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Urbanity

Gabriel M. Ahlfeldt

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Abstract

I define a composite amenity that provides aesthetic and consumption value to local residents: Urbanity. A novel data set of geo-tagged photos shared in internet communities serves as a proxy for urbanity. From the spatial pattern of house prices and photos I identify the value of urbanity in two of the largest European cities, Berlin and London. I find an elasticity of indirect utility with respect to urbanity of about 1%. The aggregated willingness to pay equates to about $1 bn per year in each city or, on average, 1.5% of household income. The results demonstrate the important role cities paly as centers of leisure, consumption and beauty.

JEL-Code: R200, R300.

Keywords: amenities, consumer city, hedonic analysis, photography geography, property prices.

Gabriel M. Ahlfeldt
London School of Economics and Political Science (LSE)
Department of Geography and Environment &
Spatial Economics Research Centre (SERC)
Houghton Street
UK – London WC2A 2AE
g.ahlfeldt@lse.ac.uk

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1 Introduction

Cities are more than centers of production. Cities are centers of leisure, consumption and beauty. This view stands in some contrast to the classic perspective economists have long taken on cities. Accordingly, economic concentrations are the outcome of either natural advantages or the mutual attraction of firms that benefit from agglomeration economies. Workers are then pulled towards these economic concentrations due to the interplay of higher wages and reduced commuting costs and despite higher congestion costs in form of land prices, noise, pollution or crime. The phenomenon that wealthier households tend to live in suburban areas rather than downtowns in many metropolitan areas has supported the view that (central) cities are, mostly, undesirable places to live.[1]

More recently, however, it has also been acknowledged that there are not only scale economies in the production of goods and services, but also in the provision of consumption amenities. Specific amenities that address diverse tastes, e.g. specialized ethnic restaurants, theaters or other entertainment establishments require a large consumer base to operate efficiently. Similarly, the payoff to architecturally more ambitious projects is naturally higher in denser areas where buildings are exposed to more people. It is often argued that as workers become richer and more educated they increasingly demand, besides natural amenities like mild climate and access to coasts, cultural, architectural and consumption diversity that, often, only cities, and within cities only particular neighborhoods, can offer. Gentrification, one of the arguably most striking contemporary urban phenomena, witnesses the growing attraction force amenity neighborhoods exert especially on the high-skilled.

The purpose of this paper is to value urbanity. I define urbanity as an urban composite aesthetic and consumption amenity that makes a particular neighborhood a more attractive place to live. An urbanity value arises from urban charm, character and atmosphere that are jointly created by consumption (bars, restaurants, art spaces, etc.) and aesthetic amenities (architecture, parks, waterfronts) and is consumed and valued locally. I distinguish urbanity from centrality, under which I subsume the benefits of locating centrally within a labor market area and a wider distribution of urban amenities. Urbanity also ex-

1 See Brückner et al. (1999) for a theoretical discussion of income segregation, accompanied by stylized facts.

cludes the quality of public services such as good transport or schools. Urbanity can be viewed as a cause and effect of urbanization and is a distinctive element of consumption cities (Glaeser, Kolko, & Saiz, 2001).

Valuing urbanity is challenging for an obvious reason: It is virtually impossible to observe *all* features that are perceived to add to the aesthetic and consumption value of their neighborhoods. To circumvent this problem and capture urbanity empirically I make use of a novel data set of geo-tagged photos shared in internet communities. More specifically, my strategy is built on the idea that urbanity can be valued using a canonical bid-rent framework extended by a photo production function in which urbanity is an input factor. My presumption is that, ceteris paribus, urbanity increases the number of photos taken at a given location either because of an aesthetic value, which increases the probability that a photo is taken, or a consumption value, which increases the number of potential photographers. Since in spatial equilibrium all the benefits a neighborhood has to offer must be offset by the price of housing services, the willingness to pay for urbanity, even though not observed directly, can be identified from the observable spatial pattern of house prices and photos.

The results further show that there is a sizable willingness to pay for urbanity. I find an estimated indirect elasticity of utility with respect to urbanity of about 1%, a willingness to pay for observable differentials in urbanity of up to 4% of the disposable household income and an aggregated willingness to pay for urbanity of about $1 bn per year and study area (about 1.5% of disposable household income on average).The results further suggest that urbanity enters the photo production function with increasing returns, i.e. places attract disproportionately more photo activity as their endowments with favorable attributes increase. This finding is backed by a comparison of the spatial distribution of photos and an unusually rich data set on observable urbanity features that includes natural (parks, lakes, canals, and rivers), gastronomic (bars, pubs and restaurants), cultural (mainstream and avant-garde establishments) and architectural (historical and contemporary) amenities. To arrive at a limited degree of generalizability at the cost of doubling the data collection and analyses efforts, I conduct the analysis for two cities: Berlin, Germany and London, UK.

In both cities I focus on a consistent 15 x 15miles excerpt of the central metropolitan area. While the London study area is significantly more populated in absolute terms, the number of households is about the same in both areas. Both cities have been political and cultural centers in Europe for centuries and possess many ingredients of urbanity that are often argued to make European downtowns particularly attractive (Brueckner, et al., 1999). Among these features is a large 19th century urban fabric, which is relatively dense but mostly height restricted (typically at about 25m). While dominant, historic structures mix up with more contemporaneous styles and a significant number of architecturally ambitious projects. Urban green spaces are relatively large and frequent and residential land use often mixes with commercial, retail and cultural activities.

There are, however, not only similarities but also differences that make a comparison interesting. London is typically recognized as one of the few truly global cities and leading economic center of the world. London, however, is also frequently cited to successfully combine economic prosperity and quality of life.[2] Berlin, to the contrary, has economically suffered from division and partial isolation (West-Berlin) and partial transformation into a non-market economy (East-Berlin) during the division period in the 20th century. It has not been until recently that the economy has started regaining some strength. Anecdotal evidence suggests that the recent recovery is led by relatively mobile and creative industries attracted by a labor force that shares similarities with the so called "creative class" (Florida, 2002). It has frequently been argued that this social milieu appreciates the leading position Berlin occupies as a hub of avant-garde culture and entertainment.[3] It is therefore maybe not surprising that my results suggest that urbanity, in relative terms, receives an even higher value in Berlin than in London.

While the specific focus on urbanity and the empirical approach employed in this paper are novel, the analysis closely connects to some important strands in the literature that has engaged with one of the most fundamental questions in spatial economics: why do cities exist and continue to grow? The paper is broadly related to the literature on the economic effects of spatial density (e.g. Ciccone, 2002; Ciccone & Hall, 1996; Glaeser, Hedi, Jose, & Andrei, 1992; Glaeser & Mare, 2001; 1993; Rosenthal & Strange, 2001) and more

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2 London leads a broad variety of popular city rankings (e.g. ATKearney, 2012; Institute for Urban Strategies, 2011; Knight Frank & citi, 2012).

3 The fertile cultural environment is often described as having emerged out of the political and legal vacuum especially in the eastern districts following unification (e.g. McGrane, 2000; Rapp, 2009; Schwannhäußer, 2007; van Heur, 2009)

specifically related to the literature on amenity values of cities (Albouy, 2009, 2012; Blomquist, Berger, & Hoehn, 1988; Gabriel & Rosenthal, 2004; Gyourko & Tracy, 1991; 1982; Tabuchi & Yoshida, 2000). My findings strengthen the emerging evidence that beauty, distinctiveness and consumption variety is valued, at least by some population groups, and can therefore contribute to the economic success of cities (Carlino & Saiz, 2008; Glaeser, et al., 2001). I also contribute to a literature that has analyzed the internal structure of cities and within-city effects on utility of residents or productivity of firms (e.g. Ahlfeldt, Redding, Sturm, & Wolf, 2012; Ahlfeldt & Wendland, 2013; Arzaghi & Henderson, 2008; Brueckner, et al., 1999; Cheshire & Sheppard, 1995; Fujita & Ogawa, 1982; Lucas & Rossi-Hansberg, 2002; McMillen, 1996; Rossi-Hansberg, Sarte, & Owens, 2010; Storper & Venables, 2004). Within this literature strand, there have been attempts to analyze specific forms of urban amenities that contribute to urbanity, e.g. sports stadia (e.g. Ahlfeldt & Kavetsos, 2013; Carlino & Coulson, 2004), architectural beauty, usually in the context of preserved historic buildings (e.g. Ahlfeldt & Maennig, 2010; Coulson & Lahr, 2005) or cultural facilities (e.g. Ahlfeldt, 2011a; Bille & Schulze, 2006; Sheppard, 2013). This study, however, is the first to attempt a valuation of the composite urbanity value, circumventing the problem of limited data on observable amenities by employing a micro-level revealed preference index of human interest: geo-tagged photos.

2 Strategy

2.1 Theoretical Framework

The aim of this paper is to provide novel evidence on the value of a specific type of urban amenity, which I will refer to as urbanity. In reference to the four categories of urban amenities [1-4] classified by Glaeser et al, (2001) I define urbanity as the composite of local consumption amenities [1], e.g. bars, pubs, restaurants, theatres, museums and other entertainment facilities, and aesthetic amenities [2], comprising both the beauty of architectural design and urban landscape. Urbanity, as defined here, is consumed and valued locally at the place of residence. I distinguish urbanity from centrality, which makes a place more attractive due to improved access to local labor markets and other attributes for which residents are willing to travel. Urbanity also excludes the remaining amenity categories defined by Glaeser et al, (2001), i.e. the quality of public services [3] and efficient transport [4]. Formally, urbanity is an index of aesthetic and consumption amenities, some of which can be observed (A_k) and some of which are unobserved (A_l):

$$A_i = \prod_k A_{ki}^{\frac{\lambda_k}{\lambda}} \times \prod_k A_{li}^{\frac{\lambda_l}{\lambda}} \tag{1}$$

, where λ_k/λ and λ_l/λ determine the weight with which selected features enter the index. The multiplicative form accounts for the complementarity among distinct urban features in creating a special neighborhood character. To estimate the value of urbanity empirically, I set up a canonical bid-rent framework, which I extend to incorporate the spatial distribu tion of photos shared in internet communities as means of capturing urbanity A_i. Geo-tagged photos help identifying the value of urbanity by a) containing information on features that are otherwise unobservable (A_l) and b) implicitly defining the weights λ_k of the observable (and unobservable) urbanity features A_k (and A_l).

The key elements of my bid-rent world are A) residents who derive a utility from the consumption of housing services and a composite non-housing good, which is shifted by the local urbanity level, B) a competitive housing construction sector using land and capital as inputs, and C) a photo production function, in which urbanity serves as an input factor. Spatial equilibrium is ensured by perfectly mobile individuals and, hence, a constant reservation utility, and perfect competition in the construction sector, which implies zero economic profits at all locations. Prices for housing services and land, the bid-rents, must therefore offset all benefits of location, including urbanity, to maintain spatial equilibrium. Combining the housing bid-rent function and the photo production function the model can be used to back out the value of urbanity from the observable spatial distributions of property prices and photos. The main purpose of this section is to briefly describe the derivation a set of preferred testable partial equilibrium conditions that can be taken to the data. A more detailed version that also includes some additional equilibrium conditions is in the appendix.

Housing demand

The city considered here consists of discrete neighborhoods i, which can vary in size. At a given neighborhood i, identical individuals derive a standard Cobb-Douglas utility from the consumption of housing services H_i and a composite non-housing good C_i. This formulation is in line with housing expenditure shares that tend to be relatively constant across population groups and geographies (Davis & Ortalo-Magné, 2011).

$$U_i = V_i {C_i}^{\alpha} {H_i}^{1-\alpha} \tag{2}$$

where housing services $H_i = F_i e^{f_i}$ are defined as a function of housing floor space F_i and a bundle of housing features f_i.

A location is a more or less attractive place to live depending on the amenities offered, which is captured by V_i.

$$V_i = \tilde{E}_i^{\gamma_E} \tilde{A}_i^{\gamma_A} \tilde{S}_i^{\gamma_S} \tag{3}$$

where $\tilde{E}_i$ is a measure of centrality, $\tilde{S}_i$ is the quality of public services a location offers (e.g. good schools or transit) and $\tilde{A}_i$ is the effective urbanity level perceived at i. Residents value the density of urbanity features in their neighborhood, which is defined as: $\tilde{A}_i = A_i/G_i$, where A_i is the aggregate urbanity in the neighborhood defined in (1) and G_i is the land area of a neighborhood. Individuals derive a utility from locating centrally in a labor market area (centrality) due to the lower (expected) inconvenience of commuting. Effective labor market access is defined as the inverse of a perceived commuting disutility $\tilde{E} = E(C)^{-1} = \sum_j \pi_j T_i$, which depends on a commuting probability $\pi_j = E_j / \sum_j E_j$ determined by the spatial distribution of workplace employment E_i and an iceberg cost $T_i = e^{-\tau D_{ij}} \in (0,1)$. The iceberg cost in turn depends on the distance between the place of residence i and a potential workplace location j and $\tau > 0$, which determines the spatial decay. This gravity type employment accessibility, which has recently enjoyed increasing popularity in the house price capitalization literature (Ahlfeldt, 2011b, 2013; McArthur, Osland, & Thorsen, in press; Osland & Thorsen, 2008), collapses to the standard monocentric framework if all workplace employment is concentrated in one location. It is notable that with the chosen formulation, I assume that residents do not value urbanity in other than their own neighborhood. Urbanity is meant to capture a specific urban atmosphere or ambience that can be enjoyed in the neighborhood. Lower inconvenience of travel to consumption amenities in other neighborhoods will be captured by centrality to the extent that these amenities are correlated with the employment distribution. In robustness checks presented in the appendix I experiment with alternative formulations for centrality that presumably capture different shades of centrality.

At all locations in the city residents maximize their utility by choosing C_i and H_i subject to a fixed budget B. The budget is net of a fixed monetary component of transport cost, e.g. the cost of owning a car, or having a monthly transit ticket. The monetary cost of distance traveled is assumed to be small relative to the inconvenience of longer journeys, which seems like a reasonable approximation for many large metropolitan areas, including Berlin and London.

Residents are perfectly mobile across neighborhoods so that the price of housing services, the bid-rent, must fully compensate for all locational differences in equilibrium. Let ψ_i be the price of housing services and the price of the composite non-housing good be the numeraire. The spatial equilibrium can be derived by substituting the indirect demand functions into (1), setting U_i to a reservation utility level $\overline{U} = 1$, and solving for ψ_i. We obtain the following housing bid-rent function in log-linearized form:[5]

$$\log(\psi_i) = \aleph + \frac{\gamma_E}{1-\alpha} \log \tilde{E}_i + \frac{\gamma_A}{1-\alpha} \log \tilde{A}_i + \frac{\gamma_S}{1-\alpha} \log \tilde{S}_i \quad (4)$$

In keeping with intuition, bid rents increase in centrality, public services quality and urbanity.

Housing Supply

Equation (4), within the constraints of assumptions made, reflects the demand for housing space in the urban economy. The supply side can be described by a homogenous competitive construction sector (Brueckner, 1987; Mills, 1972; Muth, 1969). Developers use capital K_i and land L_i as inputs in a concave production function to produce housing services, which are uniform within a neighborhood i and rented out to households at the bid-rent ψ_i.[6] Similar to Combes, Duranton & Gobillon (2012) I assume a Cobb-Douglas functional form. I present supportive estimates of a unitary elasticity of substitution between land and nonland factors in the appendix. The Cobb-Douglas form is also in line with some other estimates of housing production functions (Clapp, 1979; Epple, Gordon, & Sieg, 2010; Thorsnes, 1997).[7] Given the within city focus I abstract from a variety of geographic and regulatory supply conditions that vary across metropolitan areas (Saiz, 2010).

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5 where $\aleph = \log\left[(1-\alpha)\alpha^{\alpha} B^{1/(1-\alpha)}\right]$

6 The total amount of land occupied in a district depends on the geographical size G_i and the land share dedicated to residential use, which are exogenously given.

7 A number studies has found values of the elasticity of substitution substantially below unity. See McDonald (1981) for a survey of the early literature and Albouy (2012) for recent estimates. However, many of these estimates have been argued to be plagued by a range of specification problems (McDonald, 1981). In the appendix I show that accounting for endogeneity bias using an IV increases the implied elasticity of substitution substantially.

$$H_i = K_i^{\delta} L_i^{1-\delta} \tag{5}$$

The price of capital, which comprises all non-land inputs, is normalized to one. Land is rented from absentee land lords at a unit price Ω_i, the land bid-rent. Given free entry and exit, (economic) profits must be zero at all locations in city so that the land bid-rent must adjust to compensate for changes in the housing bid-rent to maintain the spatial equilibrium on the supply side. Making use of the first-order conditions and the zero-profit condition it follows that the land bid-rent is a log-linear transformation of the housing bid-rent.

$$\text{Log}\,\Omega_i = \frac{1}{1-\delta}\log\psi_i + \log\left[(1-\delta)\delta^{\delta}\right] \tag{6}$$

It directly follows that the value of housing services per land unit $\psi_i H_i / L_i$ is a linear transformation of the land bid-rent and, hence, log-linearly related to the housing bid-rent.

$$\log\left(\frac{\psi_i H_i}{L_i}\right) = \frac{1}{1-\delta}\log\psi_i + \log\left[\delta^{\delta}\right] \tag{7}$$

It can further be demonstrated that the capital to land ratio K_i/L_i is log-linearly related to the housing bid-rent and that the ratio of floor space over land area (floor area ratio), is a log-linear function of the housing bid-rent and housing features f_i (see the appendix for details).

Photo production

The equilibrium conditions (4) and (7) follow from more or less conventional assumptions. The key challenge when taking them to the data is that the phenomenon of interest, urbanity A_i, is not observable directly. To overcome this fundamental limitation and to create the link to the novel data set introduced here, I assume a photo production function, in which the output, i.e. the number of photos P_i taken at in a neighborhood i, is a function of the unobserved amenity level A_i and the number of residents living (POP) or working (EMP) there.

$$P_i = cEMP_i^{\theta_E} POP_i^{\theta} A_i^{\lambda}, EMP_i > 0, POP_i > 0 \tag{8}$$

, where λ>0 moderates the relationship between unobserved urbanity and observed number of photos. The expectation is that the number of photos "produced" in a given neighborhood increases in the presence of workers or residents assuming that the probability of taking photos is constant given the same urbanity level. Ceteris paribus, urbanity makes a place more attractive as a photo motif (increases the probability of taking photos) or setting (increases the number of potential photographers) and therefore increases the number of photos taken and shared in the internet. Solving the photo production function for A_i and substituting into the spatial equilibrium bid-rent function (4) yields the bid-rent as a function of centrality, quality of public services, as well as employment (*EMP*), population (*POP*), the number of photos taken and the land area of a respective neighborhood. I note that I do not assume that the photo production, ceteris paribus, depends on the land area of the neighborhood. Land area enters the equilibrium condition (9) due to the assumption that households value effective urbanity $\tilde{A}_i = A_i/G_i$, i.e. the (spatial) density of all the features constituting urbanity.

$$\begin{aligned}\log(\psi_i) = \aleph + \frac{\gamma_E}{1-\alpha}\log\tilde{E}_i + \frac{\gamma_A}{1-\alpha}\frac{1}{\lambda}\log P_i - \frac{\gamma_A}{1-\alpha}\log(G_i) \\ - \frac{\gamma_A}{1-\alpha}\frac{\theta}{\lambda}\log(EMP_i) - \frac{\gamma_A}{1-\alpha}\frac{\theta_B}{\lambda}\log(POP_i) + \frac{\gamma_S}{1-\alpha}\log\tilde{S}_i \end{aligned} \quad (9)$$

Equation (9) sets the ground for a reduced form empirical test of the housing bid-rent function based on variables that can be observed or feasibly approximated. To incorporate the supply side, equation (9) can be substituted into equation (7).

