and (4) the number of amenities within 1 km, and in columns (5) and (6) the number of amenities within a given neighborhood. I present results with and without controls. Panel A shows the linear case from equation 5 and Panel B adds the square term from equation 6. Looking at public libraries first, the linear relationship between public amenity access and neighborhood affluence seems to be negative. However, when adding the square term in Panel B, it becomes evident that the square relationship is statistically significant and goes in the same direction as the raw data suggested: with increasing property prices, access first decreases and then increases at some point again[3].

This pattern holds not only for public libraries as an illustration of a public amenity but also appears when looking at the public amenity index. Again, the linear case suggests a negative relationship between a neighborhood's public amenity accessibility and its affluence. As before, when adding the square term of neighborhood affluence, this relationship seems to be quadratic now instead.

These regression results confirm the visual pattern from Figure 2: the relationship between neighborhood affluence and public amenity access is U-shaped, with the poorest and wealthiest neighborhoods enjoying significantly better access than middle-income areas.

[3]Appendix Tables A1 – A4 show the same regressions but for different measures of neighborhood affluence and confirm this relationship

While these regressions provide a more robust view of the relationship between public amenity access and neighborhood presence, the OLS estimate may suffer from endogeneity issues. For instance, we know that people like to live close to nice amenities. If people sort based on public amenities, this will drive up demand for housing in areas close to them, resulting in a reverse causality issue. Similarly, there might be other unobserved factors determining the distribution of public amenities as well as the distribution of neighborhood affluence within cities, resulting in an omitted variable bias. Lastly, as I use property transaction prices to proxy for wealth in a neighborhood, it might well be the case that there is measurement error in the independent variable, which again might lead to biased estimates. To overcome this issue, I employ an instrumental variable strategy to isolate exogenous variation in average property transaction prices in a given neighborhood-year pair.

Instrumental variable strategy To isolate exogenous variation in neighborhood property transaction prices, I rely on an instrumental variable strategy. I leverage the national reform of the Stamp Duty Land Tax (SDLT) in the UK, implemented in December 2014. The SDLT is a transaction tax that buyers of residential property pay. The reform restructured how residential property taxes were calculated, where the previous slab system was replaced with a slice system. Under the previous slab system, a single tax rate was applied to the entire transaction price. The specific tax rate was a function of the property price and applied once a given threshold was exceeded. There were different brackets with increasing tax rates. The reform introduced a progressive slice system, comparable with an income tax system, where different portions of the property price are taxed at increasing marginal rates. Additionally, the policy introduced new thresholds and tax rates.

To give a concrete example, in the previous system (slab), a £150,000 property was entirely taxed at 1%, totaling £1500, while a £250,000 property was entirely taxed at 3%. Under the new system (slice), a £150,000 property is taxed as: first £125,000 at 0% + remaining £25,000 at 2%, totaling £500. A £250,000 property is: first £125,000 at 0% + next £125,000 at 2% + final £0 at 5%, totaling £2,500.

This creates marginal tax rate discontinuities shown in Figure 3. Around the new thresholds, the policy introduced discontinuous jumps in the marginal tax rates before vs. after the policy, which I will exploit in my analysis.

Specifically, as the changes in tax rates are at the property level, I need to aggregate the policy-induced changes to the neighborhood level. I do this in two different ways and, as such, build two different instruments, which are highly correlated nevertheless. The first instrument captures the average intensity of the tax policy change in a neighborhood and is defined as $Z_i = \frac{1}{N_i}\sum_{j\in i}\Delta\tau\left(p_j\right)$ where N_i are the number of properties in neighborhood i and $\Delta\tau(p_j)$ is the band-specific change in the property tax rate for each property. The second instrument measures the exposure share and is basically a form of a shift-share instrument where I take the share of transactions in neighborhood i in band b s_{ib} and multiply it with the jump in the marginal tax rate $\Delta\tau_b(p_j)$: $Z_i = \sum_b s_b \Delta\tau_b(p_j)$. I set both instruments equal to zero for all pre-policy periods.

To work as a valid instrument, it must satisfy two conditions: first, the change in the SDLT should have a strong effect on house prices. More precisely, in my case, I want the change in the tax rate to affect not only house prices mechanically but also change the neighborhood composition of poor versus rich households via a demand channel. The intuition is that neighborhoods with a high share of houses for which the tax rate decreased after the policy should see an increase in demand as the neighborhood becomes more affordable. Thus, we should expect more low-income households to move into this neighborhood. Similarly, areas in which the tax burden on average increased should see an increase in the density of high-income households. The literature in urban economics studying the UK's SDLT confirms that this form of transaction taxes indeed moves house prices significantly. Both Besley, Meads, and Surico (2014) and Best and Kleven (2018) find that a reduction in the transaction tax due to a tax holiday reduced post-sale house prices significantly. On top of that, and importantly for my case, Hilber and Lyytikäinen (2017) show that the SDLT also affects households' mobility and sorting responses. I can confirm the relevance condition in my data by looking at the first stage F-test, which exceeds conventional thresholds.

The second assumption for the instrument to be valid is that the exclusion restriction, which requires that the SDLT reform affects amenity provision only through its effect on house prices. Two considerations support this assumption: (1) The reform was a national policy yielding revenue to national government, not local authorities, making it unlikely to be strategically designed to favor particular neighborhoods. (2) The reform was announced in autumn and implemented in December 2014 with insufficient time for local authorities to anticipate and alter amenity investment plans. Nevertheless, the exclusion restriction cannot be directly tested, and readers should interpret results accordingly.

I estimate the following two-stage least squares regressions (one for each endogenous regressor), where the first stages are given by

$$\begin{aligned} \log(\text{ mean price })_i &= \pi_0 + \pi_1 Z_i + X_i'\pi + \gamma_{g(i)} + \varepsilon_i \\ \log(\text{ mean price })_i^2 &= \tilde{\pi}_0 + \tilde{\pi}_1 Z_i^2 + X_i'\tilde{\pi} + \tilde{\gamma}_{g(i)} + \tilde{\varepsilon}_i \end{aligned} \tag{3}$$

where Z_i is one of the instruments explained above, and the vector of controls includes population density, distance to CBD, and distance to town halls, property age, and an urban dummy, and I control for local authority-specific time trends. The second stage is then given by

$$Y_i = \beta_0 + \beta_1 \log(\widehat{\text{ mean price }})_i + \log(\widehat{\text{ mean price }})_i^2 + X_i'\beta + \gamma_{g(i)} + u_i \tag{4}$$

where Y_i is an accessibility measure to a given public amenity or the accessibility-specific amenity indices, and $\widehat{\text{mean price}}$ is the fitted value from the first stage. Controls and fixed effects are the same as in the first stage, and I cluster standard errors at the local authority level.

Tables 4 and 5 present the results of the 2SLS regressions using the exposure instrument. The resulting coefficients are statistically significant and have the same sign as the ones from the OLS regression. The 2SLS coefficients are 2–3 times larger in absolute magnitude than the OLS coefficients. For example, the OLS coefficient on log house prices for distance to library (Table 2, Column 1, Panel A) is 0.611, while the 2SLS coefficient (Table 4) is 1.715. This substantial increase has two primary explanations, as we would expect the OLS coefficients to be downward-biased by the simultaneity issue of sorting.

There are two explanations for why 2SLS coefficients exceed OLS estimates. The first is measurement error in the independent variable, leading to attenuation bias. As explained above, it is very likely that there is measurement error in the (log) mean transaction prices, which are a proxy for neighborhood affluence. Classical measurement error in house prices biases OLS coefficients toward zero. If the instrument is measured without error and captures true variation in neighborhood prices, the 2SLS estimator overcomes this attenuation, recovering larger coefficients.

Secondly, we might observe larger 2SLS coefficients due to heterogeneous treatment effects. As I am identifying a Local Average Treatment Effect (LATE), the estimates capture the response specifically among "complier neighborhoods"—those whose prices were affected by the stamp duty reform. In the instrumental variable framework, complier neighborhoods are those whose property prices responded to the SDLT reform. These are typically neighborhoods with a high concentration of properties near SDLT tax thresholds, where the reform created significant discontinuous changes in marginal tax rates. The 2SLS estimates represent the Local Average Treatment Effect (LATE)—the causal effect of price changes on amenity access specifically for these complier neighborhoods, not the population average. The empirical pattern showing largest amenity increases in both the poorest and richest areas suggests nonlinear responses at the distribution tails. In poorer complier neighborhoods where stamp duty reductions increased affordability, local authorities may have responded with targeted social infrastructure investments as lower-income household concentrations increased. In wealthier complier neighborhoods where higher transaction costs concentrated affluent households, political power might have driven amenity improvements. The LATE thus represents a weighted average of these strong tail effects among neighborhoods where the reform successfully altered sorting patterns, exceeding the more muted average relationship captured by OLS. This interpretation is post-hoc and speculative. Testing the mechanisms underlying heterogeneous treatment effects is the subject of Section 5.

4.2 Amenity quality

So far, I have looked at the extensive margin effects of the presence of physical infrastructure in response to changes in neighborhood affluence. I measure amenity quality using two approaches: (1) opening hours of public libraries from the FOI requests, which proxies for facility size and accessibility; (2) infrastructure investment spending from procurement tenders, which measures maintenance and improvement spending. These measures capture different facets of quality: availability (hours) and investment (upgrades).

Tables 6 to 9 present the OLS and 2SLS regressions, which take the same form as before, just with new outcome variables. For the public libraries, the outcome variables are the opening hours of the nearest library and the cumulative opening hours of all libraries within 1 km. For the infrastructure investments, the dependent variables are the distance to the closest investment, the number of investments within 1 km, the number of investments in a neighborhood, and the investment value of the nearest investment. I again include local authority-specific time trends to isolate purely cross-sectional variation. As before, the same pattern seems to hold, namely that there is a U-relationship between the quality of public amenities and neighborhood affluence across neighborhoods within a local authority.

Results for amenity quality (Tables 6 - 9 show less consistent patterns than for amenity presence (Tables 2 - 5). For library opening hours, the cross-sectional analysis (OLS) suggests a negative relationship with house prices, while the 2SLS results are unstable, particularly for hours within 1km (Table 7, Columns 3–4). For infrastructure investments, the U-shaped relationship documented for amenity presence is partially replicated for investment counts but not for investment values.