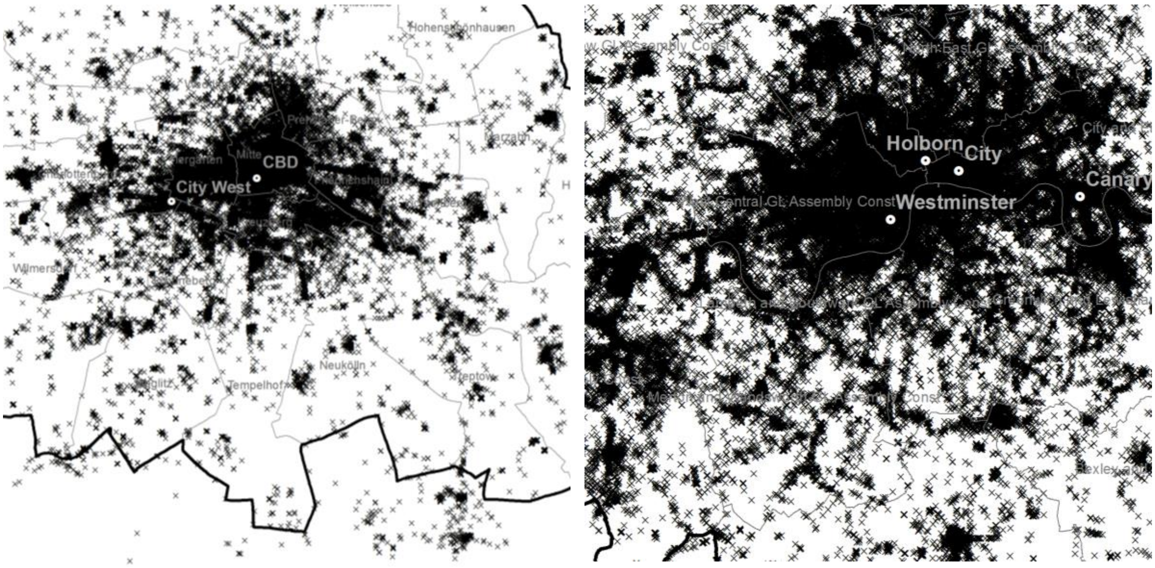
2.2 Data

Figure 1 shows the raw photo data used to generate the urbanity measure. They originally stem from Eric Fisher's Geotaggers' World Atlas, whose observations are taken from Flickr and Picasa search APIs.[8] To obtain a consistent geography in both cities only photos taken with a 15 x 15 miles square are considered. The bounds on each side are chosen to include as many geo-tagged locations as possible near the respective central cluster. While from the data set it is not possible to observe the place of residence and to sharply distinguish between residents or tourists groups, the individual pattern of photos taken by a user at various cities over time facilitates the restriction to pictures that were likely taken by residents. I follow Fisher's decision rule and define users that took pictures in one of the study cities over more than a month (and not in any other city) as residents. After this restriction and deletion of photos with incomprehensive dates the data set comprises 165,208 individual observations for Berlin and 806,851 for London, in each case taken from the initial recordings up to 2009. I note that I make use of the full set of available photos (about 1.85

[8] See for details http://www.flickr.com/photos/walkingsf/sets/72157623971287575/.

Mio for London and about 0.633 Mio for Berlin) and another subset consisting of likely tourists in robustness checks presented and discussed in the appendix.

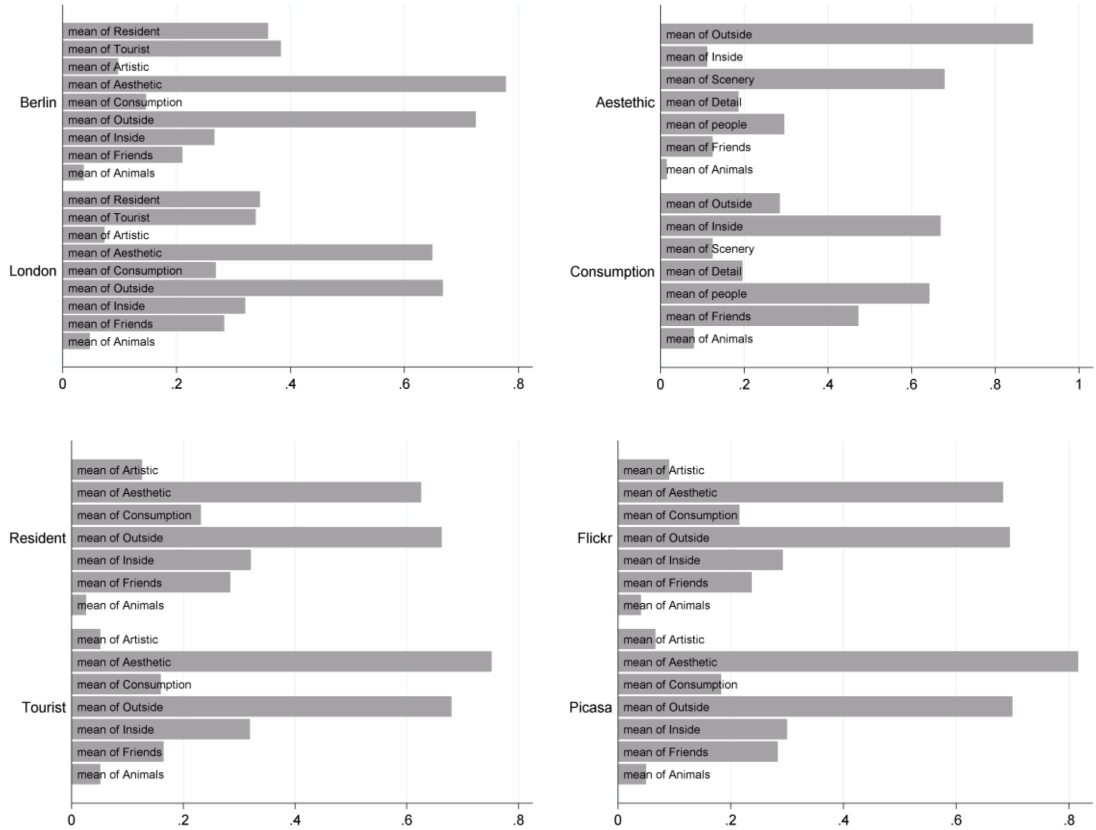
Fig. 1. Distribution of Photo Nodes in Berlin (left) and London (right)



Notes: Own illustration based on Eric Fisher Geotagger's World Atlas. Both maps show a 15x15 miles area in chosen to maximize the number if photos within the excerpt. To improve visibility, a roughly 20% (random) sample of all photos is used in these illustrations.

Figure 2 provides a brief summary of the typical photo subjects based on a subsample of about 600 photos that were randomly drawn and visually inspected using the hyperlinks provided in the data base. Of primary interest with respect to the definition of urbanity adopted here is the extent to which the motivation for taking a picture was likely driven by the *aesthetic* character of a location (photos that are e.g. focused on buildings, urban spaces and sceneries or individual objects) or the presence of *consumption* amenities that attract visitors (photos taken inside or close to museums, restaurants, etc.). A large fraction of pictures tends to focus on *aesthetic* features in open space (*outside*). Perhaps not surprisingly, residents are more likely to take pictures at *consumption* places than tourists. These pictures are more likely taken within buildings (*inside*) and of persons that seem to be well known to the photographer (*friends*), which is in line with consumption amenities constituting places of social interaction. More generally, however, it is notable that the distribution of photo subjects by category is remarkably similar across the two cities, *residents* and *tourists* groups as well as *Flickr* and *Picasa* users. Consistently, few pictures seem to be taken purely for *artistic* reasons that are unrelated to location (photos of e.g. the moon, close-ups of flowers, etc.). *Animals* don't appear particularly frequently on the photos; and if so, the majority of photos appear to have been taken in zoos, which can be regarded as consumption amenities. All in all, the admittedly casual inspection of the photo sample suggests that the data contains information that is strongly linked to urban places of human interest, broadly defined; or, put in a single word: urbanity.

Fig. 2. Photo subjects by categories



Notes: Graphs show the percentage of pictures falling into a bar category conditional on being in a group depicted to the left of the vertical axis. The figure is based on a randomly drawn samples of 267 (271) photos for Berlin (London). The exact numbers and percentages of pictures by category are tabulated in the appendix (Table A3).

All data used in the analysis are aggregated to consistent spatial units, the neighborhoods *i*. As units of analysis I use (medium level) voting precincts (Stimmbezirke) for Berlin and lower level super output areas for London. Both units are sufficiently small to be considered roughly homogenous neighborhoods and at the same time sufficiently large to yield meaningful urbanity (approximated by the number of photos taken) densities. These units also provide notable variation in the land area, which I require to identify the structural parameters. Finally, the boundaries of the chosen units are consistent with a range of spatial units for which official data such as population or employment are available. Within the 15x15 mile frame I end up with 969 (Berlin) and 2731 (London) units of observations with a mean land area of about 0.3 (Berlin) and 0.16 (London) square km. The somewhat distinct resolutions are chosen to account for the higher density of photos in London and ensure that less than 10% of the units are unpopulated with photos in each city.

I merge these data with a range of observable location characteristics. Most importantly I use property transaction data from the Committee of Valuation Experts (Berlin, 2000-2009) and the Nationwide Building Society (London, 2000-2008). The data for Berlin are unusually rich and contain a full record of property transactions, including the transaction price, total floor size and the corresponding plot area, among a range of building characteristics. A georeference is given by geographic coordinates in projected meter units. For London the data is somewhat less complete. It is restricted to properties for which Nationwide has issued mortgages. Since the company represents one of the three large mortgage providers with a market share of about 10% it still provides a comprehensive coverage. The main advantage over the land registry data set providing full coverage is that it includes a range of detailed property characteristics, although not the lot size of a building. Both data sets have been used and discussed in more detail in previous academic research (e.g. Ahlfeldt, 2011b, 2013; Ahlfeldt & Kavetsos, 2013; Gibbons & Machin, 2005).

Other data collected include resident population by age group and workplace employment from official statistical records, estimates of average household income and various distance and geographic measures computed in GIS. Geographic data on water and green areas, transport infrastructure (distance to rapid transit) and schools (Berlin) have been obtained via the Berlin Senate Department and EDiNA. For London, I compute a measure of local key-stage 2 test results as a proxy of perceived local school quality based on individual pupil test scores. I also compile a data set of less common features. Among them are cultural consumption amenities, i.e., museums, theaters and cinemas (recorded in official registers). Moreover, I borrow from Bass van Heur's fieldwork and geocode hundreds of avant-garde music venues, such as clubs, record labels, etc., to define an index of avant-garde cultural activity based on the address list provided in the appendix of his PhD (van Heur, 2008). Bars, pubs and restaurants are incorporated based on electronic maps compiled by Geofabrik based on data uploaded by web-users to OpenStreetMap. For architectural quality, besides making use of historic preservation records, I geocode hundreds of contemporary landmark buildings based on architecture guides (Allinson, 2009; Haubrich, Hoffmann, Meuser, & Uffelen, 2010). A more detailed discussion of the data is in the appendix.

2.3 Empirical Strategy

This section describes how the equilibrium conditions (7) and (9) derived in 2.1 can be taken to the data. I keep the derivation, presentation and discussion of results in the main paper to the preferred models. Because of the lack of information on the occupied land area the analysis for London can only be carried out using the conventional hedonic approach (9). With the Berlin data I am able to identify the parameters of interest using the transaction price normalized by the land area as a dependent variable, which results in estimates that are presumably less sensitive to unobserved housing features. In the appendix I complement the analysis using alternative equilibrium conditions (with e.g. the pure land value or the capital to land ratio as dependent variable), which, due to the data limitations, can also only be applied to Berlin.

Variable construction

The key phenomenon of interest in this research is urbanity, which empirically I capture by the numbers of photos k taken in a given neighborhood i, weighted by the inverse of the ratio of total photos N_t in a given year t to the total number of photos N. The social media technology used for online photo sharing is relatively young. Since a comprehensive spatial coverage of the study areas has not been reached until recently it is difficult to exploit variation over space and time. Instead, I pool all available photos over all periods to maximize the use of information with respect to the dimension of space. The measure proposed then corrects for the increasing popularity of photo sharing platforms by attaching higher weights to (earlier) years in which fewer pictures were taken. As discussed above, only photos that presumably were taken by residents enter the measure in the benchmark models. To the degree possible this restriction ensures that the capitalization measure (property prices) and the urbanity measure (photos) are based on the same population, i.e. residents of the respective cities.

$$P_{it} = \sum_k \sum_t w_{kit}\,, w_t = \frac{\frac{N_{kit}}{N_t}}{\sum \frac{N_{kit}}{N_t}} \tag{10}$$

Since it is likely that access to social media is not only increasing over time, but also varying significantly across population groups, I allow the population elasticity coefficient in the photo production function to vary in the local average age of the adult population (O) as well as in the average household income (I) of the local population in a neighborhood.

$$\theta = \theta_B + \theta_O O_i + \theta_I I_i \tag{11}$$

Since many of the features constituting urbanity are presumably concentrated in central urban areas it is important to effectively control for centrality to disentangle the two potentially spatially correlated phenomena. I capture effective labor market accessibility *EP* by the distance weighted aggregate of all workplace employment (E_j) in the city.[9] Similar measures are typically referred to as potentiality or gravity variables in the literature. The internal distance measure $D_{ij=i}$ is adopted from Redding and Venables (2004).

$$EP_i = \sum_j E_j / \sum_j E_j \, e^{-\tau D_{ij}}, D_{i,j=i} = \frac{1}{2}\sqrt{\frac{G_i}{\pi}} \tag{12}$$

While alternative approximations of centrality are imaginable and will be considered in robustness checks (in the appendix), the potentially formulation has proved superior explanatory power to a standard distance to central business district measure in previous research in both study areas (Ahlfeldt, 2011b, 2013). To generate the potentiality measure defined in (12) I borrow τ from Ahlfeldt (2013) who provides an estimate for London and shows that the results are roughly in line with evidence for other study areas, including Berlin, as well as more generally with observable commuting patterns.[10]

Capitalization models

Based on these empirical measures and the spatial equilibrium condition defined above I derive two types of reduced form equations. The first reduced form equation is based on equation (7) and uses the price per land area as dependent variable ($Y = \psi_i H_i / L_i$).

$$\log(Y_{it}) = a + a_E \log EP_i + a_A \log P_i + a_L \log(G_i) + \sum_n b_n X_n$$
$$+ b_E \log EMP_i + b_P \log POP_i + b_O \log POP_i \times O_i + b_i \log POP_i \times I_i + \varphi_t + \eta_{it} \tag{13}$$

Where EP_i and P_i are defined in (10) and (12), *G* is the geographic land area of a neighborhood (voting precincts or lower level super output areas), X_{in} is a vector of control variables capturing the quality of public services among other things, and EMP_i and POP_i are the local employment and population in a given neighborhood. The interaction of population

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9 Distances D_{ij} are approximated by straight line distances.

10 The decay parameters are rescaled so to fit with the change in dimension from minutes to km assuming an average within city velocity of 25km/h (Olson & Nolan, 2008). The implied spatial weight function (and an alternative employed in robustness checks) is depicted in the appendix.

with average age and income (both demeaned) directly follows from plugging (11) into (9). Small letters are coefficients to be estimated, φ_t is a set of yearly fixed effects and η_{it} a random error term. Note that individual transactions (and characteristics) at all stages of the analysis are aggregated to the neighborhood level to avoid multiple transactions within a neighborhood sharing the same location characteristics and different neighborhoods receiving distinct weights depending on transaction frequencies. It is a notable feature of equation (13) that unlike in many applications of the hedonic method (Rosen, 1974) under the assumptions made the internal property characteristics should not be controlled for. The reason is that the value of housing services ($R_i = \psi_i H_i$) and the plot area L_i are directly observable in the data.

The second reduced form specification is a more conventional (hedonic) price equation, which I derive by combining the baseline housing bid-rent equation (9) with the definition of housing services (see equation 2) to define the housing value R as a function of floor size and observable and unobservable housing features, i.e. $R_i = \psi_i H_i = \psi_i F_i e^{\prod_n b_n X_{in} + \mu_i}$.

$$\begin{aligned}\log(R_{it}) = a + a_E \log EP_i + a_A \log P_i + a_L \log(G_i) + \textstyle\sum_n b_n X_n + \prod_n b_m f_{mi} + b_f \log(F_i) \\ + b_E \log EMP_i + b_P \log POP_i + b_O \log POP_i \times O_i + b_i \log POP_i \times I_i + \varphi_t \\ + \omega_{it},\ \omega_{it} = \eta_{it} + \mu_{it} \qquad (14)\end{aligned}$$

As with most hedonic specifications, it is a common problem in equation (14) that not all housing features are observable and that estimates may be biased if $cov(\mu_i, \eta_i) \neq 0$. On these grounds my preferred measure is the price per unit of land (R/L) since it circumvents the problem of unobservable housing features, albeit at the cost of assuming a particular functional form of the housing production function.

Coefficient interpretation

Table 1 shows how the indirect elasticity of utility with respect to urbanity and centrality can be backed out from the reduced form coefficients of equations (13) and (14). One limitation is that the housing expenditure share parameter has to be assumed. In line with Davis & Ortalo-Magné (2011) I set the share parameter to $(1 - \alpha) = 0.25$. This value is in line with anecdotal evidence for both study areas (IVD, 2012; NHPAU, 2007). Another parameter that is required to solve for the structural parameters is the housing production share parameter δ. Given the availability of (estimated) pure land values (for Berlin), this parameter can be estimated by regressing the property price per unit of land on the pure unit value of land. This is a simplified version of the Epple, Gordon and Sieg (2010) approach, which is discussed along with a defense of the assumed Cobb-Douglas functional form of the housing production function in the appendix.

Tab. 1. Parameter interpretation

	Coefficient Interpretation	
Response variable (in logs)	E (Centrality)	A (Urbanity)
Price	$\gamma_E = (1-\alpha)\widehat{a_E}$	$\gamma_A = -(1-\alpha)\widehat{a_L}$
Price / Land unit	$\gamma_E = (1-\alpha)(1-\delta)\widehat{a_E}$	$\gamma_A = -(1-\alpha)(1-\delta)\widehat{a_L}$

Notes: The parameter interpretations follow from the equilibrium equations (7) and (9).

From a comparison of the reduced form coefficients on the (weighted number) of photos $\hat{a}_A = \gamma_A/[(1-\alpha)\lambda]$ and the neighborhood land area $\hat{a}_L = \gamma_A/[(1-\alpha)]$ it is further possible to back out $\lambda = -\hat{a}_L/\hat{a}_A$, which relates the unobserved urbanity level to the observed number of photos in the photo production function. This identification is facilitated by the assumption that the number of photos taken in a neighborhood depends on the urbanity features (and the population and the employment) within the neighborhood, but not directly the land area, while residents value urbanity density (urbanity features normalized by the land area of the respective neighborhood). The coefficient of primary interest γ_A is hence identified from the variation in geographic land area across neighborhoods, while holding the (weighted) number of photos (PR) constant. While the units of analyses were chosen so to provide sufficient variation in land area, successful identification rests on the assumption that the variable is not correlated with unobservable location effects, i.e. $cov(G_i, \eta_i) = 0$. This is a reasonably strong assumption, even though the novel amenity proxy employed helps controlling for otherwise unobservable location effects.

Photo production models

As a cross-validation check of the identified λ parameters I therefore estimate the photo production function directly, decomposing the unobserved urbanity level A_i into k observable urbanity features A_{ki} and a random error term $\varsigma_i = \sum_l \lambda_l \log(A_{li})$ capturing unobserved features. The urbanity effect is then described by $A_i^\lambda = \prod_k A_{ki}^{\lambda_k} e^{\varsigma_i}$. Substituting into the photo production function and taking logs yields the estimation equation.

$$\log(P_i) = c + \theta_E \log(E_i) + \theta_B \log(POP_i) + \theta_O POP_i \times O_i + \theta_I POP_i \times I_i$$
$$+ \sum_k \lambda_k \log(A_{ki}) + \varsigma_i \tag{15}$$

The observations are left-censored since I cannot observe less than zero photos per district (less than 10% in both cities). The model is therefore estimated using a Tobit estimator. The amenity productivity parameter can then be computed as $\tilde{\lambda} = \sum_k \lambda_k$ assuming that all observable urbanity features are jointly uncorrelated with the error, i.e. $cov(\varsigma_i, \sum_k \lambda_k \log(A_{ki})) = 0$. For this to be a reasonable assumption it is essential to observe a broad variety of features that constitute urbanity. I have therefore compiled two data sets, which are unusually rich in this respect and are explained in more detail in the data section and in the appendix. Essentially, the data cover three categories of amenities that provide aesthetic and consumption value: Natural amenities (land share of water and green areas); gastronomic (bars, pubs and restaurants) and cultural amenities (the number of mainstream and alternative cultural facilities); and architectural amenities (land share occupied by heritage buildings/conservation areas and number of signature buildings). The estimated parameter $\tilde{\lambda} = \sum_n \hat{\lambda}_n$ serves as an independent benchmark for $\lambda = -\hat{a}_L/\hat{a}_A$ parameter backed out from the capitalization regressions. Moreover, the estimated value of $\tilde{\lambda}$ offers an alternative way to back out the urbanity parameter (γ_A) from the reduced form photo coefficient, i.e. $\widetilde{\gamma_A} = (1-\alpha)\tilde{\lambda}\widehat{a_A}$. Consistent estimates of λ and $\tilde{\lambda}$ as well as γ_A and $\widetilde{\gamma_A}$ will lend some robustness to the findings.

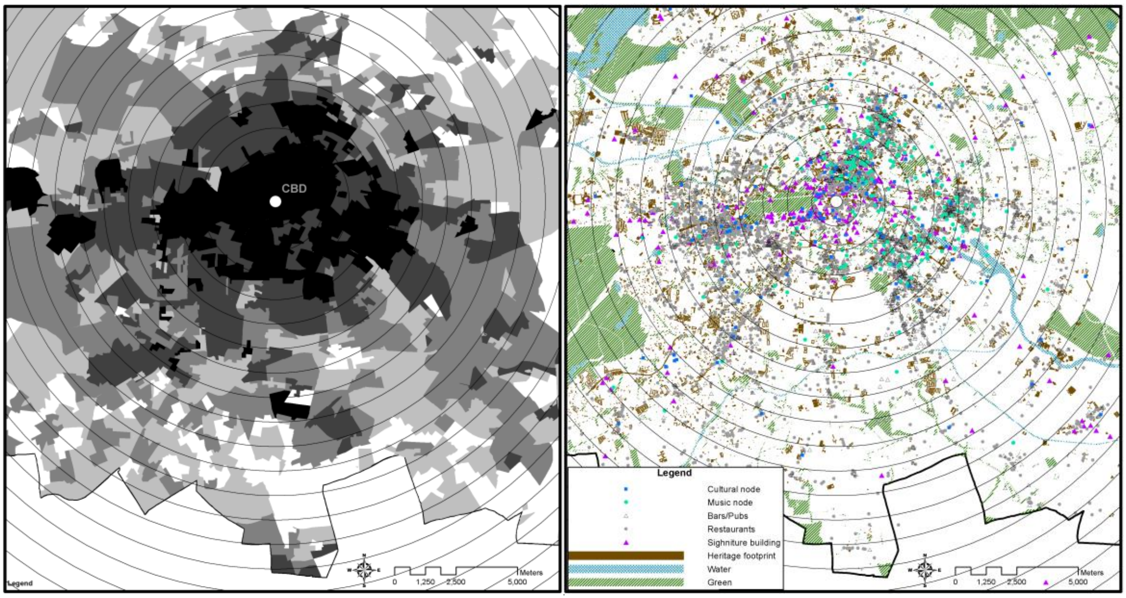
The sequence of the empirical analysis is as follows. I first present the photo production function estimates according to (15), which not only provides a benchmark for the identified λ values, but also provides a better understanding of the photo variables and the urbanity phenomenon captured. I then move on to one-stage estimates of the empirical housing market equations (13-14) and the discussion of the implied structural parameters. I complement the analysis with several robustness checks that are left to the appendix. For Berlin, I present capitalization models using land values, capital to land ratios and floor area ratios as dependent variable. For both cities I experiment with including/excluding hedonic and other controls, allowing for some form of preference heterogeneity, and using different centrality (s-shaped decay function, population potential, distance to CBD) and photo measures (all photos and photos presumably made by tourists). Finally I apply two-stage estimation strategies that introduce various components recovered from the first-stage photo production models into second stage capitalization regressions.

3 Empirical Results

3.1 Urbanity and photo production

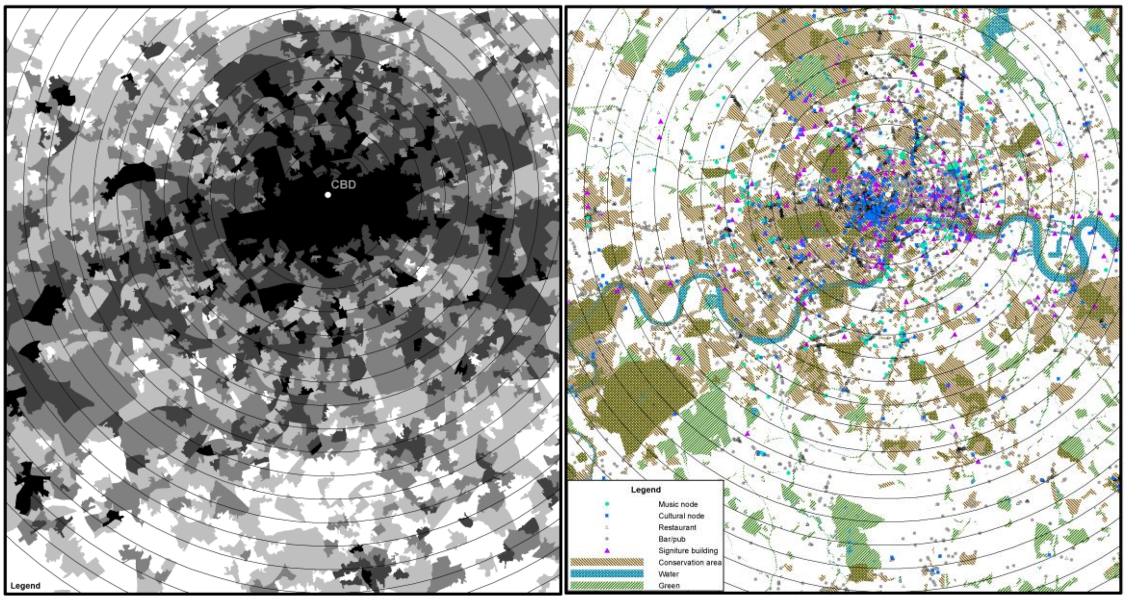
Figures 3 and 4 provide a comparison of photo density as defined in (10) and the spatial distribution of some observable features that presumably add to urbanity. With few exceptions the spatial patterns follow each other very closely.

Fig. 3. Photo densities and urbanity features in Berlin



Notes: Own illustration.

Fig. 4. Photo densities and urbanity features in London



Notes: Own illustration.

While Figures 3 and 4 are in line with photo density being a good proxy for urbanity, they are also in line with the distributions of photo and amenity clusters being jointly determined by higher population and employment densities. Table 2 separates the determinants of the spatial distribution of photo densities by means of multivariate Tobit regressions according to (15).

The results presented in Table 2 substantiate the descriptive evidence presented in Figures 3 and 4. Especially regarding the urbanity features the estimates show a remarkable degree of consistency across cities. All coefficients are positive as expected and, with few exceptions, significant and comparable across cities. The exception is *bars & pubs*, which turns out to have a small and insignificant impact in Berlin, likely because of a high (spatial) correlation with restaurants. An important finding of Table 2 is that urbanity seems to enter the photo production function with increasing returns ($\tilde{\lambda}$ >1). Doubling all urbanity features more than quadruples photos. Local population and employment densities also impact positively on the number of photos taken. The effects are significantly larger for London than for Berlin, which is in line with a more widespread use of the technology in London.[11] There is little evidence for heterogeneity in the population effect with respect to the neighborhood average age or income. I note that I find virtually the same results when replicating the models based on photo measures incorporating either all available photos or photos taken by presumable tourists. The most notable differences are a somewhat smaller population effect and slightly larger increasing returns to urbanity ($\tilde{\lambda}$) in the tourist sample (details and results are in the appendix).

[11] Within the study area, the data set contains about 0.1 photos per resident in London as opposed to about 0.06 in Berlin.

Tab. 2. Photo regressions (Tobit)

	(1) log (weighted) Photos (residential)		(2) log (weighted) Photos (residential)	
	Berlin		London	
log Population	0.388***	(0.102)	1.553***	(0.173)
log Population x average age	0.007	(0.017)	-0.003	(0.054)
log Population x Estimated income	-0.001	(0.000)	0.000*	(0.000)
log Employment	0.178***	(0.044)	0.512***	(0.040)
log Green area	0.051***	(0.019)	0.046***	(0.007)
log Water area	0.034**	(0.015)	0.057***	(0.009)
log Bars & pubs (count)	0.010	(0.112)	0.347***	(0.068)
log Restaurants (count)	0.423***	(0.080)	0.181***	(0.064)
log Music nodes (count)	0.725***	(0.155)	0.632***	(0.118)
log Cultural nodes (count)	0.322	(0.233)	0.357**	(0.144)
log Area occupied by listed buildings	0.120***	(0.016)	0.117***	(0.006)
log Architectural nodes (count)	0.737***	(0.168)	0.385***	(0.141)
Lambda ($\tilde{\lambda}$)	2.423	(0.229)	2.122	(0.166)
Income	YES		YES	
Average age	YES		YES	
N	969		2731	

Notes: Standard errors in parentheses. The standard errors for $\tilde{\lambda}$ are computed using the delta method. * p<0.1, ** p<0.05, *** p<0.01.

3.2 Valuing urbanity

Benchmark models

Table 3 presents the reduced form estimates of the capitalization regressions defined in (13) and (14) along with the implied structural parameters (in the bottom of the table). The available data permits the estimation of both specifications for Berlin, but only the classic hedonic approach (14) for London. All models include year fixed effects and the Berlin models also include year x East Berlin fixed effects to account for the potential post-unification convergence of the two formerly separated markets. Controls for housing features and floor space are only included in the hedonic regressions (2 and 3), but not in the land price per land area regression (1).

The reduced form coefficients of the photo variable are positive and generally statistically significant. The coefficient on the neighborhood land area is negative and significant. These findings are in line with the spatial equilibrium conditions derived in the previous section and point to a positive impact of urbanity on residential utility. In the hedonic models (2 and 3) an increase in the number of photos by 100% is associated with a ceteris paribus increase in property prices of about 1.5% (columns (2) and (3)). Assuming a representative property selling at \$300k (Berlin) or \$400k (London) and an opportunity cost of capital of 5% the implied WTP amount to about \$200 (Berlin) - \$300 dollar a year.[12] A more structural interpretation is that the implied indirect elasticity of utility with respect to urbanity (γ_A) is about 0.7-0.9%. The (preferred) price to land area regression (1) yields a somewhat larger effect: The capitalization effect on property prices is about 2.4% (after multiplying the reduced form parameter by the land share 1-δ). The indirect elasticity of utility with respect to urbanity is about 1.5%. One explanation for the difference is that the hedonic estimate in Berlin might be downward biased by (unobservable) adverse housing quality in the central locations close to the former wall, a likely legacy of the division period. The centrality effects, which are insignificant in the hedonic (2) model but large and significant in the preferred model (1), are suggestive of this interpretation. With an indirect elasticity of utility with respect to centrality of 7.8% (Berlin) and 12.4% (London) the positive effect of spatial density (centrality) in the preferred models (1 and 3) turns out to be slightly larger than the typical estimates of the effect of spatial density on firm productivity found in across-city comparisons (see e.g. Ciccone, 2002; Ciccone & Hall, 1996; Rosenthal & Strange, 2001). The effects are roughly within the range of more recent evidence exploiting variation within cities (Ahlfeldt, et al., 2012; Ahlfeldt & Wendland, 2013).

The structural parameters derived from the reduced form coefficients further confirm a central conclusion from the photo regressions presented in Table 2: Urbanity enters the photo production function with increasing returns as reflected by $\lambda = -\hat{a}_L / \hat{a}_A > 1$. Reassuringly, the λ estimates from Table 3 turn out to be within less than two standard error lengths of the $\tilde{\lambda}$ estimates from Table 2. The indirect elasticity utility with respect to urbanity backed out from the reduced from photo coefficient $\left(\widetilde{\gamma_A} = (1-\alpha)(1-\delta)\tilde{\lambda}\widehat{a_A}\right)$ also turns out to be close to the structural interpretation $\gamma_A = -(1-\alpha)(1-\delta)\widehat{a_L}$ in all models of Table 3.

Finally, it should be noted that the controls for the availability and quality of public services (distance to school and metro-rail stations) are positive and statistically significant in most models as expected (distances enter with inverted signs so that positive coefficients indicate positive effects).

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[12] The average property price in the London data is about £250 thousand. The Berlin data entails developed land, mostly multi-dwelling properties. An average dwelling price of €200 thousand is assumed, which corresponds to a floor space of 100 sqm and square meter price of €2000. The following excange rates dating from Nov 27, 2012 are used: \$1=€0.7732=£0.6234

Alterations and robustness

I have run a battery of alterations of the baseline capitalization models, which I summarize below. The interested reader will find a more detailed presentation in the technical appendix.

The photo regressions (Table 2) can be used to separate the urbanity effect captured by geo-tagged photos into a component that is observable (the values predicted by the amenity covariates) and another one that is unobservable (the residual). If the raw photo variable is replaced by these two components recovered from a first stage photo regression, the not directly observable urbanity effect (the residual) turns out to be statistically significant and about one fourth of the observable (the predicted) component in the preferred Table 3-type capitalization models. If the observable component (the predicted value) replaced by raw amenity variables from Table 2 the residual effect remains significant and virtually unchanged, confirming that photos contain useful urbanity information above and beyond what can be measures with even a detailed data set on observables. An interesting and novel insight gained from in these models is that a doubling of contemporary landmark architecture buildings yields a capitalization effect on the unit price of housing serves of about 4%.

It is possible to identify the structural parameters discussed above from reduced form regressions using the pure value of land, the capital to land ratio and the floor area ratio as dependent variables. The implied urbanity (and centrality) effects turn out to be within the range of the estimates presented in Table 3. The key parameter of interest also remains roughly within the same range in a number of further robustness checks. These include: Including [excluding] hedonic controls in models (1 [2,3]), adding controls for the average age and income of the location population, running a right censored Tobit model that accounts for the fact that the residential floor space index typically does not exceed a value of 2.5 due to height restrictions, adding spatial trends (x- and y- coordinates), using all available photos or only those taken by tourists and experimenting with measures that capture different shades of centrality (distance to CBD, squared exponential distance weighted access to employment and population). Across all specifications, the indirect elasticity of utility with respect to urbanity of primary interest is consistently estimated at values that fluctuate around 1-1.5%.

Given that the results presented indicate that the urbanity utility parameter (γ_A) as well as the urbanity (λ), the employment (θ) and the population (θ_B) elasticity parameters in the photo production function are positive, the reduced form coefficients on population and employment in the house price regressions are expected to take a negative sign according to the main spatial equilibrium condition (9). The fact that these coefficient turn out to be mostly insignificant or even positive and significant suggests that population and employment have a direct effect on housing prices (and quantities). The direct and indirect (via the photo production function) effects of local population and employment (densities) on property prices can be separated in a two-stage estimation procedure. Therefore, the residuals of a photo production regression (15) omitting urbanity features are first recovered and adjusted to reflect densities and to account for the increasing returns to urbanity in the photo production function.[13] The resulting variable can then be included in capitalization models (replacing the original photo variable) along with (log) population and employment density. Since the residual term captures urbanity as reflected in the number of photos net of the effect of population and employment, population and employment densities capture the direct effect on demand for housing services exclusively. Since the urbanity as well as population and employment variables are expressed as densities, the control for neighborhood land area can be omitted from the two-stage (second stage) models. The results of the two-stage estimations support the results presented and discussed above. Adding a control for neighborhood area does not alter the results substantially. This is reassuring as it suggests that the neighborhood land area variable is not correlated with an unobserved location feature of relevance, which could bias the results in the one-stage models.

[13] This approach directly follows from plugging the definition of urbanity in equation (1) into the photo produciton equation: $\log(A_i) = \log(P) - [c + \theta_E \log(E_i) + \theta_B \log(POP_i) + \theta_O POP_i \times O_i + \theta_I POP_i \times I_i]$. (log) Urbanity density is defined as $\log(\tilde{A}_i) = \log(A_i) - \log(G_i)$.