The cross-sectional analysis above isolates variation within local authorities but at a single point in time. Panel structure allows an alternative approach: examining how amenities change within neighborhoods as they grow richer over time. I employ a two-way fixed effects model with neighborhood and year fixed effects (equations 5 and 6 below), which identifies the effect of price growth on amenity quality, controlling for neighborhood-specific time-invariant characteristics. This approach addresses concerns about time-invariant omitted variables but may be more susceptible to reverse causality (amenity improvements driving price increases). In contrast to the extensive margin analysis from above, where I look at big physical buildings like libraries, parks, or pools, infrastructure investments and opening hours are a margin that is easier to adjust and where we see more variation over time (see Appendix figure A3 which shows the variation of infrastructure investments by type over time). Thus, I run the following regressions

$$y_{ilt} = \alpha_i + \tau_t + \beta_1 \log(\text{ price }_{ilt}) + \mathbf{X}'_{ilt}\theta + \psi_{ilt} \tag{5}$$

$$y_{ilt} = \alpha_i + \tau_t + \beta_1 \log(\text{ price }_{ilt}) + \beta_2 \log(\text{ price }_{ilt})^2 + \mathbf{X}'_{ilt}\theta + \iota_{ilt} \tag{6}$$

where the dependent variables are the same quality measures as before, but now α_i denotes neighborhood fixed effects and τ_t denotes year fixed effects. Tables 10 and 11 present the results of these regressions and show a different picture. When looking at variation across neighborhoods within jurisdictions, a U-relationship between the availability and quality of public amenities is revealed. On the other hand, when looking at variation over time, neighborhoods that grow richer see more infrastructure investments and quality improvements of public amenities in their vicinity. Thus, while on the extensive margin, poor and rich areas have similar access to public amenities, quality improvements are done primarily in rich areas[4].

Cross-sectional and time-series analyses reveal different patterns. Across neighborhoods within local authorities (Panels B of Tables 2 - 9), the relationship between neighborhood affluence and amenity access is U-shaped: the poorest and richest neighborhoods have better access. However, within neighborhoods over time (Tables 10 - 11), as neighborhoods grow richer, they experience

[4]Appendix Tables A5 – A8 show the same regressions but for different measures of neighborhood affluence and confirm this relationship

more infrastructure investments and improved library opening hours. This divergence suggests two distinct mechanisms: (1) Political economy factors may create a cross-sectional U-shape, where poor neighborhoods receive amenities as a form of redistribution or to address needs, and rich neighborhoods receive amenities through political power. (2) Over time, as neighborhoods gentrify, local political coalitions shift, and investment flows toward newly affluent areas. These mechanisms are explored in Section 5.

5 Mechanisms

The U-shaped relationship is surprising: why do both poor and rich neighborhoods have better access, while middle-income neighborhoods are disadvantaged? I examine two broad explanations: Firstly, public amenities might be located in areas where they are used the most, so the allocation that we observe represents an efficient allocation. Secondly, the literature has shown that political economy plays an important role in the distribution of public funds and public goods (Baskaran and Lopes Da Fonseca, 2021; Grossman and Helpman, 1996; Hodler and Raschky, 2014; Larcinese, Rizzo, and Testa, 2006; Ouasbaa, Solé-Ollé, and Viladecans-Marsal, 2025; Solé-Ollé and Sorribas-Navarro, 2008). Therefore, neighborhood affluence could translate into political power, helping these neighborhoods attract more public goods.

5.1 Public amenity usage

The observed U-shape might be explained by the fact that rich and poor people have similar tastes for public amenities. In that case we would observe the same shape in their preferences for public amenities. To run this analysis, I need public amenity usage by type of user. While this data does not exist, I use public library usage as a proxy variable. The Understanding Society Survey is a nationally representative longitudinal survey of UK households. I use three waves from YYYY to YYYY. Parents and their children can be matched via unique identifiers, allowing me to link children's library usage to parental income. In the youth questionnaire, respondents are asked how often they visit a public library[5], with answers being: most days, at least once a week, at least once a month, several times a year, once a year or less, and never/almost never. I code library usage as a binary indicator equal to one if the child visits a public library at least weekly. From the parental survey, I create deciles of parental net weekly household income and estimate the effect of each decile relative to the median (5th) decile. After matching the information on parental income with the children's public library usage, I run the following regression

$$Y_{it} = \sum_{j} \beta_j D_{it,j} + \gamma_t + \epsilon_{it} \tag{7}$$

where Y_{it} is a dummy variable equal to one if the child visits a public library at least once per week, $D_{it,j}$ are indicator variables for a child's i parental income in wave t lies in decile j,

[5] Importantly, this excludes their school libraries.

with the median decile being the reference category, γ_t is a wave fixed effect, and ϵ_{it} represents an idiosyncratic error term.

Figure 4 displays the coefficients β_j for each income decile. The effect is strongest at the extremes: children from the lowest income decile are 2 percentage points more likely to visit libraries weekly (relative to the median), while children from the highest decile are 1.5 percentage points less likely. The pattern is relatively linear across deciles. This pattern can be explained by different reasons. For instance, low-income parents are more time-constrained than high-income parents and thus need to send their children to after-school programs. Or relatedly, children from low-income backgrounds have fewer resources to spend on school books and thus use libraries more often. Heterogeneous demand can explain part of the U-shape. Children from low-income households use libraries more frequently (Figure 4), consistent with public amenities being complements to lower-income households' consumption. However, children from high-income households use libraries less, yet high-income neighborhoods have substantial public amenity provision. This suggests that demand-based sorting alone cannot explain the full U-shape. Political economy mechanisms likely explain the amenity provision in high-income areas.

5.2 Political economy of public amenity allocation

Motivated by the political economy literature on public spending and public good provision as well as by the literature on political inequality (Cagé, 2024), it is reasonable to expect political economy to play a role in explaining the empirical pattern of the relationship between public amenity availability and neighborhood affluence. An ideal identification strategy would use variation in local election outcomes to measure how political power affects amenity allocation. The spatial structure of ward boundaries and election timing provide quasi-experimental variation (not yet analyzed) but I present here preliminary evidence using observable proxies for political power. I examine two proxies for political power—voter participation (measured by age composition) and property holder interest in local outcomes (measured by homeownership rates)—to test whether political economy explains the U-shape. The evidence supports a political economy mechanism: public amenities concentrate in high-political-power neighborhoods at both ends of the income distribution.

The two proxies that I am using are the share of people above the age of 65 and the share of homeowners. Barilari, Mastrorocco, and Paradisi (2025) document that voter participation increases substantially with age. In neighborhoods with higher shares of elderly residents, older voters constitute a larger portion of the electorate, increasing politicians' incentive to respond to their preferences. Therefore, neighborhoods with high shares of residents age 65+ should have greater political influence. Secondly, the 'homevoter hypothesis' posits that homeowners, who bear the capitalized costs and benefits of local public goods, are more politically engaged in local politics (Gabriel M. Ahlfeldt and Maennig, 2015; Gabriel M. Ahlfeldt, Moeller, et al., 2017). Homeowners have incentives to lobby for amenities and public goods that increase property values, while renters—who do not directly benefit from property value appreciation—have weaker preferences for such spending. Neighborhoods with higher homeownership rates, thus, should exert greater political pressure for amenity provision.

To construct these measures, I rely on census data from 2021, which records homeownership as well as age profiles. For every neighborhood, I construct the share of homeowners and the share of people above the age of 65 and assign them into deciles with respect to these variables. Similarly, I create house price deciles as measures of neighborhood affluence. Figure 5 shows four heatmaps that plot the three-dimensional relationship between political power, neighborhood affluence, and public/private amenity accessibility. On the x-axis of each heatmap are the property transaction price deciles, and on the y-axis, the deciles of the share of people above the age of 65 (Panels (a) and (b)) and the deciles of the share of homeowners (Panels (c) and (d)). I contrast public amenity access (Panels (a) and (c)) to private amenity access (Panels (b) and (d)). Amenity accessibility is measured by the PCA based amenity indices for public and private amenities discussed in section 3.1.

Comparing Panels A and C of Figure 5 (public amenities) to Panels B and D (private amenities), a clear pattern emerges. For public amenities, provision is high in both low-affluence and high-affluence neighborhoods, and this pattern is reinforced in high-political-power areas (high on the y-axis). For private amenities, provision concentrates exclusively in high-affluence, high-power neighborhoods. This suggests that political economy factors specifically drive public amenity provision. In neighborhoods with low political power (high share of residents age 24 and below, Figure 6), public amenities are less available but still show the U-shaped pattern with respect to affluence: some provision in low-affluence neighborhoods (redistribution) and high-affluence neighborhoods (where some wealthy young adults live). Private amenities are concentrated only in high-affluence neighborhoods, showing no responsiveness to low-power neighborhoods regardless of affluence. This absence of private amenities in young neighborhoods reflects that businesses target affluent customers; young-adult areas only attract private amenities if residents are wealthy. The differential response of public vs. private amenities to neighborhood political power provides evidence that political mechanisms drive public goods provision.

This presents evidence that to explain the U-shape, one likely needs two mechanisms that work in opposite directions. I show that demand for public amenities can explain why we observe more public amenities in low-income neighborhoods, while political economy mechanisms can explain why we observe more public amenities in high-income neighborhoods.

6 Quantitative Urban Model

Note: This section outlines a quantitative urban model currently under development. The model will quantify the mechanisms documented in the empirical analysis and enable counterfactual policy simulations. Results will be available for presentation at the conference.

The model serves three purposes: (1) quantifying the welfare costs of the observed U-shaped amenity allocation, (2) decomposing the roles of household sorting versus political economy in generating this pattern, and (3) evaluating counterfactual policies such as redistributing amenities toward middle-income neighborhoods. The quantification leverages the reduced-form estimates from Section 4 to discipline key parameters.

Households

The city is comprised of $r = 1, ..., S$ residence and $l = 1, .., S$ work locations also denoted as neighborhoods. Worker ω can be of either of two types $\theta \in \{l, h\}$ and has preferences over a consumption good $C^{\theta}_{rl}(\omega)$, housing $H^{\theta}_{rl}(\omega)$ and amenities B_r

For simplicity, the utility function is Cobb-Douglas and thus

$$U^{\theta}_{rl}(\omega) = \frac{z_{rl}(\omega) B_r}{d_{rl}} \left(\frac{C^{\theta}_{rl}(\omega)}{\alpha} \right)^{\alpha} \left(\frac{H^{\theta}_{rl}(\omega)}{1-\alpha} \right)^{1-\alpha}$$

where I decompose amenities into a fundamental amenity b_r, a public amenity g_r and a private amenity x_r

$$B_r = b_r g_r^{\eta^{\theta}} x_r^{\rho^{\theta}}$$

The exponents η^{θ} and ρ^{θ} represent the marginal utility of consuming public and private amenities. I allow these marginal utilities to be type-specific. This captures that it is easier for high-type (high-income) households to substitute between public and private goods.

Plugging this back into the utility function gives

$$U^{\theta}_{rl}(\omega) = \frac{z_{rl}(\omega) b_r \, g_r^{\eta^{\theta}} \, x_r^{\rho^{\theta}}}{d_{rl}} \left(\frac{C^{\theta}_{rl}(\omega)}{\alpha} \right)^{\alpha} \left(\frac{H^{\theta}_{rl}(\omega)}{1-\alpha} \right)^{1-\alpha}$$

I assume the idiosyncratic shocks $z_{rl}(\omega)$ to be distributed according to a Fréchet distribution (type II extreme value) following the literature enabling a closed-form solution for the location choice probabilities (Gabriel M. Ahlfeldt, Stephen J. Redding, et al., 2015; Stephen J Redding and Rossi-Hansberg, 2017; Stephen J Redding, 2024). This results in the cumulative distribution function (CDF)

$$F(z_{rl}) = \text{Prob}\left[z_{rl}(\omega) \leq z\right] = e^{-z^{-\varepsilon}}$$

where $\varepsilon > 1$ is the shape parameter that regulates the dispersion of idiosyncratic preferences. This is a simplified distribution compared to Gabriel M. Ahlfeldt, Stephen J. Redding, et al. (2015) as I assume for now no scale parameters that determine the average utility of living in r and working in l respectively.

Households earn a wage w^{θ}_l and pay taxes τ on income to pay for the public goods. Households consume housing and the numeraire good. This gives the budget constraint

$$C^{\theta}_{rl}(\omega) + r_r H^{\theta}_{rl}(\omega) = w^{\theta}_l (1-\tau)$$

and results in the Lagrangian

$$\mathcal{L} = \frac{z_{rl}(\omega) b_{rl}\, g_r^{\eta^\theta}\, x_r^{\rho^\theta}}{d_{rl}} \left(\frac{C_{rl}^\theta(\omega)}{\alpha}\right)^\alpha \left(\frac{H_{rl}^\theta(\omega)}{1-\alpha}\right)^{1-\alpha} + \lambda\left(w_l^\theta(1-\tau) - C_{rl}^\theta(\omega) - r_r H_{rl}^\theta(\omega)\right)$$

Solving the Lagrangian and plugging the optimal solutions back into the utility function gives indirect utility

$$V_{rl}(\omega) = \frac{z_{rl}(\omega) b_r g_r^{\eta^\theta} x_r^{\rho^\theta}}{d_{rl}} \frac{w_l(1-\tau)}{r_r^{1-\alpha}}$$

This expression shows that households like to live in neighborhoods r with higher public amenities, higher private amenities and work in locations l where they earn a high net-of-tax wage. They dislike commutes and high rents.

Relying on properties of the Fréchet distribution, we can solve for the probability that a worker ω decides to live in neighborhood r and works in neighborhood l:

$$\pi_{rl} = \frac{(b_r g_r^{\eta^\theta} x_r^{\rho^\theta} w_l(1-\tau))^\varepsilon (d_{rl} r_r^{1-\alpha})^{-\varepsilon}}{\sum_{i=1}^S \sum_{j=1}^S (b_i g_i^{\eta^\theta} x_i^{\rho^\theta} w_j(1-\tau))^\varepsilon (d_{ij} r_i^{1-\alpha})^{-\varepsilon}} \equiv \frac{\Phi rl}{\Phi} \tag{8}$$

From this expression, it is easy to get the probability that a worker ω lives in location r, π_{Rr}, by summing over all possible work locations j and the probability that a worker ω works in location l, π_{Ml}, by summing over all possible residence locations:

$$\pi_{Rr} = \sum_{l=1}^S \pi_{rl} = \frac{\sum_{l=1}^S \Phi_{rl}}{\Phi}, \pi_{Ml} = \sum_{r=1}^S \pi_{rl} = \frac{\sum_{r=1}^S \Phi_{rl}}{\Phi} \tag{9}$$

Similarly to the choice probabilities of living in r and working in l, I can derive the conditional probability that a worker commutes to neighborhood l given that they live in r

$$\pi_{rl|r} = \frac{(w_l/d_{rl})^\varepsilon}{\sum_{j=1}^S (w_j/d_{rj})^\varepsilon} \tag{10}$$

This shows that conditional on living in a neighborhood r, the probability that a worker commutes to some neighborhood l depends on the wage paid in location l, w_l, discounted by the commuting costs d_{rl} ("bilateral resistance") relative to commuting costs weighted wages in all possible locations j ("multilateral resistance"). According to the same logic, the probability that a worker lives in neighborhood r conditional on working in neighborhood l is given by

$$\pi_{rl|l} = \frac{(b_r g_r^{\eta^\theta} x_r^{\rho^\theta})^\varepsilon (d_{rl} r_r^{1-\alpha})^{-\varepsilon}}{\sum_{i=1}^S (b_i g_i^{\eta^\theta} x_i^{\rho^\theta})^\varepsilon (d_{il} r_i^{1-\alpha})^{-\varepsilon}} \tag{11}$$

This conditional probability depends on the relative attractiveness of a residence location r determined by its fundamental amenities (b_r), public amenities (g_r), private amenities (x_r), commuting costs (d_{rl}), and rents (r_r) relative to the attractiveness of living in any other residence location i.

With the help of the commuting probabilities, I can derive the commuter market clearing condition where the total workplace population (H_{Ml}) is given by

$$H_{Ml} = \sum_{r=1}^{S} \pi_{rl|r} H_{Rr} = \sum_{r=1}^{S} \frac{(w_l/d_{rl})^{\varepsilon}}{\sum_{j=1}^{S}(w_j/d_{rj})^{\varepsilon}} H_{Rr} \tag{12}$$

with H_{Rr} being the residence population.

Local council

The local council provides public amenities subject to a budget constraint which enforces a balanced budget $c(G) = T$ With $T = \tau \sum_r H_r$. The supply of local public goods is modeled following Maskin and Tirole (2019), who study pork-barrel in local public good provision. The functional form of the utility function of the council follows Grossman and Helpman (1994).

Define the share of high-type in a given neighborhood r as $s_{rH} = \frac{H^H_{Rr}}{H_{Rr}}$ and the share of low type in a neighborhood r as $s_{rL} = 1 - s_{rH} = \frac{H^L_{Rr}}{H_{Rr}}$ with H^{θ}_{Rr} denoting the number of workers of type θ with residence in neighborhood r. Then the average utility of a given type in neighborhood r is given by

$$\bar{U}^{\theta}_r (g_r) = \frac{1}{H^{\theta}_{Rr}} \sum_{\ell} H^{\theta}_{Rr\ell} U^{\theta}_{r\ell} (g_r)$$

We aggregate these utilities following Atkinson (1970):

$$W_r(g_r) = \begin{cases} \left(s_{rL} \left(\bar{U}^L_r (g_r) \right)^{1-\varepsilon} + s_{rH} \left(\bar{U}^H_r (g_r) \right)^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}}, & \epsilon \neq 1 \\ \left(\bar{U}^L_r (g_r) \right)^{s_{rL}} \left(\bar{U}^H_r (g_r) \right)^{s_{rH}}, & \epsilon = 1 \end{cases}$$

The parameter ε controls the council's aversion to inequality in utilities. When $\varepsilon = 0$, the council values total welfare (utilitarian); as ε increases, the council increasingly weights poor households' welfare. I will assume $\varepsilon = 0$ going forward.

Aggregating over all neighborhoods

$$W(g) = \sum_r \frac{H_{Rr}}{N} W_r (g_r)$$

So that the politician maximizes

$$U^p (g; \omega^p) = (1-\gamma) \sum_r \left(\alpha^{\omega^p}_H s_{rH} + \alpha^{\omega^p}_L s_{rL} \right) g_r + \gamma W(g)$$

From the political economy literature, we know that individuals with higher resources are over-represented and participate more in politics and thus might be favored in the policy-making process (Brady, Verba, and Schlozman, 1995; Chattopadhyay and Duflo, 2004; Hodler and Raschky, 2014; Schafer et al., 2022; Elsässer and Schäfer, 2023; Cagé, 2024). Therefore, I assume that $\alpha^{\omega^P}_H > \alpha^{\omega^P}_L$. Ultimately, the goal will be to either calibrate the alphas internally or estimate them in a reduced form.

Assuming $\alpha^{\omega^P}_H > \alpha^{\omega^P}_L$, the intuitive mechanism to explain the U-shape from the data is that neighborhoods with a sufficiently high share of poor households are needy enough to ensure they get public amenities, while neighborhoods with a sufficiently high share of rich people are powerful enough to capture public amenities from the local policy maker. Areas that are neither sufficiently needy nor sufficiently powerful receive little to no public amenities.

Production

I include production to close the wage-setting mechanism. Firms hire labor and floor space in competitive markets. Productivity A_l may vary across locations (e.g., central business districts) and could be treated as exogenous or calibrated from data. Perfectly competitive firms produce the tradable final good using labour and floor space. For simplicity, the functional form follows a Cobb-Douglas:

$$y_l = A_l H_{Ml}^{\beta} L_{Ml}^{1-\beta} \tag{13}$$

with A_l denoting productivity, H_{Ml} workplace population, and L_{Ml} commercially used floorspace yielding wage-setting: $w_l = A_l H_{M,l}^{\beta} L_{M,l}^{1-\beta}$ in equilibrium.

Construction

The construction sector produces floor space competitively, with rents adjusting to equate supply and demand for housing, following Epple, Gordon, and Sieg (2010) and Combes, Duranton, and Gobillon (2019).

$$L_r = K_r^{\mu} M_r^{1-\mu}, 0 < \mu < 1 \tag{14}$$

where capital is assumed to be supplied perfectly elastically from the wider economy at a fixed price p_K. Specifically, rents satisfy $r_r = p_K^{\mu} p_M^{1-\mu}$ where p_K is the exogenous capital price and p_M is the land price (endogenously determined).

7 Conclusion

In this paper, I examine the spatial allocation of local public amenities within cities by asking a fundamental question: who gets access to public amenities like libraries, parks, and leisure centres – the poor, the middle class, or the rich? Using comprehensive data for England between 2005 and 2024, I document a striking U-shaped relationship between neighbourhood affluence and public amenity access. The poorest and wealthiest neighbourhoods enjoy the best access to public amenities, while middle-income neighbourhoods are systematically underserved. This pattern holds across different amenity types as well as an amenity index and access measures. To address endogeneity concerns arising from household sorting and amenity capitalisation into house prices, I exploit quasi-experimental variation from the 2014 Stamp Duty Land Tax reform, which provides plausibly exogenous shocks to neighbourhood affluence. The instrumental variable estimates confirm and strengthen the U-shaped relationship.

The paper makes three main contributions. First, methodologically, I construct a novel dataset combining stock measures of public amenities, flow measures of infrastructure investments, and neighbourhood-level measures of affluence and political power. Second, empirically, I provide systematic evidence on how public amenities are distributed across the urban income distribution within cities. The U-shaped pattern reveals that neither pure market forces nor pure redistribution explains amenity allocation. Instead, the findings point to political economy mechanisms in which both poor neighbourhoods (through need-based targeting) and rich neighbourhoods (through political power) secure resources, leaving middle-income areas behind. Third, theoretically, I develop a quantitative spatial equilibrium model with endogenous public amenity provision, where local politicians allocate amenities by weighing household utilities according to political power. This framework provides a bridge between reduced-form evidence on amenity provision and structural models of urban spatial equilibrium.