Tab. 3. Capitalization models

	(1) Log (Price / Land Area)		(2) Log Price		(3) Log Price	
	Berlin		Berlin		London	
log Employment Pot. (α_E)	0.803***	(0.122)	0.138	(0.087)	0.497***	(0.022)
log photos (residents) (α_A)	0.062***	(0.012)	0.015**	(0.008)	0.016***	(0.002)
log Area (α_L)	-0.167***	(0.029)	-0.035*	(0.020)	-0.030***	(0.008)
log Employment	0.003	(0.015)	0.010	(0.010)	0.028***	(0.004)
log Population	-0.004	(0.046)	-0.053**	(0.025)	-0.080***	(0.016)
log Population x av. age	-0.001	(0.008)	-0.002	(0.005)	-0.001	(0.004)
log Population x income	0.000	(0.000)	0.000	(0.000)	0.000**	(0.000)
log Dist. to station (inv.)	0.143***	(0.034)	0.049**	(0.023)	0.029***	(0.004)
School index	0.052**	(0.022)	0.022	(0.015)	0.365***	(0.031)
Income	YES		YES		YES	
Average age	YES		YES		YES	
Year Effects	YES		YES		YES	
Year Effects x East Berlin	YES		YES		-	
Hedonics	-		YES		YES	
Log Floor space	-		YES		YES	
r2	0.600		0.924		0.832	
Centrality (γ_E)	0.078		0.035		0.124	
Urbanity (γ_A)	0.016		0.009		0.007	
Urbanity ($\widetilde{\gamma_A}$)	0.015		0.009		0.009	
Lambda (λ)	2.689		2.319		1.817	
N	897		897		2639	

Notes: Property data are aggregated to medium layer voting precincts (Stimmbezirke) for Berlin and lower level super output areas for London. School index is distance to the nearest school (inverted sign) in Berlin and local average key-stage test scores in London. Distance to station refers to U- and S-Bahn stations in Berlin and underground and dock land light railway stations in London. Standard errors in parentheses. Robust standard errors. * p<0.1, ** p<0.05, *** p<0.01

3.3 Willingness to pay for urbanity

Based on the indirect elasticity of utility with respect to urbanity it is possible to compute a back of the envelope type household willingness to pay (WTP) for urbanity (and centrality). To do this, I first compute a measure of disposable household income that is (roughly) comparable across both study areas. For Berlin I use the 2008 GfK purchasing power per capita estimates by post code, multiplied by the average household size of 1.7.[14] For London I use the Neighborhood Statistics ward level estimates of the net disposable household income based on the 2001 census. Both measures reflect household income after taxes and contributions. To make the London figures comparable to the 2008 based GfK estimates for Berlin, I inflate the London household income by the growth of the gross domestic household income in London from 2001 to 2008, adjusted for the respective population growth. The resulting income estimates are then converted to reflect monthly income per

[14] Household size is based on the city population and number of households recorded as recorded in the 2011 micro-census (Mikrozensus), which is publicly available at the web-sides of the Berlin Brandenburg statistical office (www.statistik-berlin-brandenburg.de).

month in US dollars.[15] To compute the average household income within the study areas, the postcode/ward level income estimates are aggregated using weights determined by the local population. The resulting average income estimated for London surpasses the Berlin estimate by about 55% ($5004 vs. $3038) and is used to sustain an, on average, 38% larger household (2.35 vs. 1.7 individuals).

Based on these average income estimates ($\overline{income}$) and the estimated elasticities of indirect utility with respect to urbanity and centrality ($\gamma_{(A/E)}$), the monetary equivalents to the utility effect of a doubling urbanity or centrality can be computed ($\gamma \times \overline{income}$). While interestingly the implicit WTP for urbanity is within the same range in both cities ($46 vs. $36), the WTP for centrality in London is more than 2.5 times the one in Berlin ($621 vs. $234). To account for the distinct variation of urbanity and centrality within both study areas I compute the WTP for moving from a low centrality/urbanity (1st percentile) to a high centrality/urbanity (99th percentile) neighborhood ($\gamma \times \overline{income} \times \Delta \log(Q)$, where Q stands either for the urbanity or the centrality level). The results indicate that major increases in centrality and urbanity are associated with sizable utility effects in both cities. The centrality effect in London is, again, substantially larger than in Berlin ($739 vs. $281). Though smaller, the difference is also substantial when expressed in proportions of the average income 14.8% vs. 9.2%. The urbanity effects are closer to each other, and slightly larger in Berlin when expressed in proportionate terms (4.8% vs. 3.6%). For more moderate changes (from 10th to 90th or 25th to 75th percentile) the proportionate WTP for improvements in centrality are more similar in both cities. Increases in urbanity are associated with a WTP that is roughly comparable in absolute terms, but significantly larger in Berlin when expressed in proportionate terms.

While the centrality and urbanity elasticity parameters have been assumed to be constant across all neighborhoods so far, it is entirely possible that in reality the parameters vary across space depending on observable and unobservable characteristics of the local population. To estimate the monetary equivalent to the utility derived from centrality and urbanity differentials within the study area in account of potentially heterogenous preferences I run two series of locally weighted regressions (Cleveland & Devlin, 1988; McMillen, 1996) based on the two benchmark specifications (columns 1 and 3 in Table 3).

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[15] For the conversion I use the official exchange rates from Nov 27, 2012: $1=€0.7732=£0.6234.

At each location *i*, I fit a separate regression weighting all locations *j* by an exponential distance weight function $\left(e^{-\Gamma D_{ij}}\right)$ to obtain location *i* specific parameters $\left(\gamma_{A_i/E_i}\right)$. This kernel weight is motivated by the assumption that people living near to each other should have similar preferences. Facing the typical tradeoff in non-parametric analyses, I choose a value of $\Gamma = 0.25$ as a compromise that produces at the same time a relatively smooth fit to the data and coefficient estimates with relatively local character.[16] Figure 5 plots the implied neighborhood specific indirect utility elasticity parameters $\left(\gamma_{A_i} \text{ and } \gamma_{E_i}\right)$ against each other as well as the local levels of centrality and urbanity. The results indicate that households with higher preferences for centrality tend to live in more central areas, while the relationship is less clear for urbanity. Preferences for urbanity and centrality seem to be negatively correlated across space, suggesting that centrality and urbanity are distinct urban phenomena that appeal to different population groups. A more detailed analysis that is inspired by Bajari & Kahn (2005) and Koster, Van Ommeren, & Rietveld (2012) is presented in the appendix. In line with the distinct stages of gentrification in the two cities urbanity tends to attract higher income groups in London, while the opposite is true in Berlin.

A total WTP in a neighborhood (WTP_i) can be computed based on these local elasticity estimates $\left(\gamma_{(E/A)i}\right)$, the neighborhood population (pop_i) adjusted for the average household size at the city level (HH), the local average household *income* and the local endowment relative to the least attractive (in terms of centrality and urbanity) neighborhood, i.e. $WTP_i = \gamma_i \times income_i \times pop_i \times 1/HH \times \Delta\log(Q_i)$. Summing over all neighborhoods the (monthly) WTP for centrality amounts to about \$600 Mio in Berlin and about \$1.1 Bn in London – for relative location advantages within the study area only. While significantly lower, the respective WTP for urbanity with about \$90 Mio per month, or about \$1 Bn per year, is still sizable in both cities. The WTP expressed as proportions at the monthly disposable incomes turns out to be within the same range in both cities (about 12.5% for centrality and 1.5% for urbanity). If location specific preferences and income levels are ignored, the WTP estimates for centrality tend to come down while the urbanity effects remain virtually the same. This pattern likely reflects preference based sorting that occurs mainly with respect to centrality, but to a lesser extent with respect to urbanity.

[16] The half-life distance of the employed function is about 3km. The results are relatively insensitive to reasonable variations of the decay parameter.

Tab. 4. Willingness to pay

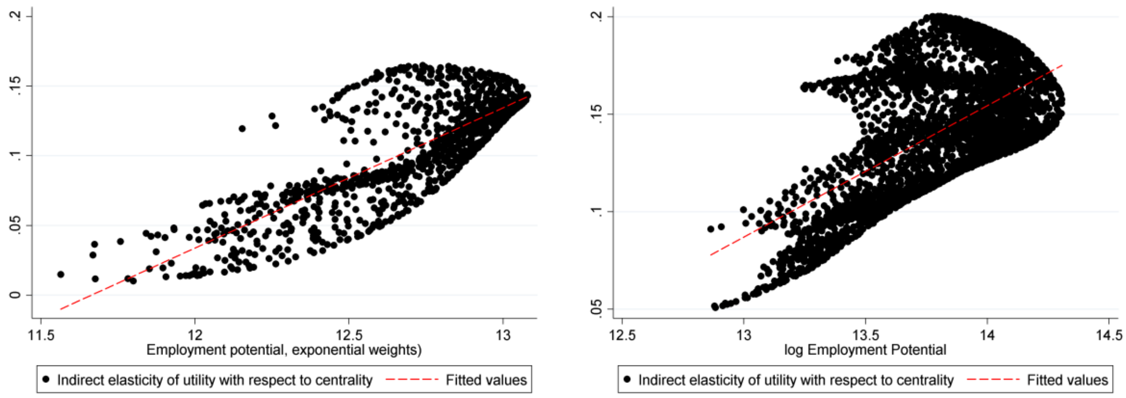
		Berlin		London	
		Centrality	Urbanity	Centrality	Urbanity
Total Population (persons)		2.767 Mio.		4.013 Mio.	
Average household size		1.7		2.35	
Households		1.63 Mio		1.71 Mio	
Mean 2008 disposable household income		3038 ($/month)		5299 ($/month)	
Indirect elasticity of utility		0.077	0.015	0.124	0.008
Doubling	($)	234	46	621	36
From 1st to 99th percentile	($)	281	147	739	178
(mean age / income)	(%)	9.2%	4.8%	14.8%	3.6%
From 10th to 90th percentile	($)	182	99	372	81
(mean age / income)	(%)	6.0%	3.3%	7.4%	1.6%
From 25th to 75th percentile	($)	106	51	208	42
(mean age /income)	(%)	3.5%	1.7%	4.2%	0.8%
Aggregated WTP		597,500,000	87,496,729	1,096,000,000	93,119,851
WTP / household	($)	367	54	642	55
	($)	12.1%	1.8%	12.8%	1.1%
Aggregated WTP (repr. hh.)		561,000,000	86,975,440	1,074,000,000	91,307,688
WTP / repr. household		345	53	629	53
		11.3%	1.8%	12.6%	1.1%

Notes: The aggregated WTP is estimated based location specific elasticity parameters estimated by means of geographically weighted regressions (GWR). For representative household the average elasticities of utility with respect to urbanization and urbanity (mean of GWR) as well the average income in a study area are assumed.

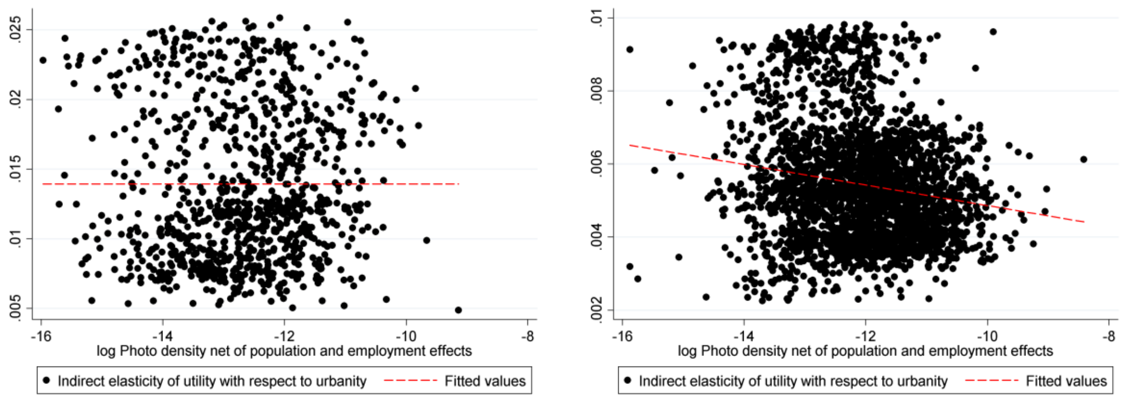
Fig. 5. Centrality and WTP for centrality and urbanity

Berlin **London**

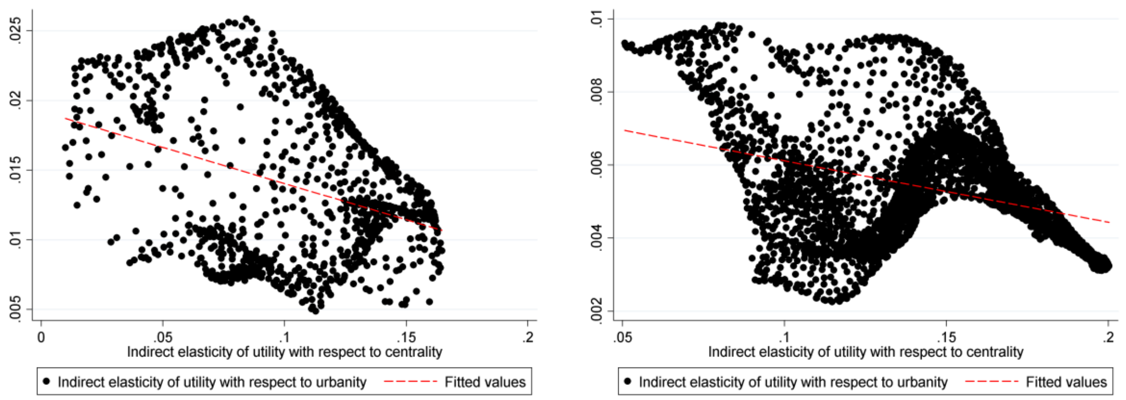
Centrality



Urbanity



Urbanity vs. Centrality



Notes: Indirect elasticities of utility with respect to centrality and urbanity are estimated for individual neighbourhoods (Stimmbezirke and lower level super output areas) using geographically weighted regressions.

4 Conclusion

This analysis provides a novel attempt to value the leisure, consumption and aesthetic value that (some) urban neighborhoods offer. I have subsumed this composite value of a local charm, character or atmosphere constituted by aesthetic, cultural and consumption amenities under *urbanity*. I have distinguished urbanity from centrality, which comprises all the benefits of access to labor markets and other desirable features in a metropolitan area. Urbanity is, hence, a localized phenomenon which makes urban neighborhoods attractive places to live because of a local consumption value and not because of an ease of access to jobs and other economic activates. Urbanity is also unrelated to the quality of public services.

To capture urbanity empirically, I let residents vote with their cameras in two European capital cities that are often argued to offer particularly attractive (urban) areas to live: Berlin, Germany and London, UK. I presume that urbanity increases the numbers of photos taken and shared in internet communities by either increasing the probability of photos being taken conditional on a given number of people living and working in a neighborhood and/or by attracting visitors (potential photographers) to the neighborhood for consumption and recreational purposes.

I further argue that the spatial distribution of (geo-tagged) photos therefore represents an index of human interest that serves as a proxy for urbanity, which is otherwise not observable directly. Combining a canonical bid-rent framework with a photo production function, in which urbanity is an input factor, the value of urbanity can be backed out from the observable spatial distribution of property prices (and quantities) and photos. My results suggest a sizable willingness to pay for urbanity even though it turns out to be significantly smaller than for centrality. The indirect elasticity of utility with respect to urbanity is estimated at values that fluctuate around 1%. The aggregated willingness to pay for urbanity equates to about $1 bn per year in each city, or about 1.5% of the disposable household income.

My results complement a number of strands of research investigating the determinants of the ongoing attraction force of cities. More than 50% of the world population already lives in cities and it is relatively uncontroversial that this figure will continue to grow. Within cities, the recent decades have shown a tendency of re-orientation towards the downtowns, often referred to as gentrification, following a long period of sub-urbanization during the 20th century. Phenomena like reverse commuting have been argued to witness that the increasing demand for density to some extent must be attributable to other than production related factors. The evidence provided in this analysis adds to the consumer city argument that cities not only make workers more productive and provide ease of access to labor markets, but are, at least in parts and for some population groups, also enjoyable places to live.

The results also suggest that urban renaissance policies, to the extent that they stimulate the emergence of urbanity, i.e. help generating architecturally and culturally distinctive neighborhoods with an appropriate mix of density and recreational spaces, can promote the revitalization of downtowns that have been left behind. This is especially important given that the massive decentralization of production during the 20th century, which has transformed many traditional urban economies dominated by a CBD into dispersed metropolitan area clusters, has questioned the role many downtowns should play in the future. Indeed, for some downtowns the future may lie in a role as centers of consumption and places to live (rather than work) if they can deliver the specific combination of density, recreational value, architectural and cultural distinctiveness that arguably only urban neighborhoods can offer: urbanity.

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Gabriel M. Ahlfeldt[♣]

Technical appendix to Urbanity

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1 Introduction

This technical appendix complements the main paper by providing complementary evidence and additional detail on the data and empirical framework used. The appendix is not designed to stand alone or to replace the main paper. Section 2 presents an extended version of the theoretical framework as well as details on the data and the empirical approaches used to complement the main analyses. Section 3 provides complementary evidence that consists of estimates of the photo production function using different photo measures, estimates of a housing production function used to identify the structural parameters, robustness checks of the one-stage benchmark models, results of a two-stage estimation approach and models that address potential heterogeneity in urbanity and centrality preferences.

2 Strategy

Following the same structure as section 2 in the main paper, this section provides additional detail on the theoretical framework, data and the empirical strategy.

2.1 Theoretical Framework

This (sub) section presents the derivation of the equilibrium conditions introduced in the main paper in greater detail and introduces additional equilibrium relationships. To improve readability it partially replicates the respective section of the main paper.