Future work will strengthen the causal evidence on mechanisms and complete the quantitative model. On mechanisms, I plan to exploit close-election regression discontinuity designs at the ward level to identify the causal effect of political power on amenity allocation. By comparing neighbourhoods in wards where a party narrowly won versus narrowly lost local elections, I can isolate the impact of political representation on public amenity provision, holding constant neighbourhood characteristics. This will provide cleaner identification of the political economy channel beyond the suggestive evidence from age composition and homeownership rates presented in Section 5. Additionally, I will leverage variation in local fiscal pressure—arising from changes in central government grants and statutory service obligations—to test whether amenity cutbacks disproportionately affect middle-income neighbourhoods during austerity periods.

On the quantitative side, I will complete the calibration and estimation of the spatial equilibrium model outlined in Section 6. The model will be disciplined by the reduced-form estimates, using the instrumental variable coefficients to pin down key parameters governing household preferences for public amenities and the responsiveness of amenity supply to neighbourhood characteristics. Once calibrated, the model will enable counterfactual policy simulations, including redistributing amenities toward middle-income neighbourhoods, and altering the political weights assigned to different income groups. These counterfactuals will quantify the welfare implications of the observed U-shaped allocation and assess whether alternative rules could improve efficiency or equity. Ultimately, this quantitative framework will allow me to answer questions that reduced-form analysis cannot address: What are the general equilibrium effects of amenity reallocation on house prices, residential sorting, and aggregate welfare? How much of the observed spatial inequality in amenity access is due to political distortions versus heterogeneous preferences?

Together, these extensions will deepen our understanding of how political economy shapes urban space and provide practical guidance for designing local public good provision in an equitable and efficient manner.

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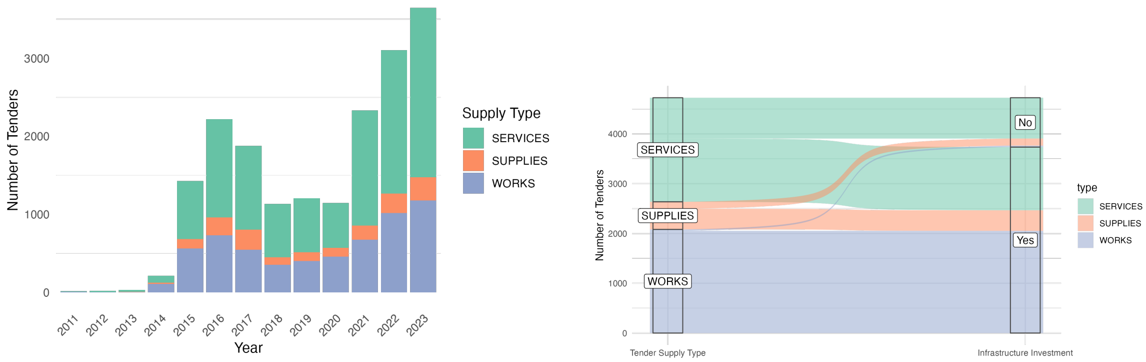
Figures and tables

Figures

Figure 1: Procurement tenders and their classification as infrastructure investments

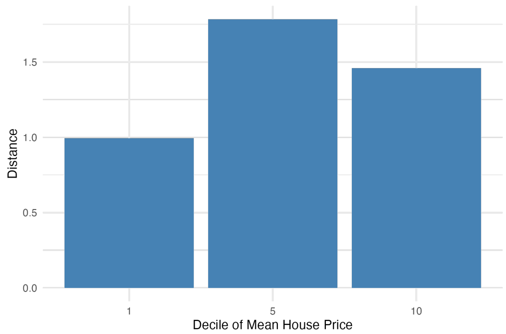
Panel A: Tenders by type over time

Panel B: Classification into infrastructure investments

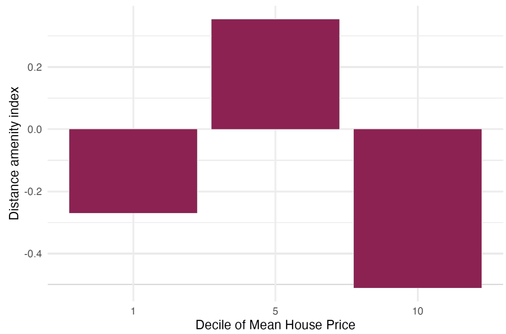


Notes: Panel A shows the number of tenders in every year since the data are available by the type of the tender. These types come from the data. Panel B shows how the tender types translate into infrastructure investments based on the local LLM described in section 3.

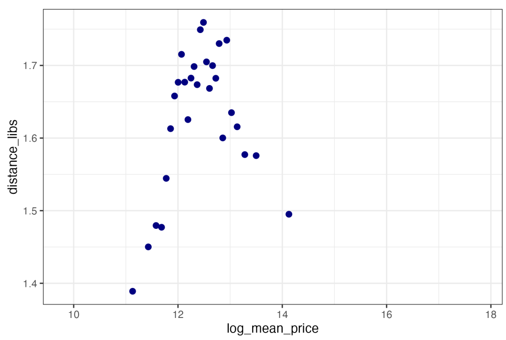
Figure 2: Poorest and richest areas have the best access to public amenities



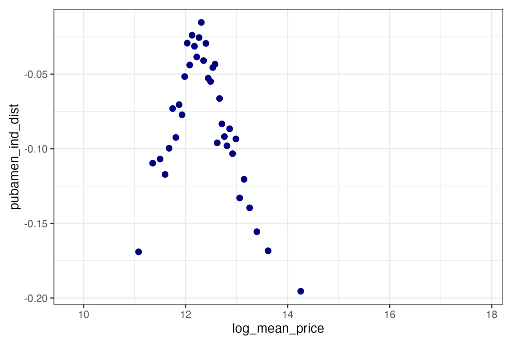
Panel A: Distance to library (mean by decile)



Panel B: Distance-based amenity index (mean by decile)



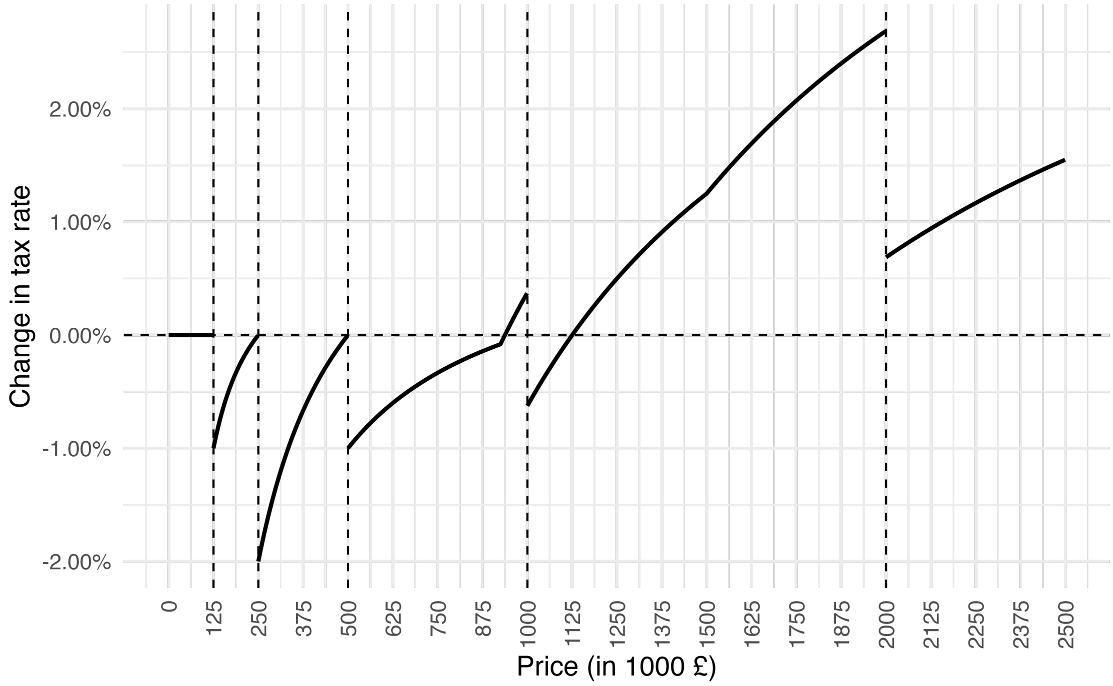
Panel C: Distance to library (binscatter)



Panel D: Distance-based amenity index (binscatter)

Notes: The figure shows the relationship between amenity access measured as distance to the closest amenity and neighborhood affluence measured as (log) mean property transaction prices. Panels A and B show the average of distance to the closest library and the average distance based amenity index presented in section 3.1 against the first, fifth, and tenth decile of the house price distribution. Panels C and D show binned scatter plots of the same two amenity access variables against a continuous measure of the house price distribution. In each binned scatter plot I control for a LAD fixed effect, distance to CBD, distance to townhouse, population density, age of the property stock, and an urban vs. rural indicator variable.

Figure 3: Stamp duty reform induced change in tax rate across the house price distribution



Notes: The figure shows the change in average transaction tax rates for properties of a given value induced by the Stamp Duty Land Tax reform in the UK implemented in December 2014. Source: HMRC; author's calculations, following Gabriel M. Ahlfeldt, Szumilo, and Tripathy (2024).

Figure 4: Children from low-income background use libraries the most

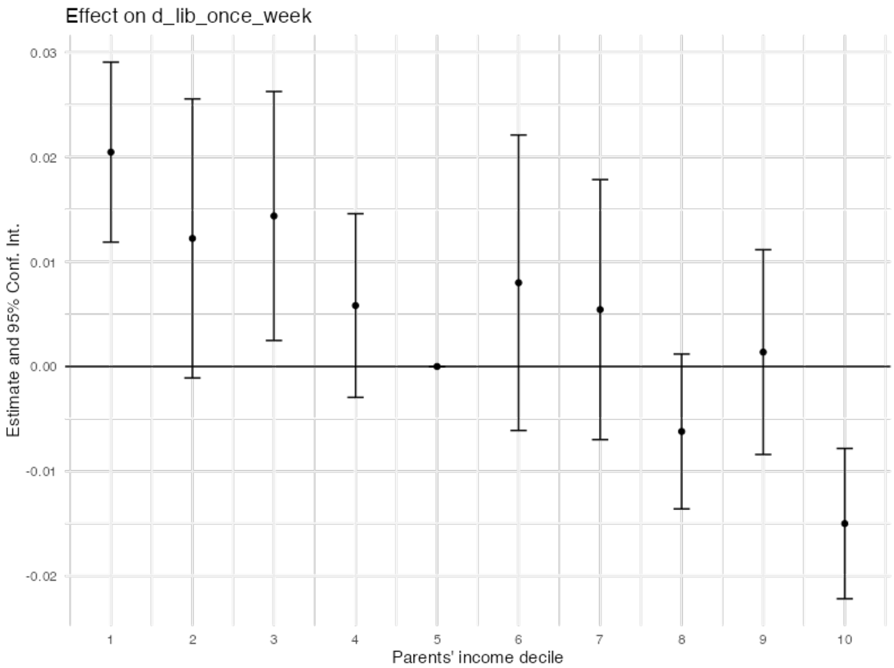
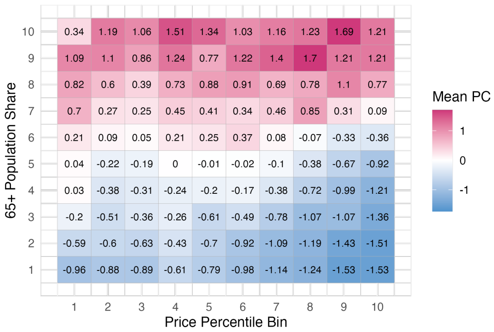
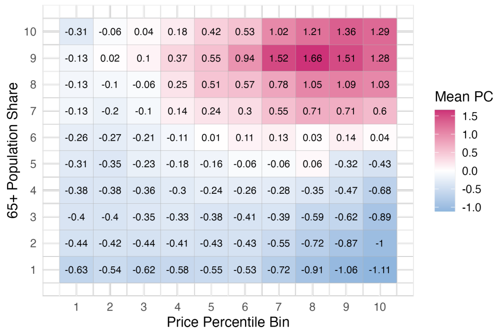


Figure 5: Public amenities in areas of high political power, private amenities in high price areas

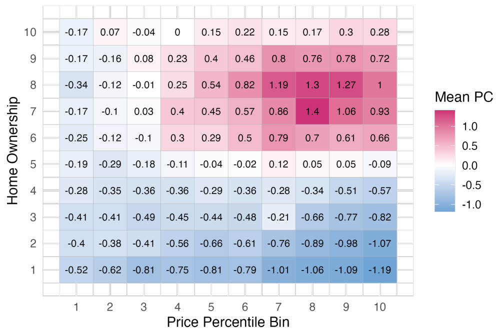


(a) Public amenities and share of old people



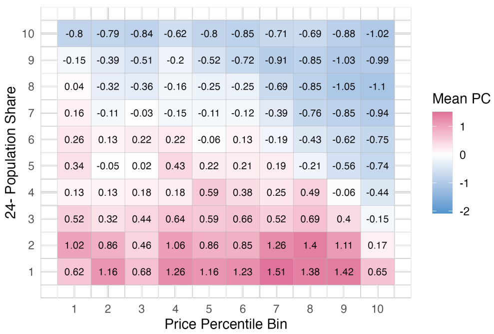
(b) Private amenities and share of old people

(c) Public amenities and share of homeowners



(d) Private amenities and share of homeowners

Figure 6: Less public amenities in areas of low political power, private amenities in high price areas



(a) Public amenities and share of young people

(b) Private amenities and share of young people

Tables

Table 1: Summary Statistics

Variables:	Mean	SD	25th Percentile	75th Percentile	Missing
Distance to library (km)	6.730	13.290	0.870	6.350	0.100
Distance to tender (km)	20.500	32.980	3.560	20.270	0.350
Public amenity index (distance)	0.090	0.830	-0.390	0.280	0.000
Private amenity index (distance)	0.000	0.860	-0.510	0.190	0.450
Libraries within 1km	0.350	0.580	0.000	1.000	0.100
Tenders within 1km	0.280	5.650	0.000	0.000	0.350
Public amenity index (within 1km)	-0.020	0.650	-0.400	0.220	0.000
Private amenity index (within 1km)	0.000	0.970	-0.380	-0.030	0.450
Opening hours nearest library	37.900	14.430	26.500	48.000	0.100
Tender value nearest	1,216,338.580	11,923,715.510	28,635.000	135,045.000	0.590
Mean house price	296,662.530	475,023.360	150,949.680	338,717.210	0.000
Share with university degree	0.304	0.131	0.207	0.380	0.902
Net weekly household income (£)	631.330	141.070	530.000	720.000	0.760
Population density (per km^2)	4,618.460	5,888.680	1,300.810	5,937.110	0.000
Share aged 65+	0.179	0.079	0.120	0.230	0.903
Share homeownership	0.641	0.204	0.496	0.810	0.903
Distance to CBD (km)	3.380	2.440	1.500	4.680	0.000
Distance to townhall (km)	3,834.110	3,240.670	1,527.190	5,146.260	0.000
Urban area	0.829	0.376	1.000	1.000	0.000
Share houses buildt pre 1945	0.630	0.284	0.423	0.876	0.000
IV: exposure	-0.004	0.003	-0.006	-0.002	0.003
IV: average intensity	0.000	0.000	-0.010	0.000	0.000

Table 2: Public libraries and housing prices – **OLS**

Dependent variable	Distance		# 1km		# Presence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
Housing value	0.6113***	0.2871**	-0.1458***	-0.0911***	-0.0302***	-0.0440***
	(0.1268)	(0.1307)	(0.0108)	(0.0103)	(0.0033)	(0.0036)
Dependent variable mean	6.7321	6.7321	0.34887	0.34887	0.10073	0.10073
R^2	0.90958	0.91098	0.38482	0.40515	0.01379	0.02024
Observations	605,870	605,870	605,870	605,870	605,870	605,870
Panel B: Adding square						
Housing value	3.6538***	1.8833	-1.0246***	-0.6031***	-0.3579***	-0.3666***
	(1.2668)	(1.2778)	(0.1600)	(0.1488)	(0.0423)	(0.0441)
Housing value square	-0.1208**	-0.0633	0.0349***	0.0203***	0.0130***	0.0128***
	(0.0467)	(0.0470)	(0.0063)	(0.0059)	(0.0016)	(0.0017)
Dependent variable mean	6.7321	6.7321	0.34887	0.34887	0.10073	0.10073
R^2	0.90961	0.91099	0.38615	0.40560	0.01442	0.02084
Observations	605,870	605,870	605,870	605,870	605,870	605,870
Regression specification:						
LAD x Year FE	X	X	X	X	X	X
Controls		X		X		X

Notes: The table presents estimated coefficients for the relationship between public library access and neighborhood affluence, measured as (log) mean transaction prices. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 3: Amenity index and housing prices – OLS

Dependent variable	Distance		# 1km		# Presence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
Housing value	0.1377***	0.0433***	-0.1360***	-0.0438***	0.0047	-0.0198**
	(0.0111)	(0.0065)	(0.0147)	(0.0148)	(0.0091)	(0.0089)
Dependent variable mean	0.08817	0.08817	-0.02282	-0.02282	0.00031	0.00031
R^2	0.85853	0.88230	0.37956	0.42389	0.01684	0.02658
Observations	673,342	673,342	673,342	673,342	673,342	673,342
Panel B: Adding square						
Housing value	0.7949***	0.1863**	-2.0761***	-1.3698***	-1.2553***	-1.1936***
	(0.1060)	(0.0720)	(0.2305)	(0.2421)	(0.2495)	(0.2415)
Housing value square	-0.0260***	-0.0057**	0.0768***	0.0524***	0.0499***	0.0464***
	(0.0040)	(0.0027)	(0.0092)	(0.0097)	(0.0100)	(0.0097)
Dependent variable mean	0.08817	0.08817	-0.02282	-0.02282	0.00031	0.00031
R^2	0.85889	0.88232	0.38473	0.42626	0.01918	0.02857
Observations	673,342	673,342	673,342	673,342	673,342	673,342
Regression specification:						
LAD x Year FE	X	X	X	X	X	X
Controls		X		X		X

Notes: The table presents estimated coefficients for the relationship between public amenity access, measured as the amenity index outlined in 3.1, and neighborhood affluence, measured as (log) mean transaction prices. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 4: Public libraries and housing prices – **2SLS** transaction tax instrument

Dependent variable	Distance		# 1km		# Presence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
Housing value	1.7145***	0.9742	-0.4248***	-0.3179***	-0.2005***	-0.2734***
	(0.5583)	(0.7084)	(0.0680)	(0.0690)	(0.0407)	(0.0625)
Dependent variable mean	6.7321	6.7321	0.34887	0.34887	0.10073	0.10073
R^2	0.90854	0.91062	0.34994	0.38479	-0.03042	-0.05070
Observations	605,870	605,870	605,870	605,870	605,870	605,870
F-test (1st stage), Housing value	31,763.5	20,851.1	31,763.5	20,851.1	31,763.5	20,851.1
Panel B: Adding square						
Housing value	5.0571***	3.3729	-1.0386***	-0.9265***	-0.5621***	-0.8559***
	(1.6780)	(2.2216)	(0.2333)	(0.2324)	(0.1133)	(0.1381)
I(log_mean_price$\hat{2}$)	-0.1618***	-0.1086	0.0297***	0.0261***	0.0175***	0.0270***
	(0.0581)	(0.0749)	(0.0092)	(0.0089)	(0.0045)	(0.0051)
Dependent variable mean	6.7321	6.1113	0.34887	0.36429	0.10073	0.10087
R^2	0.90949	0.90941	0.37675	0.37629	0.00169	-0.00535
Observations	605,870	467,795	605,870	467,795	605,870	467,795
F-test (1st stage), Housing value	35,383.4	13,840.9	35,383.4	13,840.9	35,383.4	13,840.9
F-test (1st stage), I(log_mean_price$\hat{2}$)	31,653.6	13,470.7	31,653.6	13,470.7	31,653.6	13,470.7
Regression specification:						
LAD x Year FE	X	X	X	X	X	X
Controls		X		X		X

Notes: The table presents estimated coefficients for the 2SLS regression of public library access and neighborhood affluence, measured as (log) mean transaction prices. Transaction prices are instrumented using the exposure to the SDLT reform instrument. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 5: Amenity index and housing prices – **2SLS** transaction tax instrument