[♣] London School of Economics and Political Sciences (LSE), Department of Geography and Environment & Spatial Economics Research Centre (SERC), Houghton Street, London WC2A 2AE, g.ahlfeldt@lse.ac.uk, www.ahlfeldt.com

Housing demand

The city considered here consists of discrete neighborhoods i, which can vary in size. At a given neighborhood i, identical individuals derive a standard Cobb-Douglas utility from the consumption of housing services H_i and a composite non-housing good C_i. This formulation is in line with housing expenditure shares that tend to be relatively constant across population groups and geographies (Davis & Ortalo-Magné, 2011).

$$U_i = V_i {C_i}^{\alpha} {H_i}^{1-\alpha} \tag{A1}$$

Housing services H_i are defined as a function of housing floor space F_i and a bundle of housing features f_i:

$$H_i = F_i e^{f_i} \tag{A2}$$

A location is a more or less attractive place to live depending on the amenities offered, which is captured by V_i.

$$V_i = \tilde{E}_i^{\gamma_E} {\tilde{A}_i}^{\gamma_A} \tilde{S}_i^{\gamma_S} \tag{A3}$$

where $\tilde{E}_i$ is a measure of centrality, $\tilde{S}_i$ is the quality of public services a location offers (e.g. good schools or transit) and $\tilde{A}_i$ is the effective urbanity level perceived at i. Residents value the density of urbanity features in their neighborhood, which is defined as: $\tilde{A}_i = A_i / G_i$, where A_i is the aggregate urbanity level in the neighborhood and G_i is the geographic size of a neighborhood. Individuals derive a utility from locating centrally in a labor market area (centrality) due to the lower (expected) inconvenience of commuting. Effective labor market access is defined as the inverse of a perceived commuting disutility $\widetilde{E_i} = E(C_i)^{-1} = \sum_j \pi_j T_{ij}$, which depends on a commuting probability $\pi_j = E_j / \sum_j E_j$ determined by the spatial distribution of workplace employment E_i and an iceberg cost $T_i = e^{-\tau D_{ij}} \in (0,1)$. The iceberg cost in turn depends on the distance between the place of residence i and a potential workplace location j and $\tau > 0$, which determines the spatial decay. This gravity type employment accessibility, which has recently enjoyed increasing popularity in the house price capitalization literature (Ahlfeldt, 2011, in press; McArthur, Osland, & Thorsen, in press; Osland & Thorsen, 2008), collapses to the standard monocentric framework if all workplace employment is concentrated in one location. It is notable that with the chosen formulation, I assume that residents do not value urbanity in other than their own neighborhood. Urbanity is meant to capture a specific urban atmosphere or ambience that can be enjoyed in the neighborhood. Lower inconvenience of travel to consumption amenities in other neighborhoods will be captured by centrality to the extent that these amenities are correlated the with the employment distribution. In robustness checks presented in the appendix I experiment with alternative formulations for centrality that presumably capture different shades of centrality.

At all locations in the city residents maximize their utility by choosing C_i and H_i subject to a fixed budget B. The budget is net of a monetary component of transport cost, which is assumed to be the same across the city. This assumption does not imply that monetary transport costs are irrelevant: they may still represent a substantial share of the budget. But the location varying component is relatively small compared to the fixed cost, e.g., of owning a car, or using public transport, where an increase in distance traveled in practice, if at all, only leads to a marginal increase in monetary transport cost. Minimally, the implication is that the marginal increase in monetary cost in distance traveled is small relative to the inconvenience of longer journeys, which seems like a reasonable approximation for many large metropolitan areas, including Berlin and London.

Residents are perfectly mobile across neighborhoods so that the price of housing services, the bid-rent, must fully compensate for all locational differences in equilibrium. Let ψ_i be the price housing services and the price of the composite non-housing good be the numeraire. The indirect demand functions are then given as:

$$C_i = \alpha B_i \tag{A4a}$$

$$H_i = (1-\alpha)\frac{B_i}{\psi_i} \tag{A4b}$$

The spatial equilibrium can be derived by substituting the indirect demand functions into (A1) and setting U_i to a reservation utility level $\overline{U} = 1$.

$$U_i = \overline{U} = V_i(\alpha B_i)^{\alpha}\left((1-\alpha)\frac{B_i}{\psi_i}\right)^{1-\alpha} = 1 \tag{A5}$$

Solving for ψ_i we obtain the following housing bid-rent function in log-linearized form:[1]

$$\log(\psi_i) = \aleph + \frac{\gamma_E}{1-\alpha}\log\tilde{E}_i + \frac{\gamma_A}{1-\alpha}\log\tilde{A}_i + \frac{\gamma_S}{1-\alpha}\log\tilde{S}_i \tag{A6}$$

[1] $\aleph = \log\left[(1-\alpha)\alpha^{\alpha}B^{1/(1-\alpha)}\right]$

In keeping with intuition, bid rents increase in centrality, public services quality and urbanity.

Housing Supply

Equation (4), within the constraints of assumptions made, reflects the demand for housing space in the urban economy. The supply side can be described by a homogenous competitive construction sector (Brueckner, 1987; Mills, 1972; Muth, 1969). Developers use capital K_i and land L_i as inputs in a concave production function to produce housing services, which are uniform within a neighborhood i and rented out to households at the bid-rent ψ_i.[2] Given the within city focus I abstract from a variety of geographic and regulatory supply conditions that vary across metropolitan areas (Saiz, 2010).

$$H_i = K_i^{\delta} L_i^{1-\delta} \tag{A7}$$

The price of capital, which comprises all non-land inputs, is normalized to one. Land is rented from absentee land lords at a unit price Ω_i, the land bid-rent. Given free entry and exit, (economic) profits must be zero at all locations in city so that the land bid-rent must adjust to compensate for changes in the housing bid-rent to maintain the spatial equilibrium on the supply side.

$$\pi_i = \psi_i H_i - K_i - \Omega_i L_i = \psi_i K_i^{\delta} L_i^{1-\delta} - K_i - \Omega_i L_i = 0 \tag{A8}$$

First order conditions define the capital to land ratio as a function of the land bid-rent.

$$\frac{K_i}{L_i} = \frac{\delta}{1-\delta} \Omega_\mathrm{i} \tag{A9}$$

Substituting the first order condition into the zero-profit condition and solving for Ω_i yields the land bid-rent as a log-linear transformation of the housing bid-rent.

$$\mathrm{Log}\, \Omega_i = \frac{1}{1-\delta} \log \psi_i + \log\left[(1-\delta)\delta^{\delta}\right] \tag{A10}$$

Similar, the zero profit condition and the first order condition jointly determine the housing services per land unit $\psi_i H_i / L_i$ as function of the land bid-rent.

2 The total amount of land occupied in a district depends on the geographical size G_i and the land share dedicated to residential use, which are exogenously given.

$$\frac{\psi_i H_i}{L_i} = \frac{K_i+\Omega_i L_i}{L_i} = \frac{\delta}{1-\delta}\Omega_i + \Omega_i = \frac{1}{1-\delta}\Omega_i \quad \text{(A11)}$$

Combing the price per land unit function and the first order condition with A10, it directly follows that the value of housing services per land unit $\psi_i H_i/L_i$ and the capital to land ratio K_i/L_i are log-linearly related to the housing bid-rent.

$$\log\left(\frac{\psi_i H_i}{L_i}\right) = \frac{1}{1-\delta}\log\psi_i + \log[\delta^{\delta}], \log\left(\frac{K_i}{L_i}\right) = \frac{1}{1-\delta}\log\psi_i + \log[\delta^{1+\delta}] \quad \text{(A12)}$$

Combining (A2) with the zero-profit and first order conditions it can be shown that the ratio of floor space over land area (floor area ratio) is a function of the land bid rent, the housing bid rent and housing features.

$$\frac{F_i}{L_i} = \frac{H_i}{L_i}e^{-f_i} = \frac{K_i+\Omega_i L_i}{\psi_i L_i}e^{-f_i} = \frac{K_i/L_i+\Omega_i}{\psi_i}e^{-f_i} = \frac{\frac{1}{1-\delta}\Omega_i}{\psi_i}e^{-f_i} \quad \text{(A13)}$$

Taking logs and substituting in (A6), the floor area ratio is demonstrated to be a log-linear function of the housing bid-rent and housing features f_i.

$$\log\left(\frac{F_i}{L_i}\right) = \frac{\delta}{1-\delta}\log\psi_i - f_i + \log(\delta^{\delta}) \quad \text{(A14)}$$

Photo production

The equilibrium conditions (A4), (A6) and (A10-14) all follow from more or less conventional assumptions. The key challenge when taking them to the data is that the phenomenon of interest, urbanity A_i, is not observable directly. To overcome this fundamental limitation and to create the link to the novel data set introduced here, I assume a photo production function, in which the output, i.e. the number of photos P_i taken at in a neighborhood i, is a function of the unobserved amenity level A_i and the number of residents living (POP) or working (EMP) there.

$$P_i = EMP_i^{\theta_E} POP_i^{\theta} A_i^{\lambda} \quad \text{(A15)}$$

The expectation is that the number of photos "produced" in a given neighborhood increases in the presence of workers or residents assuming that the probability of taking photos is constant given the same urbanity level. Ceteris paribus, urbanity makes a place more attractive as a photo motif (increases the probability of taking photos) or setting (increases the number of potential photographers) and therefore increases the number of photos taken and shared in the internet. Solving the photo production function for A_i and substituting into the spatial equilibrium bid-rent function (A6) yields the bid-rent as a function of centrality, quality of public services, as well as employment (EMP), population (POP), the number of photos taken and the land area of a respective neighborhood. I note that I do not assume that the photo production, ceteris paribus, depends on the land area of the neighborhood. Land area enters the equilibrium condition (A15) due to the assumption that households value effective urbanity $\tilde{A}_i = A_i/G_i$, i.e. the density of all the features constituting urbanity.

$$\begin{aligned}\log(\psi_i) = \aleph + \frac{\gamma_E}{1-\alpha}\log\tilde{E}_i + \frac{\gamma_A}{1-\alpha}\frac{1}{\lambda}\log P_i - \frac{\gamma_A}{1-\alpha}\log(G_i) \\ -\frac{\gamma_A}{1-\alpha}\frac{\theta}{\lambda}\log(EMP_i) - \frac{\gamma_A}{1-\alpha}\frac{\theta_B}{\lambda}\log(POP_i) + \frac{\gamma_S}{1-\alpha}\log\tilde{S}_i\end{aligned} \quad \text{(A15)}$$

Equation (A15) sets the ground for a reduced form empirical test of the housing bid-rent function based on variables that can be observed or feasibly approximated. Similar specifications incorporating the housing supply side can be obtained by substituting (A15) into (A10-A14).

$$\begin{aligned}\log(\Omega_i) = \aleph_6 + \frac{\gamma_E}{(1-\alpha)(1-\delta)}\log\tilde{E}_i + \frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{1}{\lambda}\log P_i - \frac{\gamma_A}{(1-\alpha)(1-\delta)}\log(G_i) \\ -\frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{\theta}{\lambda}\log(EMP_i) - \frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{\theta_B}{\lambda}\log(POP_i) + \frac{\gamma_S}{(1-\alpha)(1-\delta)}\log\tilde{S}_i\end{aligned} \quad \text{(A16)}$$

$$\begin{aligned}\log\left(\frac{\psi_i H_i}{L_i}\right) = \aleph_{7A} + \frac{\gamma_E}{(1-\alpha)(1-\delta)}\log\tilde{E}_i + \frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{1}{\lambda}\log P_i - \frac{\gamma_A}{(1-\alpha)(1-\delta)}\log(G_i) \\ -\frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{\theta}{\lambda}\log(EMP_i) - \frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{\theta_B}{\lambda}\log(POP_i) + \frac{\gamma_S}{(1-\alpha)(1-\delta)}\log\tilde{S}_i\end{aligned} \quad \text{(A17)}$$

$$\begin{aligned}\log\left(\frac{K_i}{L_i}\right) = \aleph_{7B} + \frac{\gamma_E}{(1-\alpha)(1-\delta)}\log\tilde{E}_i + \frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{1}{\lambda}\log P_i - \frac{\gamma_A}{(1-\alpha)(1-\delta)}\log(G_i) \\ -\frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{\theta}{\lambda}\log(EMP_i) - \frac{\gamma_A}{(1-\alpha)(1-\delta)}\frac{\theta_B}{\lambda}\log(POP_i) + \frac{\gamma_S}{(1-\alpha)(1-\delta)}\log\tilde{S}_i\end{aligned} \quad \text{(A18)}$$

$$\begin{aligned}\log\left(\frac{F_i}{L_i}\right) = \aleph_8 + \frac{\gamma_E\delta}{(1-\alpha)(1-\delta)}\log\tilde{E}_i + \frac{\gamma_A\delta}{(1-\alpha)(1-\delta)}\frac{1}{\lambda}\log P_i - \frac{\gamma_A\delta}{(1-\alpha)(1-\delta)}\log(G_i) \\ -\frac{\gamma_A\delta}{(1-\alpha)(1-\delta)}\frac{\theta}{\lambda}\log(EMP_i) - \frac{\gamma_A\delta}{(1-\alpha)(1-\delta)}\frac{\theta_B}{\lambda}\log(POP_i) + \frac{\gamma_S\delta}{(1-\alpha)(1-\delta)}\log\tilde{S}_i - f_i\end{aligned} \quad \text{(A19)}$$

2.2 Data

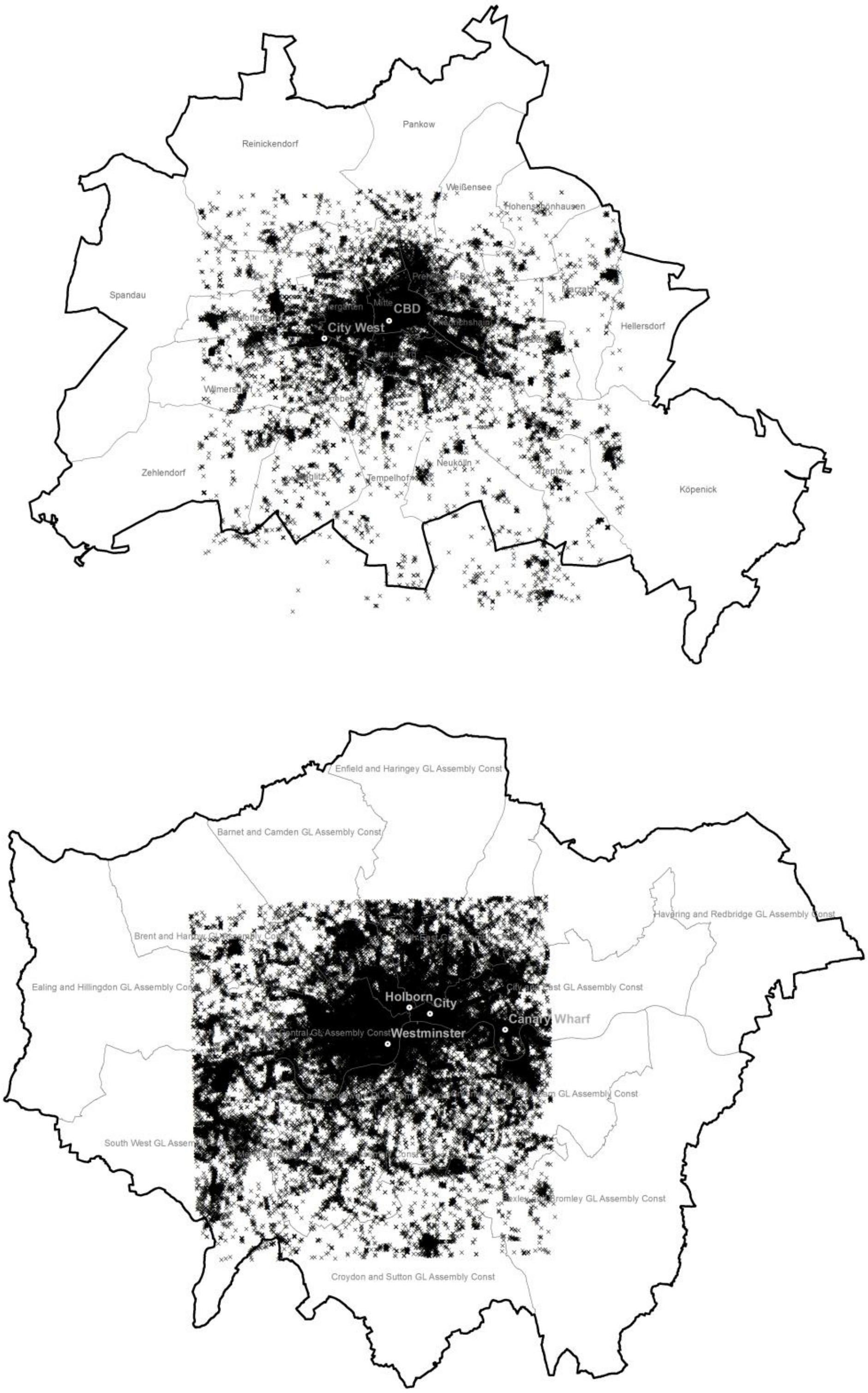
This section presents the data used in the analysis in greater detail. Compared to the data section in the main paper I add information on sources and processing of the data and some descriptive evidence on the spatial distribution of photos in both cities. To improve readability the section partially replicates the data section in the main paper.

The photo data used in this analysis stem from Eric Fisher's Geotaggers' World Atlas, whose observations are taken from Flickr and Picasa search APIs.[3] To obtain a consistent

[3] See for details http://www.flickr.com/photos/walkingsf/sets/72157623971287575/.

geography in both cities only photos taken with a 15 x 15 miles square are considered. The bounds on each side are chosen to include as many geo-tagged locations as possible near the respective central cluster. Figure A1 shows the raw photo data for the study areas against the boundaries of Berlin and the Greater London Authority area.

Fig A1.Distribution of Photo Nodes in Berlin (Top) and London (Bottom)



Notes: Own illustration based on Eric Fisher Geotagger's World Atlas. To improve visibility, a roughly 20% (random) sample of all photos is used in these illustrations.

While from the data set it is not possible to observe the place of residence and to sharply distinguish between residents or tourists groups, the individual pattern of photos taken by a user at various cities over time facilitates the restriction to pictures that were likely taken by residents. I follow Fisher's decision rule and define users that took pictures in one of the study cities over more than a month (and not in any other city) as residents. After this restriction and deletion of photos with incomprehensive dates the data set comprises 165,208 individual observations for Berlin and 806,851 for London, in each case taken from the initial recordings up to 2009. I use these photos in all baseline analyses, but also consider all photos and a sub-sample that was presumably taken by tourists in robustness checks. I define users that took pictures in one of the study cities over less than one month and over a longer period in another city as tourists. Table A1 tabulates the numbers of photos in the data base by city, year and samples (all, residents, tourists). The figures show how rapidly the file sharing communities gained popularity over the recent years.