Dependent variable	Distance		# 1km		# Presence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
Housing value	0.4381***	0.1365***	-0.8220***	-0.6554***	-0.6059***	-0.8030***
	(0.0972)	(0.0505)	(0.1929)	(0.2065)	(0.1760)	(0.2627)
Dependent variable mean	0.08817	0.08817	-0.02282	-0.02282	0.00031	0.00031
R^2	0.83847	0.88060	0.21067	0.30543	-0.12649	-0.18150
Observations	673,342	673,342	673,342	673,342	673,342	673,342
F-test (1st stage), Housing value	22,625.5	13,983.0	22,625.5	13,983.0	22,625.5	13,983.0
Panel B: Adding square						
Housing value	1.2657***	0.5160***	-2.4833***	-1.7584***	-1.9089***	-1.9923***
	(0.1410)	(0.1048)	(0.3245)	(0.2927)	(0.3864)	(0.3360)
I(log_mean_price$\hat{2}$)	-0.0423***	-0.0174***	0.0848***	0.0603***	0.0665***	0.0678***
	(0.0052)	(0.0037)	(0.0134)	(0.0123)	(0.0164)	(0.0141)
Dependent variable mean	0.08817	0.08941	-0.02282	-0.01435	0.00031	-0.00405
R^2	0.85795	0.88508	0.36975	0.40922	-0.00185	-0.00497
Observations	673,342	467,795	673,342	467,795	673,342	467,795
F-test (1st stage), Housing value	32,244.4	13,840.9	32,244.4	13,840.9	32,244.4	13,840.9
F-test (1st stage), I(log_mean_price$\hat{2}$)	29,398.4	13,470.7	29,398.4	13,470.7	29,398.4	13,470.7
Regression specification:						
LAD x Year FE	X	X	X	X	X	X
Controls		X		X		X

Notes: The table presents estimated coefficients for the 2SLS regression of public amenity access, measured as the amenity index outlined in 3.1, and neighborhood affluence, measured as (log) mean transaction prices. Transaction prices are instrumented using the exposure to the SDLT reform instrument. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 6: Public library opening hours and housing prices – **OLS**

Dependent variable	Hours nearest library		Hours within 1km	
	(1)	(2)	(3)	(4)
Panel A: Linear				
Housing value	-1.0620***	0.4686	0.2011	0.5232
	(0.3095)	(0.2902)	(0.4072)	(0.3396)
Dependent variable mean	37.892	37.892	40.036	40.036
R^2	0.39879	0.42393	0.35213	0.42231
Observations	605,870	605,870	182,423	182,423
Panel B: Adding square				
Housing value	-5.8408*	6.5529**	-8.4069**	2.3839
	(3.3216)	(2.9274)	(3.8589)	(3.1139)
Housing value square	0.1897	-0.2412**	0.3392**	-0.0733
	(0.1260)	(0.1122)	(0.1444)	(0.1190)
Dependent variable mean	37.892	37.892	40.036	40.036
R^2	0.39885	0.42403	0.35241	0.42233
Observations	605,870	605,870	182,423	182,423
Regression specification:				
LAD x Year FE	X	X	X	X
Controls		X		X

Notes: The table presents estimated coefficients of a regression of public library quality on neighborhood affluence, measured as (log) mean transaction prices. Transaction prices are instrumented using the exposure to the SDLT reform instrument. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 7: Public library opening hours and housing prices – **2SLS** Transaction tax instrument

Dependent variable	Hours nearest library		Hours within 1km	
	(1)	(2)	(3)	(4)
Panel A: Linear				
Housing value	-3.8065***	1.6941	-36.5411	-12.8891
	(1.2963)	(1.3804)	(57.6651)	(19.9661)
Dependent variable mean	37.892	37.892	40.036	40.036
R^2	0.39331	0.42296	-0.62710	0.29657
Observations	605,870	605,870	182,423	182,423
Panel B: Adding square				
Housing value	-7.1294	9.7007**	-36.0478***	-13.0895
	(5.0735)	(4.6248)	(13.6939)	(9.7089)
I(log_mean_price$\hat{2}$)	0.1608	-0.4131**	1.1276**	0.3372
	(0.1900)	(0.1764)	(0.4961)	(0.3551)
Dependent variable mean	37.892	37.892	40.036	40.036
R^2	0.39589	0.42307	0.30865	0.40404
Observations	605,870	605,870	182,423	182,423
Regression specification:				
LAD x Year FE	X	X	X	X
Controls		X		X

Notes: The table presents estimated coefficients of a 2SLS regression of public library quality on neighborhood affluence, measured as (log) mean transaction prices. Transaction prices are instrumented using the exposure to the SDLT reform instrument. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 8: Infrastructure investments and housing prices – **OLS**

Dependent variable	Distance		# 1km		# Presence		Investment value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Linear								
Housing value	0.4720***	0.1002	0.0069	0.1033*	0.0534***	0.0549***	-0.0137	-0.0178
	(0.0964)	(0.0898)	(0.0465)	(0.0534)	(0.0177)	(0.0168)	(0.0125)	(0.0131)
Dependent variable mean	20.482	20.482	0.27713	0.27713	0.04258	0.04258	11.328	11.328
R^2	0.97882	0.97917	0.08396	0.08662	0.00997	0.01058	0.74086	0.74096
Observations	438,234	438,234	438,234	438,234	438,234	438,234	278,260	278,260
Panel B: Adding square								
Housing value	5.7535***	3.2083**	-2.5838***	-1.6068*	-0.3700	-0.2595	0.2195	0.1933
	(1.3313)	(1.2873)	(0.8524)	(0.8603)	(0.2621)	(0.2747)	(0.1769)	(0.1720)
Housing value square	-0.2073***	-0.1218**	0.1017***	0.0670**	0.0166	0.0123	-0.0092	-0.0083
	(0.0493)	(0.0479)	(0.0327)	(0.0332)	(0.0104)	(0.0108)	(0.0070)	(0.0068)
Dependent variable mean	20.482	20.482	0.27713	0.27713	0.04258	0.04258	11.328	11.328
R^2	0.97884	0.97917	0.08411	0.08669	0.01000	0.01060	0.74087	0.74097
Observations	438,234	438,234	438,234	438,234	438,234	438,234	278,260	278,260
Regression specification:								
LAD x Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X

Notes: The table presents estimated coefficients of a regression of infrastructure investments on neighborhood affluence, measured as (log) mean transaction prices. Transaction prices are instrumented using the exposure to the SDLT reform instrument. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 9: Infrastructure investments and housing prices – **2SLS** Transaction tax instrument

Dependent variable	Distance		# 1km		# Presence		Investment value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Linear								
Housing value	6.1444	6.2471	-6.2395	-13.1071	-1.2841	-3.0363	0.0808	0.0899
	(5.2743)	(13.0212)	(5.8765)	(28.3137)	(1.2022)	(6.4668)	(0.1089)	(0.1488)
Dependent variable mean	20.482	20.482	0.27713	0.27713	0.04258	0.04258	11.328	11.328
R^2	0.97374	0.97382	-0.12638	-0.75580	-0.05696	-0.30954	0.74036	0.74038
Observations	438,234	438,234	438,234	438,234	438,234	438,234	278,260	278,260
Panel B: Adding square								
Housing value	7.8081***	3.2380	-7.8740***	-7.1187***	-1.6354***	-1.6325***	0.2482	0.2083
	(1.8560)	(1.9782)	(2.2795)	(2.3426)	(0.4957)	(0.5164)	(0.3308)	(0.3170)
I(log_mean_price$\hat{2}$)	-0.2789***	-0.1236*	0.2740***	0.2460***	0.0589***	0.0577***	-0.0096	-0.0083
	(0.0659)	(0.0700)	(0.0793)	(0.0811)	(0.0186)	(0.0191)	(0.0136)	(0.0131)
Dependent variable mean	20.482	20.482	0.27713	0.27713	0.04258	0.04258	11.328	11.328
R^2	0.97883	0.97917	0.07932	0.08194	0.00849	0.00884	0.74086	0.74096
Observations	438,234	438,234	438,234	438,234	438,234	438,234	278,260	278,260
Regression specification:								
LAD x Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X

Notes: The table presents estimated coefficients of a 2SLS regression of infrastructure investments on neighborhood affluence, measured as (log) mean transaction prices. Transaction prices are instrumented using the exposure to the SDLT reform instrument. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 10: Public library opening hours and housing prices – **OLS**, **TWFE**

Dependent variable	Hours nearest library		Hours within 1km	
	(1)	(2)	(3)	(4)
Panel A: Linear				
Housing value	1.0007***	0.9793***	1.6101***	1.5867***
	(0.3130)	(0.3104)	(0.3439)	(0.3415)
Dependent variable mean	37.892	37.892	40.036	40.036
R^2	0.58533	0.58538	0.75325	0.75333
Observations	605,870	605,870	182,423	182,423
Panel B: Adding square				
Housing value	1.6903	1.6714	-3.5423	-3.5137
	(3.9451)	(3.9439)	(4.1053)	(4.1060)
Housing value square	-0.0265	-0.0266	0.1969	0.1949
	(0.1507)	(0.1507)	(0.1574)	(0.1574)
Dependent variable mean	37.892	37.892	40.036	40.036
R^2	0.58533	0.58538	0.75330	0.75338
Observations	605,870	605,870	182,423	182,423
Turning point	31.854	31.384	8.9966	9.0148
Turning point decile	10	10	1	1
Regression specification:				
LSOA FE	X	X	X	X
Year FE	X	X	X	X
Controls		X		X

Notes: The table presents estimated coefficients of a regression of public library quality on neighborhood affluence, measured as (log) mean transaction prices. Transaction prices are instrumented using the exposure to the SDLT reform instrument. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 11: Infrastructure investments and housing prices – **OLS**, **TWFE**

Dependent variable	Distance		# 1km		# Presence		Investment value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Linear								
Housing value	3.5632***	3.5384***	0.0710**	0.0739**	0.0369**	0.0369**	-0.0641***	-0.0642***
	(0.8704)	(0.8687)	(0.0347)	(0.0348)	(0.0178)	(0.0178)	(0.0243)	(0.0241)
Dependent variable mean	20.482	20.482	0.27713	0.27713	0.04258	0.04258	11.328	11.328
R^2	0.59236	0.59246	0.31625	0.31630	0.36193	0.36193	0.26230	0.26230
Observations	438,234	438,234	438,234	438,234	438,234	438,234	278,260	278,260
Panel B: Adding square								
Housing value	-47.6188***	-47.8057***	1.3136	1.3350	0.1164	0.1165	-0.0268	-0.0271
	(12.8957)	(12.8869)	(1.3775)	(1.3759)	(0.3278)	(0.3278)	(0.6105)	(0.6109)
Housing value square	1.9573***	1.9634***	-0.0475	-0.0482	-0.0030	-0.0030	-0.0014	-0.0014
	(0.4843)	(0.4839)	(0.0517)	(0.0516)	(0.0121)	(0.0121)	(0.0235)	(0.0235)
Dependent variable mean	20.482	20.482	0.27713	0.27713	0.04258	0.04258	11.328	11.328
R^2	0.59318	0.59328	0.31627	0.31632	0.36193	0.36193	0.26230	0.26230
Observations	438,234	438,234	438,234	438,234	438,234	438,234	278,260	278,260
Turning point	12.165	12.174	13.822	13.841	19.146	19.143	-9.3296	-9.4847
Turning point decile	5	5	10	10	10	10	1	1
Regression specification:								
LSOA FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X

Notes: The table presents estimated coefficients of a regression of infrastructure investments on neighborhood affluence, measured as (log) mean transaction prices. Transaction prices are instrumented using the exposure to the SDLT reform instrument. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

A Appendix Figures

Figure A1: Successful FOI requests

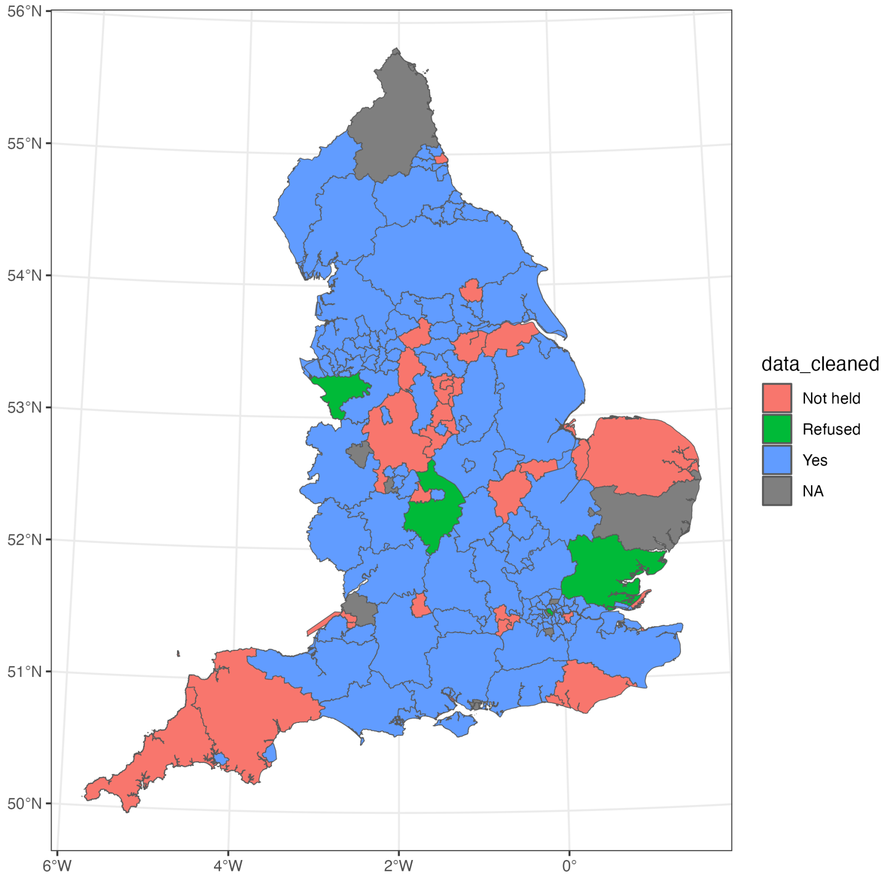


Figure A2: Correlation between average and PCA-based amenity indices

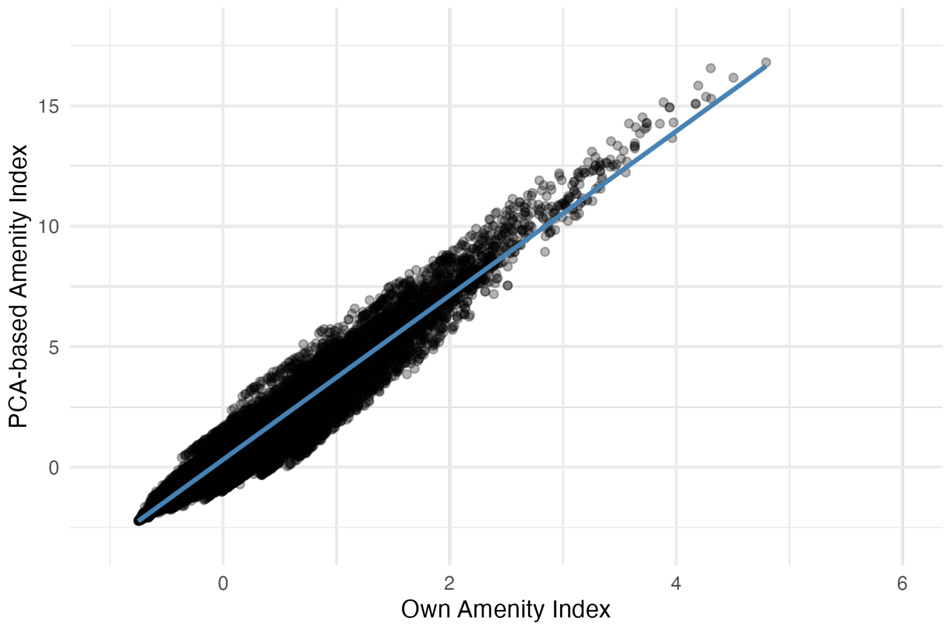
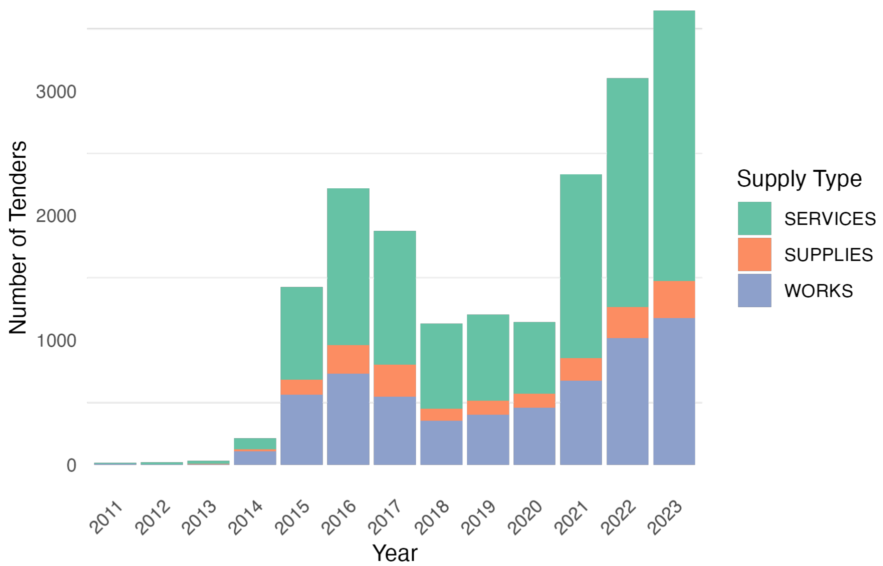


Figure A3: Procurement tenders by type over time



B Appendix Tables

B.1 OLS analysis

Table A1: Public libraries and share of people with university degree – **OLS**

Dependent variable	Distance		# 1km		# Presence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
Share with degree	1.5428***	0.5295	-0.2954***	-0.1897***	-0.1062***	-0.1546***
	(0.5435)	(0.5678)	(0.0537)	(0.0545)	(0.0161)	(0.0175)
Dependent variable mean	6.5696	6.5696	0.34046	0.34046	0.10090	0.10090
R^2	0.90680	0.90857	0.36408	0.39743	0.01376	0.02014
Observations	66,026	66,026	66,026	66,026	66,026	66,026
Panel B: Adding square						
Share with degree	6.0026***	2.6882	-0.9538***	-0.4081**	-0.2758***	-0.3783***
	(1.7984)	(1.9055)	(0.2057)	(0.1926)	(0.0521)	(0.0505)
Share with degree square	-6.3629***	-3.0578	0.9393***	0.3094	0.2419***	0.3168***
	(1.9143)	(2.0170)	(0.3153)	(0.2973)	(0.0726)	(0.0693)
Dependent variable mean	6.5696	6.5696	0.34046	0.34046	0.10090	0.10090
R^2	0.90689	0.90859	0.36520	0.39755	0.01400	0.02054
Observations	66,026	66,026	66,026	66,026	66,026	66,026
Regression specification:						
LAD x Year FE	X	X	X	X	X	X
Controls		X		X		X

Notes: The table presents estimated coefficients for the relationship between public library access and neighborhood affluence, measured as the share of people with a university degree. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A2: Public libraries and household income – **OLS**

Dependent variable	Distance		# 1km		# Presence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
log_net_weekly_income	-0.1134***	-0.1280***	1.8267***	0.5911***	-0.6266***	-0.3951***
	(0.0116)	(0.0117)	(0.2091)	(0.1401)	(0.0474)	(0.0493)
Dependent variable mean	0.10163	0.10163	2.4828	2.4828	0.46299	0.46299
R^2	0.01499	0.01977	0.78759	0.81800	0.29474	0.33072
Observations	133,331	133,331	133,331	133,331	133,331	133,331
Panel B: Adding square						
log_net_weekly_income	-0.7977**	-0.6639**	8.8831**	1.1905	-5.7758***	-3.2484**
	(0.3138)	(0.3059)	(4.2195)	(3.5739)	(1.4661)	(1.2752)
log_net_weekly_income square	0.0534**	0.0418*	-0.5505*	-0.0467	0.4017***	0.2225**
	(0.0243)	(0.0237)	(0.3279)	(0.2802)	(0.1149)	(0.1003)
Dependent variable mean	0.10163	0.10163	2.4828	2.4828	0.46299	0.46299
R^2	0.01507	0.01982	0.78765	0.81801	0.29590	0.33108
Observations	133,331	133,331	133,331	133,331	133,331	133,331
Regression specification:						
LAD x Year FE	X	X	X	X	X	X
Controls		X		X		X

Notes: The table presents estimated coefficients for the relationship between public library access and neighborhood affluence, measured as (log) average estimated net weekly household income. The unit of observation is an aggregation of neighborhoods (MSOA). Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A3: Amenity index and share of people with university degree – **OLS**

Dependent variable	Distance		# 1km		# Presence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
Share with degree	0.1658***	0.0100	-0.1977***	-0.0721	-0.0283	-0.1535***
	(0.0329)	(0.0222)	(0.0603)	(0.0506)	(0.0209)	(0.0231)
Dependent variable mean	0.26279	0.26279	0.00154	0.00154	0.00794	0.00794
R^2	0.90973	0.92637	0.35744	0.42773	0.02114	0.03640
Observations	66,026	66,026	66,026	66,026	66,026	66,026
Panel B: Adding square						
Share with degree	0.7786***	0.0840	-1.0037***	-0.2654	-0.1722**	-0.4028***
	(0.0850)	(0.0688)	(0.2073)	(0.1759)	(0.0734)	(0.0741)
Share with degree square	-0.8742***	-0.1048	1.1499***	0.2737	0.2053**	0.3531***
	(0.1018)	(0.0822)	(0.3332)	(0.2820)	(0.1032)	(0.1062)
Dependent variable mean	0.26279	0.26279	0.00154	0.00154	0.00794	0.00794
R^2	0.91016	0.92638	0.35953	0.42785	0.02123	0.03664
Observations	66,026	66,026	66,026	66,026	66,026	66,026
Regression specification:						
LAD x Year FE	X	X	X	X	X	X
Controls		X		X		X