Tab. A1. Photos by type and year

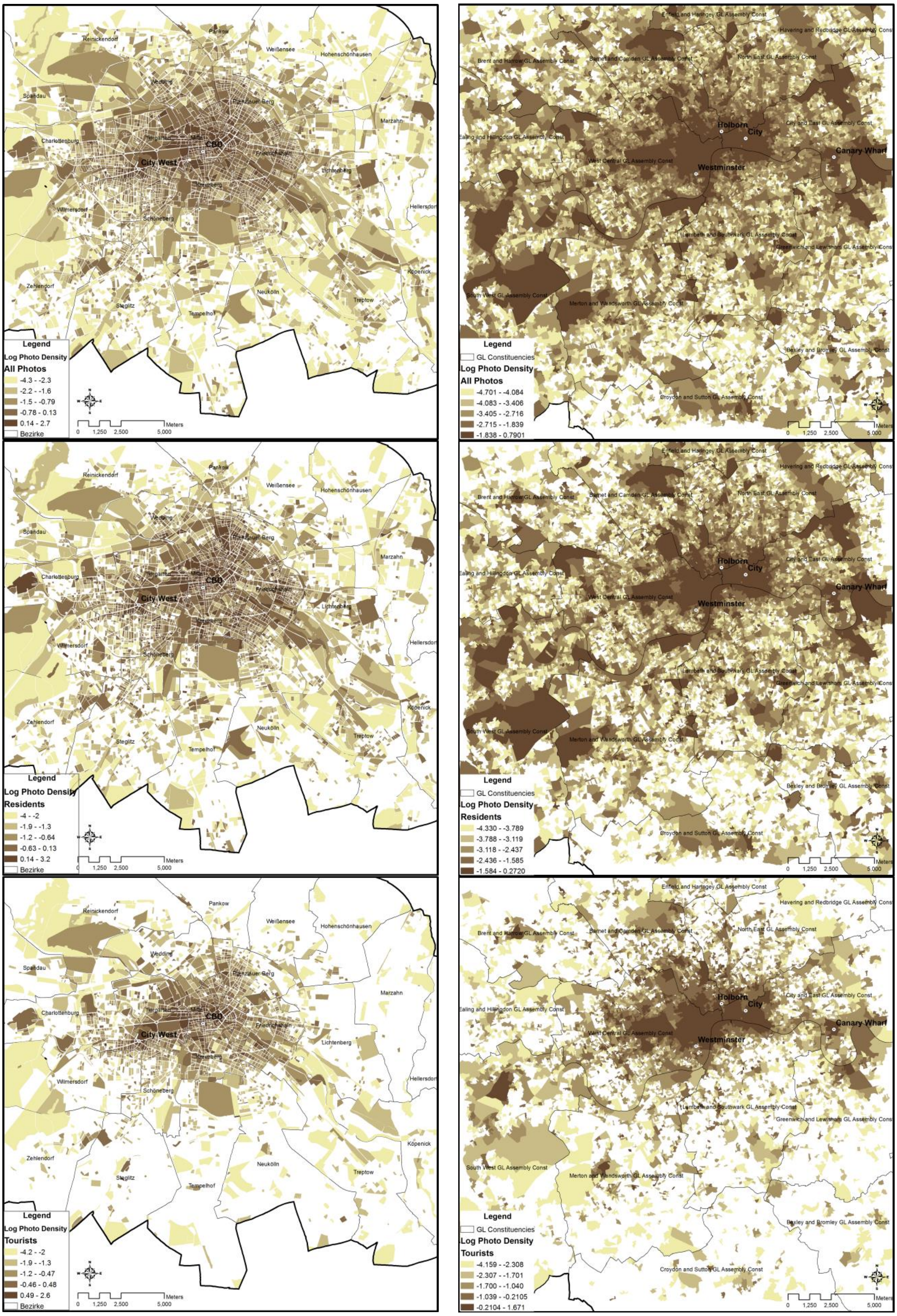
	Berlin			London		
	All	Residents	Tourists	All	Residents	Tourists
2002	2,216	672	797	10,043	3,707	3,963
2003	4,414	1,248	1,591	17,909	5,869	7,654
2004	9,128	1,443	3,861	39,910	10,995	18,449
2005	24,335	5,497	9,676	81,840	37,850	24,397
2006	76,875	21,424	28,204	226,447	110,342	58,297
2007	135,456	33,774	44,101	427,319	182,256	104,473
2008	187,859	48,497	49,895	486,999	218,655	109,278
2009	193,481	52,653	54,908	558,936	237,177	112,587
Total	633,764	165,208	193,033	1,849,403	806,851	439,098

Notes: Differences between totals and the sum of residents and tourists exist because some pictures could not be assigned to either category

Figure A2 plots the spatial distribution of photos in the different samples in the form of densities, i.e. the number of photos normalized by land area of the neighbourhood. In line with Figure A1 photo densities are generally higher in more central areas. The spatial pattern is relatively uniform across the three samples. If anything photos that were presumably taken by tourists tend to be more concentrated in central areas.

Fig A2. Photo Densities

Berlin **London**



Notes: Maps show photo densities (photos per neighbourhood land area) for Berlin (left) and London (right).

For the empirical analyses I merge these photo data with a variety of other spatial data sets. Therefore, all data are aggregated to consistent spatial units, the neighborhoods *i*. As units of analysis I use (medium level) voting precincts (Stimmbezirke) for Berlin and lower level super output areas for London. Both units are sufficiently small to be considered roughly homogenous neighborhoods and at the same time sufficiently large to yield meaningful urbanity densities (approximated by the number of photos taken). These units also provide notable variation in the land area, which I will make use of to identify the structural parameters. Finally, the boundaries of the chosen units are consistent with a range of spatial units for which official data such as population or employment are available. Within the 15 x 15 mile frame I end up with 969 (Berlin) and 2731 (London) units of observations with a mean land area of about 0.3 (Berlin) and 0.16 (London) square km. The somewhat distinct resolutions are chosen to account for the higher density of photos in London and ensure that less than 10% of the units are unpopulated with photos in each city.

I merge these data with a range of observable location characteristics. Most importantly I use property transaction data from the Committee of Valuation Experts (Gutachterausschuss fuer Grundstueckswerte, Berlin, 2000-2009) and the Nationwide Building Society (London, 2000-2008). The data for Berlin are unusually rich and contain a full record of property transactions, including the transaction price, total floor size and the corresponding plot area, among a range of building characteristics. A georeference is given by geographic coordinates in projected meter units. For London the data is somewhat less complete. It is restricted to properties for which Nationwide has issued mortgages. Since the company represents one of the three large mortgage providers with a market share of about 10% it still provides a comprehensive coverage. The main advantage over the land registry data set providing full coverage is that it includes a range of detailed property characteristics, although not the lot size of a building. Both data sets have been used and discussed in more detail in previous academic work (e.g. Ahlfeldt, 2011, 2013; Ahlfeldt & Kavetsos, 2013; Gibbons & Machin, 2005).

Other data collected include resident population by age group and workplace employment from official statistical records. Based on the official records I compute an index of the average age of the adult population ($AVAGE$) as follows:

$$AVAGE_i = \sum_a \frac{1}{2}(AT - AB)_{ia} \frac{POP_{ia}}{\sum_a POP_{ia}} \tag{A20}$$

, where AT and AB are the upper and lower bounds of an age category a and POP_{ia} is the total population within the category a in neighbourhood i. To compute the average age of the adult population I make use of the following age groups defined in the official statistics: Berlin 18-27, 45-55, 55-65, 65+ (I define the upper bound of the last age group as 75); London 20-29, 45-59, 60-74, 75+ (I define the upper bound in the last group as 85). To approximate disposable household income I use 2008 estimates of the purchasing power per capital by postcodes provided by the GfK group for Berlin and 2001 estimates by the Office of National Statistics on net disposable household income by wards. Both measures reflect household income after taxes and contributions.

Various geographic measures have been computed in GIS. These include the land area covered by green and water spaces, listed buildings (Berlin) and conservation areas (London) as well as distance to the nearest metro rail stations (U- and S-Bahn in Berlin, Underground and Dockland Light Rail in London). A distinction is made in the way schools are treated. Since school quality is arguably more homogenous in Berlin I use a geographic measure that emphasizes access to these public serves. To the extent that the spatial distribution of other public services (e.g. nurseries) is spatially correlated with schools their effects will be captured by the school variable. The London school measure instead emphasizes school quality to the extent that it is reflected in key stage 2 (KS2) results. The KS2 are externally marked national tests occurring upon completion of primary school education at age 11. Due to confidentiality restrictions the KS2 test scores are provided for output areas with at least three registered pupils in the period from 2002 to 2007. The problem is mitigated since I aggregate all data to the level of lower level super output area. For a handful of output areas I interpolate missing values based on the scores available for adjacent output areas.

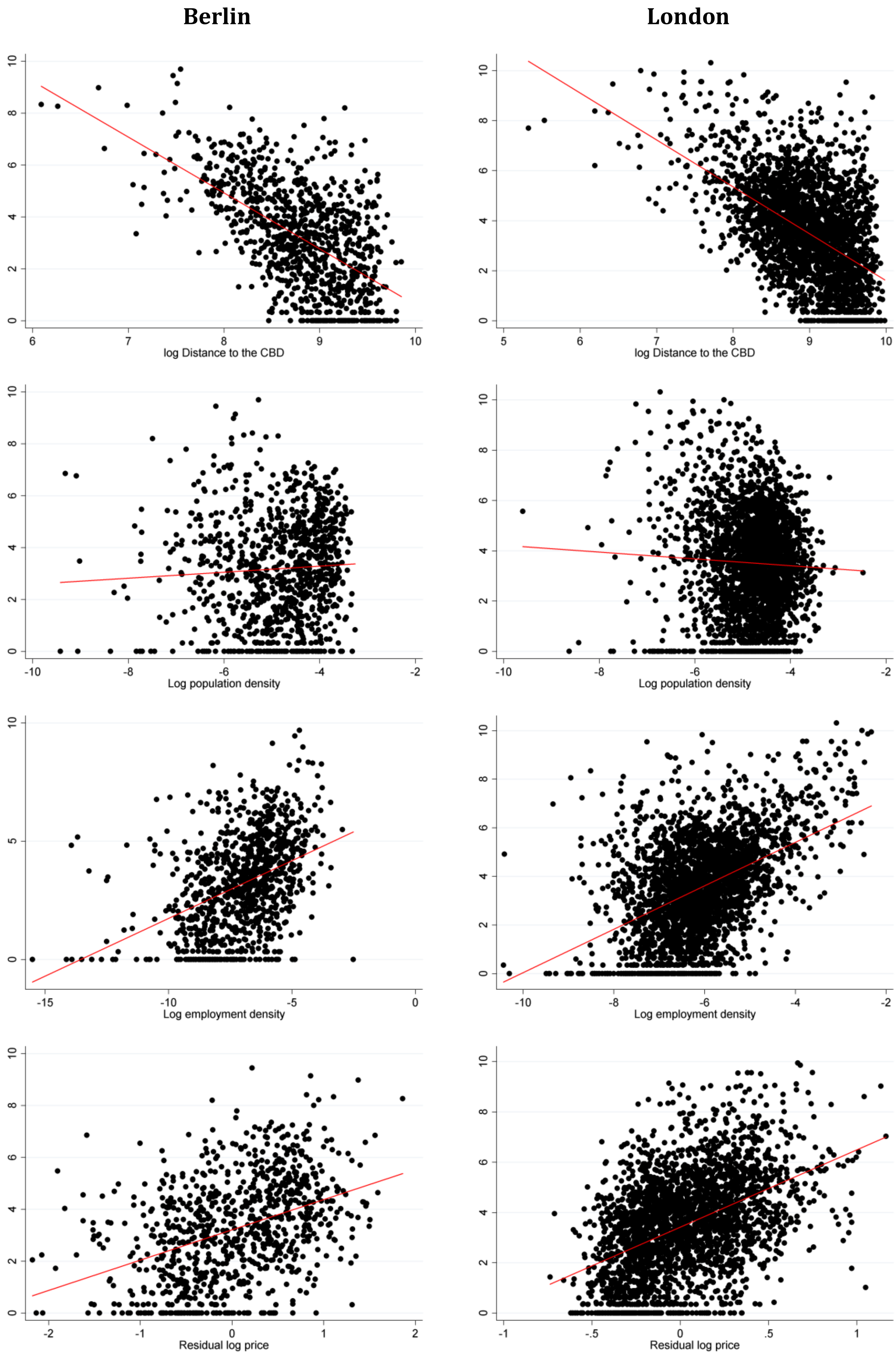
I also compile a data set of less common features. Among them are cultural consumption amenities, i.e., important museums, theaters and cinemas (132 in Berlin and 375 in London). Moreover, I borrow from Bass van Heur's fieldwork and geocode hundreds (297 in Berlin and 433 in London) of avant-garde music venues, such as clubs, record labels, etc., to define an index of alternative cultural activity based on the address list provided in the appendix of his PhD (van Heur, 2008). The data set also includes bars and pubs (1183 in Berlin, 2575 in London) as well as restaurants (3940 in Berlin, 2527 in London). For architectural quality besides making use of official preservation records I geocode hundreds

(284 in Berlin and 346 in London) of contemporary landmarks based on architecture guides. Table A2 summarized the data used and the sources.

Tab. A2. Data overview

	Berlin	London
Photos	Photos from Flickr and Picasa accessed via the official APIs and geocoded based on latitude/longitude coordinates	Photos from Flickr and Picasa accessed via the official APIs and geocoded based on latitude/longitude coordinates
Property transaction data	Provided by the committee of valuation experts (Gutachterausschuss fuer Grundstueckswerte). Covers all transactions of developed land. Includes transaction prices and dates, land value estimates, floor space, lot area and a range of housing features (see Table A6).	Provided by the Nationwide Building Society. Covers properties with mortgages issues by Nationwide (about 10%). Includes transactions prices and dates, floor space, and a range of housing features (see Table A5).
Population (by age groups)	2005 population by age groups from official records of local statistical office (Amt fuer Statistik Berlin Brandenburg). Provided at the level of statistical blocks (statistische Bloecke).	2001 population by age groups accessed via the neighbourhood statistics hosted by the Office for National Statistics. Based on the 2001 census and available at output area level.
Employment	2003 workplace employment comprising all workers contributing to social insurances. Available from the company register (Unternehmensregister). Provided at the level of statistical blocks (statistische Bloecke).	Accessed via the neighbourhood statistics hosted by the Office for National Statistics. Based on the 2001 census and available at output area level.
Household income	2008 estimates of purchasing power per capita (after taxes and contributions) obtained from GfK. Available at the postcode level.	Neighborhood Statistics estimates of the net disposable household income based on the 2001 census. Available at the ward level.
Green	Area covered by parks and forests. Computed in GIS based on shapefiles from the Berlin Urban and Environmental Information System.	Area covered by parks. Computed in GIS based on shapefiles from EDiNA.
Water	Area covered by lakes, rivers and canals. Computed in GIS based on shapefiles from the Berlin Urban and Environmental Information System.	Area covered by Thames river and canals. Computed in GIS based on shapefiles from EDiNA.
Distance to stations	Computed in GIS based on shapefiles provided by Berlin Urban and Environmental Information System.	Computed in GIS based on shapefiles provided by Transort for London.
School	Distance to nearest school. Computed in GIS based on a shapefile form the Berlin Urban and Environmental Information System	Average KS2 test score by output areas. Aggregated scores based on individual test results. Missing output area information (due to confidentiality restriction) filled by spatial interpolation in GIS
Bars, pubs and restaurants	Shapefiles provided by Geofabrik based on data uploaded to OpenStreetMap	Shapefiles provided by Geofabrik based on data uploaded to OpenStreetMap
Cultural nodes	Number of Museums, theatres and cinemas geocoded based on addresses collected from a range of websites and guides, e.g. http://www.kinokompendium.de, www.berlin.de	Number of Museums, theatres and cinemas geocoded based on addresses collected from a range of websites and guides, e.g. http://www.londonnet.co.uk http://www.timeout.com
Music nodes	Compiled by Bass van Heur (2008) during PhD Fieldwork. Geocoded based on address list provided in the appendix.	Compiled by Bass van Heur (2008) during PhD Fieldwork. Geocoded based on address list provided in the appendix.
Heritage	Area covered by listed buildings. Computed in GIS based on a shapefile from by the Berlin Urban and Environmental Information System	Area covered by designated conservation areas. Based on a shapefile provided by English Heritage
Signature buildings	Contemporary landmark buildings geocoded based on addresses provided by (Allinson, 2009)	Contemporary landmark buildings geocoded based on addresses provided by (Haubrich, Hoffmann, Meuser, & Uffelen, 2010)

Fig A3. Photo Density Distribution in Berlin and London



Notes: Y-variable is log of photo density (residents) in all plots. Data are aggregated to the level of medium level voting precincts in Berlin (statistische Bloecke) and lower level output areas in London. Selected outliers have been dropped to improve visibility.

Figure A3 compares photo densities to a range of other local characteristics. Photo densities are defined as weighted photos (see equation 10 in the main paper for a definition of weights) taken by residents divided by the land area of a neighborhood. One of the resulting stylized facts is that photo densities tend to (log-linearly) decrease in distance to the CBD. Interestingly, the rate of decline is fairly similar in both cities. While there is no clear relationship between photo densities and population densities apparent in either city, a positive relationship exists with employment density. The last panel in Figure A3 compares photo densities to a measure of local housing values. The housing value measure is obtained from an auxiliary regression:

$$\log(Y_{qt}) = \sum_n b_n f_{qn} + \phi_t + \varphi_i + \xi_q \tag{A21}$$

, where q is an individual housing unit, Y is either the property transaction price (London) or the property price per unit of land (Berlin), f_n is a vector of housing characteristics (see Table A7) only included in the London model, ϕ_t and φ_i are year and neighborhood fixed effects. The neighborhood effects are then recovered and used as a measure of locational value that is adjusted for time effects. The scatter plots quite evidently indicate that more photos are taken in more expensive areas. While the stylized facts presented in Table A3 are interesting, the unconditional correlations obviously need to be interpreted with care given that employment densities and house prices and distance to the CBD are themselves relatively closely correlated.

2.3 Empirical Strategy

2.3.1 One-stage estimation

This section extends the description of the one-stage estimation strategy from the main paper by introducing additional empirical tests based on the equilibrium conditions derived in 2.1 in the appendix. Due to the constrained data availability these additional models using estimated land values, capital to land ratios and floor area rations as dependent variable can only be applied to Berlin, but not to London.

Based on these empirical measures and the spatial equilibrium condition defined above I derive three types of reduced form price and quantity equations. The first reduced form equation is based on (A11) and (A12) and, hence, referring to the following dependent variables Y_i: Housing services per land area (empirically approximated by the transaction price divided by the plot area), the pure per unit land value (an estimate provided by the local committee of valuation experts) or the capital to land ratio (the property price net of total plot value divided by the land area).

$$\log(Y_{it}) = a + a_E \log EP_i + a_A \log P_i + a_L \log(G_i) + \sum_n b_n X_n$$
$$+ b_E \log EMP_i + b_P \log POP_i + b_O \log POP_i \times O_i + b_i \log POP_i \times I_i + \varphi_t + \eta_{it} \quad \text{(A22)}$$

Where EP_i and P_i are defined in (10) and (12), G is the geographic land area of a neighborhood (voting precincts or lower level super output areas), X_{in} is a vector of control variables capturing the quality of public services among other things, and EMP_i and POP_i are the local employment and population in a given neighborhood. The interaction of population with average age and income (both demeaned) directly follows from plugging (11) into (A15). Small letters are coefficients to be estimated, φ_t is a set of yearly fixed effects and η_{it} a random error term. Note that individual transactions (and characteristics) at all stages of the analysis are aggregated to the neighborhood level to avoid multiple transactions within a neighborhood sharing the same location characteristics and different neighborhoods receiving distinct weights depending on transaction frequencies.

It is a notable feature of equation (A22) that unlike in many applications of the hedonic method (Rosen, 1974) under the assumptions made the internal property characteristics should not be controlled for. The reason is that the value of housing services $R_i = \psi_i H_i$ and the plot area L_i are directly observable. Similarly, the land value and the capital to land ratio are provided in the data or can be constructed based on the data. Of course, successful identification depends on the appropriateness of the assumed functional form of the housing production function. I will therefore evaluate the robustness to the inclusion of hedonic controls in specification (A22).

The second empirical equation is a quantity equation based on (A19) with the ratio of a building's total floor to plot area as a dependent variable (*FSI*). Defining the composite housing feature term f_i as a function of m observable f_{mi} components and an unobservable μ_i component, i.e. $f_i = \prod_n b_m f_{mi} + \mu_i$, I obtain the following reduced form:

$$\log(FSI_{it}) = a + a_E \log EP_i + a_A \log PR_i + a_L \log(G_i) + \sum_n b_n X_n + \sum_m b_m f_{mi}$$
$$+ b_E \log EMP_i + b_P \log POP_i + b_O \log POP_i \times O_i + b_i \log POP_i \times I_i$$
$$+ \varphi_t + \omega_{it},\ \omega_{it} = \eta_{it} + \mu_{it} \quad \text{(A23)}$$

Similar to conventional hedonic price equations this specification attempts to control for observable housing features f_m. These features, however, do not include a control for the actual floor (and lot) size of a building, which forms part of the dependent variable. To obtain the third and the arguably most conventional (hedonic) price equation I combine the baseline housing bid-rent equation (A15) with the definition of housing services (2) to define the housing value R as a function of floor size and observable and unobservable housing features, i.e. $R_i = \psi_i H_i = \psi_i F_i e^{\prod_m b_n f_{im} + \mu_i}$.

$$\log(R_{it}) = a + a_E \log EP_i + a_A \log P_i + a_L \log(G_i) + \sum_n b_n X_n + \prod_n b_m f_{mi} + b_f \log(F_i)$$
$$+ b_E \log EMP_i + b_P \log POP_i + b_O \log POP_i \times O_i + b_i \log POP_i \times I_i + \varphi_t$$
$$+ \omega_{it},\ \omega_{it} = \eta_{it} + \mu_{it} \qquad \text{(A24)}$$

As with most hedonic specifications, it is a common problem in equation (A23) and (A24) that not all housing features are observable and that estimates may be biased if $cov(\mu_i, \eta_i) \neq 0$. On these grounds my preferred measure is the price per unit of land (R/L) since it circumvents the problem of unobservable housing features, albeit at the cost of assuming a particular functional form of the housing production function. Compared to standard land values (and the capital to land ratio incorporating that measure) the price per unit of land has the advantage of not being an estimated value, but a directly observable market outcome.

Equations (A22-A24) are reduced form versions of (A15-A19). Table A1 shows how the structural coefficients can be backed out from the reduced form coefficients. One limitation is that the housing expenditure share parameter has to be assumed. In line with Davis & Ortalo-Magné (2011) I set the share parameter to $(1 - \alpha) = 0.25$. This value is in line with anecdotal evidence for both study areas (IVD, 2012; NHPAU, 2007). Given the availability of (estimated) pure land values (for Berlin), the housing production function share parameter can be estimated by regressing the property price per unit of land on the pure unit value of land. The results are presented in section 3.2 of this appendix along with some estimates of the elasticity of substitution of land for capital that support the assumed Cobb-Douglas functional form.

Tab. A1. Parameter interpretation

	Coefficient Interpretation	
Response variable (in logs)	E (Centrality)	A (Urbanity)
Price	$\gamma_E = (1-\alpha)\widehat{a_E}$	$\gamma_A = -(1-\alpha)\widehat{a_L}$
Price / Land unit Land value / Land unit Capital / Land ratio	$\gamma_E = (1-\alpha)(1-\delta)\widehat{a_E}$	$\gamma_A = -(1-\alpha)(1-\delta)\widehat{a_L}$
Floor space / Land unit (Floor space index FSI)	$\gamma_E = \frac{(1-\alpha)(1-\delta)}{\delta}\widehat{a_E}$	$\gamma_A = -\frac{(1-\alpha)(1-\delta)}{\delta}\widehat{a_L}$

Notes: The distinct response variables relate to structural and empirical equations as follows: Price: (A15) and (A24). Price / land unit: (A17) and (A22). Land value / land unit: (A16) and (A22). Capital / Land ratio: (A18) and (A22). FSI: (A19) and (A24).

2.3.2 Two-stage estimation

This section complements section 2.3 in the main paper by introducing a two-stage estimation strategy as an alternative to the one-stage strategy used in the main paper. The motivation for the estimation of this alternative approach is twofold. Frist, the two-stage estimation strategy allows separating the direct effects of employment and population on the property market outcomes from the indirect effects that operate via the photo production process. Second, it allows evaluating whether a correlation of unobserved housing and location characteristics with the neighborhood land area (G_i) may affect the successful identification in the one-stage regressions. The advantages come at the cost of using a presumably noisy measure of urbanity (the residual of the first-stage photo regression), which may affect the estimation precision. The arguably conceptually more important limitation is that the two-stage approach does not allow for an identification of the structural photo productivity parameter λ, which has to be borrowed from the estimation of the full photo production model ($\tilde{\lambda}$, specification 15 and Table 2 in the main paper).

The starting point is a reduced version of the empirical photo production function (15), which is estimated in the first-stage:

$$\log(P_i) = c + \theta_E \log(E_i) + \theta_B \log(POP_i) + \theta_O POP_i \times O_i + \theta_I POP_i \times I_i + \epsilon_i \tag{A25}$$

where $\epsilon_i = \lambda \log(A_i) + \Xi_i$ and, hence, $\log(A_i) = (\epsilon_i - \Xi_i)/\lambda$ and Ξ captures potential measurement error. Given that $\tilde{A}_i = A_i/G_i$, substituting into the basic equilibrium bid rent condition (A6) yields:

$$\log(\psi_i) = \aleph + \frac{\gamma_E}{1-\alpha}\log\tilde{E}_i + \frac{\gamma_A}{1-\alpha}\log\left(\frac{1}{\lambda}\widehat{\epsilon_i} - \log(G_i)\right) + \frac{\gamma_S}{1-\alpha}\log\tilde{S}_i - \frac{\gamma_A}{(1-\alpha)\lambda}\Xi_i \tag{A26}$$

The corresponding empirical specification takes the following form for the following dependent variables Y_i: Housing services per land area (empirically approximated by the transaction price divided by the plot area), the pure per unit land value (an estimate provided by the local committee of valuation experts) or the capital to land ratio (the property price net of total plot value divided by the land area).

$$\begin{aligned}\log(Y_{it}) &= a + a_E \log EP_i + a_P \log \widetilde{P_i} + \textstyle\sum_n b_n X_n \\ &\quad + d_E EMPD_i + d_P POPD_i + \varphi_t + \Lambda_{it},\ \Lambda_{it} = \eta_{it} - \tfrac{\gamma_A}{(1-\alpha)\lambda} \Xi_i \end{aligned} \tag{A27}$$

where $\widetilde{P_i} = \left(\hat{\epsilon}_i / \tilde{\lambda} - \log(G_i)\right)$ and $EMPD_i = EMP_i/G_i$ and $POPD_i = POP_i/G_i$ and Λ_{it} is a composite of two (random) error components capturing measurement error in the first stage (Ξ_i) photo regressions and the second stage housing market regressions (η_{it}). Essentially, this estimation approach makes use of a photo measure that is rescaled to reflect a density measure and to correct for increasing returns to urbanity in the photo production process. Compared to the one-stage approach the control for neighborhood land area disappears. Neighborhood employment (*EMPD*) and population (*POPD*) are added to the empirical equation in densities so that d_E and d_P give the direct effect of local employment and population densities on property market outcomes. Adding a control for neighborhood land area (G) in this specification, if anything, will capture factors that are unrelated to the distribution of photos, employment and population. If the parameters of interest remain robust to the inclusion of the variable this will indicate that the one-stage results are unlikely to be contaminated by such factors.

The estimation equations for the dependent variable *FSI* (floor area ration) and *R* (property price) are obtained in complete analogy to (A23) and (A24) in the main paper.

$$\begin{aligned}\log(FSI_{it}) &= a + a_E \log EP_i + a_P \log \widetilde{P_i} + \textstyle\sum_n b_n X_n + \sum_m b_m f_{mi} \\ &\quad + d_E EMPD_i + d_P POPD_i + \varphi_t + \widetilde{\Lambda}_{it},\ \widetilde{\Lambda}_{it} = \eta_{it} + \mu_{it} - \tfrac{\gamma_A}{(1-\alpha)\lambda} \Xi_i \end{aligned} \tag{A28}$$

$$\begin{aligned}\log(R_{it}) &= a + a_E \log EP_i + a_P \log \widetilde{P_i} + \textstyle\sum_n b_n X_n + \sum_m b_m f_{mi} + b_f \log(F_i) \\ &\quad + d_E EMPD_i + d_P POPD_i + \varphi_t + \widetilde{\Lambda}_{it},\ \widetilde{\Lambda}_{it} = \eta_{it} + \mu_{it} - \tfrac{\gamma_A}{(1-\alpha)\lambda} \Xi_i \end{aligned} \tag{A29}$$

2.3.3 Preference heterogeneity

The bid-rent framework outlined in section 2.1, while allowing for photo production elasticities that vary in income and age of the local population, assumes homogenous preferences with respect to centrality and urbanity (and all considered controls). This is obviously a strong assumption. Evaluating heterogeneity of preferences with respect to location characteristics is challenging since the dimensions along which preferences vary are often difficult to observe and even to determine a priory. To gain limited insights into preference heterogeneity with respect to urbanity and centrality I allow preferences to vary in some arguably arbitrary selected neighborhood characteristics, i.e. average income and age, and in space. The data set does not allow for the second stage analysis suggested by Rosen (1974) due to missing socio-demographic information on buyers (and sellers).

To allow for urbanity and centrality preferences that vary in the local income and average age of the population I make the respective elasticity parameters functions of these attributes.

$$\gamma_E = \gamma_{E0} + \gamma_{EO} O_i + \gamma_{EI} I_i \tag{A30a}$$

$$\gamma_A = \gamma_{A0} + \gamma_{AO} O_i + \gamma_{AI} I_i \tag{A30b}$$

This approach is similar to the way I model heterogeneity in the photo production elasticity described in specification (11) of the main paper and I adopt the same notations here. Substituting into the spatial equilibrium conditions yields following variations of the baseline empirical specifications (A22) and (A24):

$$\begin{aligned}
\text{Log}(Y_{it}) = a &+ a_E \text{log} EP_i + a_P \log P_i + a_L \log(G_i) + \textstyle\sum_n b_n X_n \\
&+ b_E \log EMP_i + b_P \log POP_i + b_O \log POP_i \times O_i + b_i \log POP_i \times I_i \\
&+ a_{E0} \text{log} EP_i + a_{EO} \text{log} EP_i \times O_i + a_{EI} \log EP_i \times I_i \\
&+ a_{A0} \log PR_i + a_{AO} \text{log} EP_i \times O_i + a_{AI} \log EP_i \times I_i \\
&+ a_{L0} \log(G_i) + a_{LO} \text{log} EP_i \times O_i + a_{LI} \log EP_i \times I_i \\
&+ \varphi_t + \eta_{it}
\end{aligned} \tag{A31}$$

$$\begin{aligned}
\log(R_{it}) = a &+ a_E \text{log} EP_i + a_A \log P_i + a_L \log(G_i) + \textstyle\sum_n b_n X_n + \prod_n b_m f_{mi} + b_f \log(F_i) \\
&+ b_E \log EMP_i + b_P \log POP_i + b_O \log POP_i \times O_i + b_i \log POP_i \times I_i \\
&+ a_{E0} \text{log} EP_i + a_{EO} \text{log} EP_i \times O_i + a_{EI} \log EP_i \times I_i \\
&+ a_{A0} \log PR_i + a_{AO} \text{log} EP_i \times O_i + a_{AI} \log EP_i \times I_i \\
&+ a_{L0} \log(G_i) + a_{LO} \text{log} EP_i \times O_i + a_{LI} \log EP_i \times I_i \\
&+ \varphi_t + \omega_{it},\ \omega_{it} = \eta_{it} + \mu_{it}
\end{aligned} \tag{A32}$$

To allow for urbanity and centrality preferences that vary in all observable and unobservable neighborhood characteristics that are correlated in space I define local preference parameters as a function of surrounding preference parameters at locations j weighted by distance.

$$\gamma_{Ei} = \sum_j \frac{v_j}{\sum_j v_j} \gamma_{Ej} \tag{A33a}$$

$$\gamma_{Ai} = \sum_j \frac{v_j}{\sum_j v_j} \gamma_{Aj} \tag{A33b}$$

, where $v_j = e^{-\Gamma D_{ij}}$ and Γ determines the decay in the spatial autoregressive structure. I estimate these localized parameters by means of locally weighted regressions (Cleveland & Devlin, 1988; McMillen, 1996), i.e. I estimate a full set of parameters for each location i in a separate regression where all observations receive the weights defined above: $\sum_j \frac{v_j}{\sum_j v_j}$.

3 Empirical Results

This section complements section 3 of the main paper. Note that the numbering of the sub-section does not follow the section in the main paper except for the first sub-section, which adds variations of the photo production function estimates using different photo measures. Section 3.2 presents estimates of the housing production function of Berlin. Sections 3.3 and 3.4 complement the baseline empirical findings from the main paper by presenting hedonic estimates of the effects of housing features and various robustness tests. Sections 3.5 and 3.6 present the results of the two-stage estimation procedure and the approaches to preference heterogeneity introduced in 2.3.

3.1 Urbanity and photo production

Determinants of the spatial distribution of photos

Table 2 in the main paper presents the estimates of the photo production function (15) using a photo measure (10) that is based on a sample of users who presumably are residents. Table A3 below complements the evidence by comparing the baseline residential models (1 and 4) to derivatives using similarly constructed photo measures incorporating all available photos (2 and 5) and photos taken by users who presumably are tourists (3 and 6). In general, the results tend to be remarkably stable indicating that the perception of what constitutes attractive urban spaces does not vary enormously between residents and tourists. One of the notable differences is that unsurprisingly the number of residents living in a neighborhood turns out to be a less important determinant for photos taken by presumable tourists than residents. Alternative cultural facilities (music nodes) and signature buildings tend to attract somewhat more attention by tourists. In general, the increasing returns with respect to urbanity in the photo production function are slightly higher in the tourist sample. All of these findings consistently apply to both cities.

Tab. A2. Photo regressions (Tobit)

	(1) log Photos (residential)	(2) log Photos (all)	(3) log Photos (Tourists)	(4) log Photos (residential)	(5) log Photos (all)	(6) log Photos (Tourists)
	Berlin	Berlin	Berlin	London	London	London
log Population	0.388***	0.462***	0.201	1.553***	1.590***	0.689***
	(0.102)	(0.098)	(0.132)	(0.173)	(0.153)	(0.235)
log Population x	0.007	0.012	-0.015	-0.003	0.030	0.070
average age	(0.017)	(0.016)	(0.020)	(0.054)	(0.047)	(0.075)
log Population x Estimated	-0.001	-0.001	-0.000	0.000*	0.000	0.000
income	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
log Employment	0.178***	0.210***	0.197***	0.512***	0.516***	0.668***
	(0.044)	(0.042)	(0.058)	(0.040)	(0.037)	(0.052)
log Green area	0.051***	0.057***	0.037	0.046***	0.038***	0.032***
	(0.019)	(0.018)	(0.024)	(0.007)	(0.006)	(0.009)
log Water area	0.034**	0.033**	0.052***	0.057***	0.053***	0.060***
	(0.015)	(0.015)	(0.019)	(0.009)	(0.009)	(0.012)
log Bars & Pubs (count)	0.010	-0.018	0.070	0.347***	0.276***	0.192**
	(0.112)	(0.109)	(0.143)	(0.068)	(0.063)	(0.088)
log Restaurants (count)	0.423***	0.379***	0.520***	0.181***	0.206***	0.316***
	(0.080)	(0.077)	(0.103)	(0.064)	(0.059)	(0.082)
log Music nodes (count)	0.725***	0.710***	0.866***	0.632***	0.597***	0.662***
	(0.155)	(0.151)	(0.194)	(0.118)	(0.110)	(0.150)
log Cutural nodes (count)	0.322	0.381*	0.394	0.357**	0.352***	0.222
	(0.233)	(0.227)	(0.293)	(0.144)	(0.133)	(0.182)
log Area occupied by	0.120***	0.123***	0.145***	0.117***	0.113***	0.137***
listed buildings	(0.016)	(0.016)	(0.022)	(0.006)	(0.006)	(0.008)
log Architectural nodes	0.737***	0.897***	1.191***	0.385***	0.609***	1.135***
(count)	(0.168)	(0.163)	(0.211)	(0.141)	(0.131)	(0.178)
Income	YES	YES	YES	YES	YES	YES
Age	YES	YES	YES	YES	YES	YES
aic	3505.202	3542.170	3301.859	9758.862	9516.232	8975.669
Lambda ($\tilde{\lambda}$)	2.423	2.562	3.273	2.122	2.243	2.758
N	969	969	969	2731	2731	2731

Notes: All photo measures a constructed according to specification (11) in the main paper. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Content of photos

Figure 2 in the main paper provides a categorization of about 600 randomly drawn photo motives that were visually inspected. Table A3 adds to the Figure 2 by tabulating the number and the percentage of pictures falling into the distinct categories that were defined.

Tab. A3. Photo subjects by categories (unconditional)

	Berlin		London	
N	267	100.00%	271	100.00%
Flickr	204	76.40%	214	78.97%
Picasa	63	23.60%	57	21.03%
Residents	96	35.96%	94	34.69%
Tourists	102	38.20%	92	33.95%
Unknown	68	25.47%	85	31.37%
Artistic	26	9.74%	20	7.38%
Aesthetic	207	77.53%	176	64.94%
Scenery	124	46.44%	111	40.96%
Detail	76	28.46%	62	22.88%
Consumption	39	14.61%	73	26.94%
Outside	193	72.28%	181	66.79%
Inside	71	26.59%	87	32.10%
People	91	34.08%	124	45.76%
Stranger	35	13.11%	57	21.03%
Friends	56	20.97%	77	28.41%
Animals	10	3.75%	13	4.80%

Notes: Except Flickr/Picasa and Residents/Tourists/Unknown the categories are not mutually exclusive. From the full sample of photos reported in Table A1 654 photos were selected in separate random draws for Berlin (337) and London (317). The samples reported in this table are lower due to broken links (primarily to Picasa pictures).