Notes: The table presents estimated coefficients for the relationship between public amenity access and neighborhood affluence, measured as the share of people with a university degree. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A4: Amenity index and household income – **OLS**

Dependent variable	Distance		# 1km		# Presence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
Log net weekly income	0.4684***	0.1284***	-0.5847***	-0.3038***	-0.2043***	-0.2242***
	(0.0352)	(0.0243)	(0.0441)	(0.0414)	(0.0199)	(0.0217)
Dependent variable mean	0.07774	0.07774	-0.00710	-0.00710	-0.00619	-0.00619
R^2	0.83839	0.88865	0.36996	0.44581	0.02987	0.04843
Observations	164,595	164,595	164,595	164,595	164,595	164,595
Panel B: Adding square						
Log net weekly income	3.0306***	-0.0070	-5.8635***	-2.6004**	-3.7379***	-2.9362***
	(0.6922)	(0.4504)	(1.1997)	(1.1376)	(0.5457)	(0.5595)
Log net weekly income square	-0.1999***	0.0106	0.4119***	0.1791**	0.2757***	0.2115***
	(0.0538)	(0.0347)	(0.0941)	(0.0892)	(0.0420)	(0.0433)
Dependent variable mean	0.07774	0.07774	-0.00710	-0.00710	-0.00619	-0.00619
R^2	0.83857	0.88865	0.37168	0.44613	0.03083	0.04899
Observations	164,595	164,595	164,595	164,595	164,595	164,595
Regression specification:						
LAD x Year FE	X	X	X	X	X	X
Controls		X		X		X

Notes: The table presents estimated coefficients for the relationship between public library access and neighborhood affluence, measured as (log) average estimated net weekly household income. The unit of observation is an aggregation of neighborhoods (MSOA). Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A5: Infrastructure investments and share of people with university degree – **OLS**

Dependent variable	Distance		# 1km		# Presence		Investment value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Linear								
Share with degree	-0.6762	-1.6202**	0.5472*	0.5899*	0.0881***	0.0434	-0.1962	-0.2005
	(0.7154)	(0.8080)	(0.3307)	(0.3423)	(0.0340)	(0.0412)	(0.1380)	(0.1426)
Dependent variable mean	34.960	34.960	0.24755	0.24755	0.03615	0.03615	11.681	11.681
R^2	0.98310	0.98327	0.09083	0.09335	0.01213	0.01283	0.82518	0.82521
Observations	66,026	66,026	66,026	66,026	66,026	66,026	48,643	48,643
Panel B: Adding square								
Share with degree	0.9542	-2.8597	-0.3027	0.7036	0.1625	0.2022**	-0.4179	-0.4323
	(2.3263)	(2.4506)	(1.0518)	(1.1588)	(0.1042)	(0.1018)	(0.3229)	(0.3337)
Share with degree square	-2.3262	1.7557	1.2126	-0.1610	-0.1061	-0.2250	0.3262	0.3384
	(2.5733)	(2.6203)	(1.2532)	(1.3750)	(0.1433)	(0.1513)	(0.5948)	(0.6099)
Dependent variable mean	34.960	34.960	0.24755	0.24755	0.03615	0.03615	11.681	11.681
R^2	0.98310	0.98328	0.09085	0.09335	0.01214	0.01284	0.82520	0.82523
Observations	66,026	66,026	66,026	66,026	66,026	66,026	48,643	48,643
Regression specification:								
LAD x Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X

Notes: The table presents estimated coefficients for the relationship between infrastructure investments and neighborhood affluence, measured as the share of people with a university degree. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A6: Infrastructure investments and household income – **OLS**

Dependent variable	Distance		# 1km		# Presence		Investment value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Linear								
Log net weekly income	0.5928	-0.4479	-0.8265**	-0.5955*	-0.1238*	-0.1183	0.1280**	0.1121**
	(0.4853)	(0.5199)	(0.3704)	(0.3354)	(0.0703)	(0.0759)	(0.0497)	(0.0507)
Dependent variable mean	23.165	23.165	0.16655	0.16655	0.02726	0.02726	11.253	11.253
R^2	0.98184	0.98204	0.02842	0.03153	0.00577	0.00621	0.76842	0.76860
Observations	164,595	164,595	164,595	164,595	164,595	164,595	104,254	104,254
Panel B: Adding square								
Log net weekly income	6.2586	-1.6089	-20.0916	-18.8313	-3.9542	-3.8979	-1.7650	-1.9991
	(10.9454)	(11.0933)	(16.2677)	(17.0111)	(3.4724)	(3.6072)	(1.4597)	(1.4488)
Log net weekly income square	-0.4421	0.0905	1.5031	1.4221	0.2989	0.2947	0.1487	0.1658
	(0.8283)	(0.8401)	(1.2426)	(1.3023)	(0.2658)	(0.2757)	(0.1162)	(0.1153)
Dependent variable mean	23.165	23.165	0.16655	0.16655	0.02726	0.02726	11.253	11.253
R^2	0.98184	0.98204	0.02901	0.03205	0.00586	0.00629	0.76845	0.76863
Observations	164,595	164,595	164,595	164,595	164,595	164,595	104,254	104,254
Regression specification:								
LAD x Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X

Notes: The table presents estimated coefficients for the relationship between infrastructure investments access and neighborhood affluence, measured as (log) average estimated net weekly household income. The unit of observation is an aggregation of neighborhoods (MSOA). Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A7: Public library quality and share of people with university degree – **OLS**

Dependent variable	Hours nearest library		Hours within 1km	
	(1)	(2)	(3)	(4)
Panel A: Linear				
Share with degree	1.5004	3.7162***	10.2784***	7.6638***
	(1.4217)	(1.3513)	(1.8184)	(1.6257)
Dependent variable mean	36.313	36.313	38.210	38.210
R^2	0.43138	0.45723	0.43665	0.50425
Observations	66,026	66,026	19,646	19,646
Panel B: Adding square				
Share with degree	-8.1274**	5.4174	4.0503	4.5838
	(4.0391)	(3.8057)	(5.3697)	(4.9189)
Share with degree square	13.7364**	-2.4096	8.3324	4.1142
	(5.9462)	(5.5811)	(7.6052)	(6.7075)
Dependent variable mean	36.313	36.313	38.210	38.210
R^2	0.43176	0.45724	0.43684	0.50429
Observations	66,026	66,026	19,646	19,646
Regression specification:				
LAD x Year FE	X	X	X	X
Controls		X		X

Notes: The table presents estimated coefficients for the relationship between public amenity access and neighborhood affluence, measured as the share of people with a university degree. The unit of observation is a neighborhood. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A8: Public library quality and household income – **OLS**

Dependent variable	Hours nearest library		Hours within 1km	
	(1)	(2)	(3)	(4)
Panel A: Linear				
Log net weekly income	-4.5267***	0.5175	-5.0395***	-0.7786
	(1.2166)	(1.1311)	(1.9146)	(1.5698)
Dependent variable mean	37.619	37.619	39.418	39.418
R^2	0.39438	0.42312	0.36306	0.42786
Observations	164,595	164,595	53,885	53,885
Panel B: Adding square				
Log net weekly income	-92.8344***	-37.6984	-166.2485***	-88.4547**
	(30.1354)	(28.6272)	(40.5630)	(37.7749)
Log net weekly income square	6.8900***	2.9802	12.5857***	6.8436**
	(2.3526)	(2.2501)	(3.1352)	(2.9446)
Dependent variable mean	37.619	37.619	39.418	39.418
R^2	0.39495	0.42322	0.36562	0.42861
Observations	164,595	164,595	53,885	53,885
Regression specification:				
LAD x Year FE	X	X	X	X
Controls		X		X

Notes: The table presents estimated coefficients for the relationship between public library access and neighborhood affluence, measured as (log) average estimated net weekly household income. The unit of observation is an aggregation of neighborhoods (MSOA). Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

B.2 First differences

Table A9: Amenity index and housing prices – **First differences, OLS**

Dependent variable	Distance		# 1km		# Presence		$\mathbb{1}$(Presence)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Linear								
Housing value	-0.0103*	0.0924***	0.0857***	0.0624***	-0.0084	0.0821***	0.0791***	0.0479***
	(0.0061)	(0.0236)	(0.0182)	(0.0100)	(0.0066)	(0.0250)	(0.0196)	(0.0102)
Dependent variable mean	-0.66533	0.06097	0.03067	0.07540	-0.66661	0.05643	0.02782	0.07222
R^2	0.85026	0.24689	0.02709	0.03130	0.85082	0.25271	0.03299	0.03850
Observations	33,600	33,600	33,600	33,600	31,772	31,772	31,772	31,772
Panel B: Adding square								
Housing value	0.0024	0.0472*	0.0810***	0.0867***	0.0133	0.0141	0.0473**	0.0488***
	(0.0149)	(0.0264)	(0.0222)	(0.0189)	(0.0161)	(0.0275)	(0.0233)	(0.0187)
Housing value square	-0.0056	0.0199*	0.0021	-0.0107	-0.0098*	0.0307**	0.0144	-0.0004
	(0.0046)	(0.0119)	(0.0129)	(0.0081)	(0.0052)	(0.0135)	(0.0148)	(0.0075)
Dependent variable mean	-0.66533	0.06097	0.03067	0.07540	-0.66661	0.05643	0.02782	0.07222
R^2	0.85026	0.24718	0.02709	0.03139	0.85085	0.25330	0.03314	0.03850
Observations	33,600	33,600	33,600	33,600	31,772	31,772	31,772	31,772
Turning point	0.21669	-1.1877	-19.504	4.0552	0.67884	-0.22927	-1.6463	59.292
Turning point decile	1	1	1	1	1	1	1	10
Regression specification:								
LAD x Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X

Notes: The table presents estimated coefficients for the relationship between public library access and neighborhood affluence measured as house price metrics. The unit of observation is a UK Lower Layer Super Output Area (LSOA). Investment value is in logs. House prices are in logs. Controls include distance to CBD, distance to townhouses, an urban-rural dummy, and population density. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

C Classification of tenders

```
                 tender_title
                       <char>
1: Birchwood Basketball Court

tender_description

<char>
1: This is a request for a quote to install a full size outdoor basketball court (without
fencing) into a grassed area.  Applications are by email to town.clerk@hatfield-herts.gov.
Appointments to view the site can be arranged through 01707 280401.
```

Figure A4: Tender classified as WORKS