3.2 The housing production function

There is a reasonably long tradition in the housing economics literature to model housing production according to a CES (constant elasticity of substitution) (and constant returns to scale) function (Arrow, Chenery, Minhas, & Solow, 1961). McDonald (1981) provides an excellent survey of the early literature. Estimating the elasticity of substation between land and nonland factors is important in the context of this analysis to motivate the Cobb-Douglas function, which is a special case of the more general CES function where the elasticity of substitution is unitary. To arrive at an estimation equation in an approach related to e.g. Clapp (1979) or Koenker (1972) let's assume the following CES function:

$$H_j = Z\left(\delta K_j^c + (1-\delta)L_j^c\right)^{\frac{1}{c}} \tag{A34}$$

where output and input factors are now property j specific and $\sigma = 1/(1-c)$ is the elasticity of substitution. The first order conditions given the assumptions made in section two are then defined as:

$$\frac{H_j}{L_j} = Z^{-\frac{c}{1-c}}(1-\delta)^{-\frac{c}{1-c}}\left(\frac{\Omega_j}{\psi_j}\right)^{\frac{1}{1-c}}, \frac{H_j}{K_j} = Z^{-\frac{c}{1-c}}\delta^{-\frac{c}{1-c}}\left(\frac{1}{\psi_j}\right)^{\frac{1}{1-c}} \tag{A35}$$

Solving for the capital to land ratio (K/L) defined in section two and taking logs yields:

$$\log\left(\frac{K_j}{L_j}\right) = \log\left(\frac{(\psi_j H_j - \Omega_j L_j)}{L_j}\right) = -\sigma\log\left(\frac{(1-\delta)}{\delta}\right) + \sigma\Omega_j \tag{A36}$$

This condition can be used to motivate an estimation equation as used by Koenker (1972):

$$\log Y_j = e_0 + b \log LV_j + \zeta_j \tag{A37}$$

where Y is the capital to land ratio (the property price net of total plot value divided by the land area) as used in specification (13) of the main paper and LV is the estimated per unit land value from the Committee of Valuation Experts. The error term in such an equation is obviously supposed to be uncorrelated with land values. In practice, this is unlikely the case given that the estimated land value shows up on the right-hand and left-hand side of the estimation equation. Given how the dependent variable is constructed, any shock to the land value estimate (e.g. due to measurement error) should lead to a downward bias in the estimated elasticity of substitution.

Columns (1-4) in Table A4 show the results of an estimation of (A37). Column (1) begins with an OLS estimation. The elasticity estimate is remarkably close to Koenker (1972) who found a value of 0.71. The elasticity is positive and highly statistically significantly different from zero, but also from one. Column (2) addressed the mechanical endogeneity problem described above by instrumenting the independent variable using a second order polynomial distance to the central business district (CBD) variable. As one would expect, the first stage is very strong and the estimated elasticity of substitution increases substantially. The estimated value is now significantly larger than one. While the first stage in (2) is strong, it is not necessarily the best description of the spatial structure of Berlin given the particular history of the city (Ahlfeldt, Redding, Sturm, & Wolf, 2012). The long lasting period of division has led to market segmentation into East and West Berlin, which is only gradually disappearing due to costly spatial arbitrage. Moreover, the disconnection of West Berlin from the historic center in East Berlin has led to an upgrade of the formerly secondary business center around the Kurfürstendamm (Kud.) in West Berlin, giving the city an effectively duo centric-structure. Column (3) accounts for the particularities in the spatial structure of the city by adding a second order polynomial of distance to the Kurfürstendamm and a dummy variable distinguishing between former East and West Berlin to the set of instruments. With this modification the estimated elasticity is no longer statistically distinguishable from unity. Adding further variables to the set of instruments does not change this result (4). Columns (5) and (6) estimate the elasticity of substitution based on a regression of log property price per unit of land on land value as previously estimated by e.g. Clapp (1979). Clapp, following Fountain (1977), motivates the estimation equation by taking logs of the first of the two first-order condition noted above adding log price of housing services on both sides of the equation and assuming that the price of housing services is constant. As discussed by McDonald (1981) the last step is problematic and can lead to biased estimates. Similar to the replication of the Koenker approach, I find a relatively low elasticity of substitution in the OLS estimates (in line with Clapp's results and other early results) and an elasticity parameter not distinguishable from one in the IV results.

These results help reconcile the early results of the substitution elasticity, which as summarized by McDonald (1981) tend to be generally below one, with more recent estimates (Epple, Gordon, & Sieg, 2010) and engineering estimates (Clapp, 1979), which suggest a unitary elasticity.

Tab. A4. Estimated elasticity of substitution (Berlin)

	(1) OLA Log (Capital / Land Ratio)	(2) IV Log (Capital / Land Ratio)	(3) IV Log (Capital / Land Ratio)	(4) IV Log (Capital / Land Ratio)	(5) OLS Log (Price / Land Area)	(6) IV Log (Price / Land Area)
Log (Land Value / Land Area)	0.702*** (0.015)	1.360*** (0.024)	0.991*** (0.018)	1.009*** (0.018)	0.816*** (0.008)	0.994*** (0.010)
Constant	1.848*** (0.084)	-1.886*** (0.136)	0.208** (0.102)	0.108 (0.100)	1.842*** (0.048)	0.828*** (0.059)
Instruments		Distance to CBD (quadratic)	Distance to CBD (quadratic) Distance to Kud. (quadratic) East Berlin	Distance to CBD (quadratic) Distance to Kud. (quadratic) East Berlin Distance to park / water / station / school		Distance to CBD (quadratic) Distance to Kud. (quadratic) East Berlin
r2	0.088	0.011	0.073	0.071	0.276	0.262
N	25894	25894	25894	25894	29163	29163
aic	85169.224	87262.784	85586.537	85638.650	65532.109	66055.720
Sigma=1 P Value	0.000	0.000	0.619	0.617	0.000	0.571
Cragg Donald F		8867.384	10154.255	6541.257		11051.430
Hansen J		87.699	1078.204	1233.361		1487.388
Hansen J P Value		0.000	0.000	0.000		0.000

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Given an elasticity of substitution between land and nonland factors of one, the CES production function collapses to the Cobb-Douglas special case. Hence, a simple estimation equation that helps determining the housing production function share parameter δ can be motivated using the non-profit and first order conditions discussed in section 2.1 of this appendix document. Equation A1 gives the house price per unit of land $R_j/L_j = \psi_j H_j/L_j$ as a function of the land rent Ω_j. As for the estimation of the elasticity of substitution all information are available at the level of individual properties j, which are therefore chosen as the unit of observation in these regressions.

A simple empirical equation that corresponds to this condition takes the following form:

$$\frac{R_j}{L_j} = b_{LV} LV_j + \tilde{\zeta}_j \tag{A38}$$

where $1-\delta = \frac{1}{b_{LV}}$ and $\delta = \frac{b_{LV}-1}{b_{LV}}$ and LV are standard land values/m² and ζ_i is an error.

I estimate (A38) omitting the constant using OLS and an instrumental variable (IV) approaches to account for the possibility that some housing features impacting on house prices also affect land values estimated by the committee of valuation experts. The results are generally similar in all models and particularly so in the IV models. I use the estimated value from column (3) with my preferred set of IVs for the interpretation of the reduced form parameters estimated in the capitalization models of primary interest.

Tab. A5. Estimated land share parameters (Berlin)

	(1) OLS Price / Land Area		(2) IV Price / Land Area		(3) IV Price / Land Area	
Land Value	2.354***	(0.101)	2.634***	(0.015)	2.574***	(0.014)
Instruments			Distance to CBD (quadratic)		Distance to CBD (quadratic) Distance to Kud. (quadratic) East Berlin	
r2	0.562		0.554		0.557	
N	29163		29163		29163	
δ	0.575		0.620		0.611	
$1-\delta$	0.425		0.380		0.389	
Cragg Donald F			29786.802		14447.177	
Sargan J			98.952		1048.011	
Sargan J P-Value			0.000		0.000	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

3.3 Hedonic estimates

The estimates of the hedonic attribute effects (implicit prices) have been omitted from Table 3 in the main paper and various tables in this appendix) to save space and improve readability, but are reported below in Tables A6 and A7. Note that while the reduced form coefficients are expected to be qualitatively similar in the floor area ratio model and the classic hedonic price regressions, the magnitudes are not directly comparable (due to the different underlying equilibrium conditions). The results generally are in line with expectations and provide little surprise. The single family house effect, perhaps, stands out as more interesting result. While c.p. prices are significantly higher than for multi-family buildings, the floor area ratio is typically lower.

Tab. A6. Hedonic estimates (Berlin)

	(1) Log (Floor Space / Land Area)		(2) Log Price	
log Employment Potential	0.246***	(0.058)	0.089*	(0.054)
log photos (residents)	0.020**	(0.009)	0.015*	(0.008)
log Area	-0.105***	(0.024)	-0.033*	(0.020)
log Population	0.093***	(0.032)	-0.054**	(0.026)
log Population x average age	-0.004***	(0.001)	-0.000	(0.001)
log Employment	-0.010	(0.012)	0.009	(0.010)
log Population x Estimated income	-0.008*	(0.004)	0.042***	(0.004)
log Dist to school (sign inverted)	-0.013	(0.018)	0.021	(0.015)
log Dist to station (sign inverted)	0.046*	(0.026)	0.051**	(0.023)
Single family house (dummy)	-1.389***	(0.076)	0.267**	(0.104)
Building Age (Years)	-0.009***	(0.003)	-0.004*	(0.002)
Building Age squared	0.000***	(0.000)	0.000	(0.000)
Condition: good (Dummy)	0.344***	(0.094)	0.498***	(0.083)
Condition: Bad (Dummy)	-0.110	(0.084)	-0.267***	(0.079)
Attic flat (Dummy)	-0.022	(0.074)	0.104*	(0.059)
Elevator (Dummy)	0.440***	(0.103)	0.305***	(0.086)
Basement (Dummy)	0.508***	(0.117)	0.232**	(0.108)
Underground car park (Dummy)	2.023**	(0.786)	1.114**	(0.432)
Charge for local public infrastructure	0.036	(0.084)	-0.034	(0.074)
Property is not occupied by renter	0.064	(0.076)	-0.077	(0.072)
Share (%) secondary structure at sales price	-4.645	(2.999)	-1.202	(0.866)
Month	-0.001	(0.010)	-0.004	(0.010)
Log Floor space			0.698***	(0.036)
log Plot area			0.221***	(0.040)
Year Effects	Yes		Yes	
Year Effects x East	Yes		Yes	
r2	0.885		0.924	
Centrality (γ_E)	0.038		0.022	
Urbanity (γ_A)	0.016		0.008	
Urbanity ($\widetilde{\gamma_A}$)	0.008		0.009	
Lambda (λ)	5.128		2.211	
N	897		897	

Notes: Standard errors in parentheses. Robust standard errors. * p<0.1, ** p<0.05, *** p<0.01. Reference models are models (4) and (5) in Table 3 in the main paper.

The hedonic results for the London data set are similarly mostly in line with expectations. If anything, it is notable that while in Berlin the building age effect follows the typical u-shape the price of properties in London seems to monotonically increase in the building age (the quadratic term virtually has no impact) This finding is in line with recent evidence based on transactions across the whole of England (Ahlfeldt, Holman, & Wendland, 2012).

Tab. A7. Hedonic estimates (London)

	(1) Log Price	
log Employment Potential	0.496***	(0.022)
log photos (residents)	0.016***	(0.002)
log Area	-0.032***	(0.008)
log Employment	0.028***	(0.004)
log Population	-0.087***	(0.014)
log Population x average age	0.001***	(0.000)
log Population x Estimated income	0.167***	(0.005)
log Distance to metro station (inverted sign)	0.031***	(0.004)
Log average key stage 2 score	0.355***	(0.031)
Log Floorsize	0.537***	(0.033)
Number of bedrooms	0.026*	(0.014)
Number of bathrooms	0.166***	(0.019)
Building Age (Years)	0.003***	(0.000)
Building Age squared	-0.000	(0.000)
Central Heating (Full)	0.048	(0.036)
Central Heating (Partial)	0.055	(0.064)
Garage (Single or Double)	0.098***	(0.021)
Parking Space	0.113***	(0.019)
Property Type: Detached	0.219***	(0.084)
Property Type: Semi-Detached	-0.012	(0.053)
Property Type: Terraced	-0.092*	(0.052)
Property Type: Cottage	0.027	(0.170)
New Property	0.199***	(0.063)
Property sells under leasehold	-0.103**	(0.051)
Share of housing in poor condition	-0.189***	(0.054)
Year Effects	Yes	
r2	0.832	
Centrality (γ_E)	0.124	
Urbanity (γ_A)	0.008	
Urbanity ($\widetilde{\gamma_A}$)	0.008	
Lambda (λ)	2.019	
N	2639	

Notes: Standard errors in parentheses. Standard errors are robust. * p<0.1, ** p<0.05, *** p<0.01. Reference model is (1) in Table 4 in the main paper.

3.4 One-stage regressions: Alternative models and robustness tests

Observable and unobservable urbanity

Arguably, the two main benefits of capturing urbanity by geo-tagged photos are that a) photos contain information on features that are otherwise unobservable and b) photos provide an aggregated measure of urbanity that implicitly attaches weights λ_k to the observable urbanity features. In the first three columns of Table A8 I replicate the baseline capitalization models from Table 3 in the main text separating the (log) photo effect into a component that is observable, in principle, and another one that is unobservable. The observable component is the joint effect of the observable amenities $\left(\sum_k \hat{\lambda}_k A_k\right)$ in the first-stage regressions reported in Table 1 of the main text. The unobserved component is simply the residual of the respective regressions ($\varsigma = \sum_l \lambda_l A_l$). When replacing the (log) photo measure with these two separate variables the latter provides a statistical test of the significance of the (urbanity) information contained in the photo data that is otherwise not observable. With the exception of the weaker standard hedonic Berlin specification (2), the results reveal that the photo variable contains information above and beyond the information contained even in the comprehensive amenity data sets used in this analysis. Relative to the urbanity component attributable to observable urbanity features (*predicted* effect) the effect of unobservable amenities (*residual* effect) consistently amounts to about one fourths. The urbanity effect (the predicted component) is slightly larger but within the range of the baseline models. The estimates imply that conditional on the not directly observed urbanity component, the observable urbanity component is roughly linearly related to urbanity (as implied by a λ that is relatively close to 1).

The residual urbanity effect is robust to replacing the predicted effect recovered from Table 1 models by the individual amenity variables (columns 4-6). The coefficients of the individual amenity variables need to be interpreted with care as these variables are individually more likely correlated with unobserved locational attributes than the joint effect captured by the photo variable. The perhaps most notable feature of these models is that architectural amenities seem to have a positive and quite robust capitalization effect. A twice as high number of signature buildings (conservation area) in a neighborhood implies about 4% (1%) higher property prices in London. Multiplying the reduced form coefficients in the preferred Berlin model by the land share ($1-\delta=0.39$, see section 3.2) the comparable figure amounts to 4.3% (0.43%).

In terms of utility effects the implication is that that doubling the number of signature buildings in a neighborhood in the preferred models is associated with an increase in utility by about 1% (the indirect elasticity of utility with respect to these features is obtained by multiplying the reduced form coefficients by the expenditure shares on housing $1-\alpha$ and, in addition, the land share $1-\delta$ in the price per land area regression (4)). Likewise, a similar increase in the number of listed buildings or the conservation area is associated with an increase in utility of about 0.01-0.02%.

Tab. A8. Urbanity effects by observable and unobservable component

	(1) Log (Price / Land Area)	(2) Log Price	(3) Log Price	(4) Log (Price / Land Area)	(5) Log Price	(6) Log Price
	Berlin	Berlin	London	Berlin	Berlin	London
log Employment Potential	0.697***	0.105	0.449***	0.748***	0.134	0.438***
	(0.119)	(0.088)	(0.022)	(0.119)	(0.088)	(0.022)
Predicted log photo density	0.164***	0.066***	0.049***			
	(0.021)	(0.017)	(0.004)			
Residual log photo density	0.041***	0.007	0.010***	0.038***	0.007	0.011***
	(0.012)	(0.008)	(0.002)	(0.012)	(0.008)	(0.002)
log Area	-0.204***	-0.057***	-0.049***	-0.188***	-0.053**	-0.043***
	(0.029)	(0.021)	(0.008)	(0.029)	(0.021)	(0.009)
log Employment	-0.013	0.001	0.023***	-0.025	-0.003	0.026***
	(0.016)	(0.011)	(0.004)	(0.015)	(0.011)	(0.004)
log Population	0.022	-0.046*	-0.056***	0.001	-0.059**	-0.056***
	(0.045)	(0.025)	(0.016)	(0.045)	(0.027)	(0.016)
log Population x average age	0.004	0.000	0.000	0.006	0.002	0.000
	(0.008)	(0.005)	(0.004)	(0.007)	(0.005)	(0.004)
log Population x Estimated income	-0.000	-0.000	0.000**	-0.000	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log Dist to school (sign inverted)	0.041*	0.019	0.029***	0.044**	0.021	0.031***
	(0.021)	(0.015)	(0.004)	(0.021)	(0.015)	(0.004)
School index	0.115***	0.039*	0.344***	0.106***	0.036	0.334***
	(0.033)	(0.023)	(0.031)	(0.034)	(0.023)	(0.031)
log Green area				-0.002	0.002	0.001
				(0.007)	(0.004)	(0.001)
log Water area				0.016***	0.003	0.002**
				(0.004)	(0.003)	(0.001)
log Music nodes (count)				-0.010	-0.007	0.009
				(0.039)	(0.027)	(0.013)
log Cutural nodes (count)				0.060	0.081	0.029
				(0.071)	(0.050)	(0.020)
log Area occupied by listed buildings				0.011*	0.005	0.008***
				(0.006)	(0.005)	(0.001)
log Architectural nodes (count)				0.110*	0.013	0.041**
				(0.059)	(0.035)	(0.018)
log Bars/pubs (count)				0.030	0.017	0.003
				(0.030)	(0.020)	(0.007)
log Restaurants (count)				0.159***	0.069***	0.011
				(0.022)	(0.016)	(0.008)
Income	YES	YES	YES	YES	YES	YES
Average age	YES	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES	YES
Year E. x East Berlin	YES	YES		YES	YES	
Hedonics	-	YES	YES	-	YES	YES
r2	0.616	0.925	0.838	0.631	0.926	0.839
Centrality (γ_E)	0.068	0.026	0.113			
Urbanity (γ_A)	0.020	0.014	0.012			
Lambda (λ)	1.240	0.859	0.955			
N	897	897	2639	897	897	2639

Notes: Baseline models are in Table 3 in the main text. Standard errors in parentheses. Robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

Alternative dependent variables

Table A9 presents the alternatives to the benchmark models in Table 3 of the main paper using different dependent variables. The specifications correspond to (A22-A24) and follow from the equilibrium relationships (A16), (A18) and (A19) derived in section 2.1 of this appendix document. While there is some variation in the parameters of interest and (γ_A) and ($\widetilde{\gamma_A}$) turn out to be estimated slightly less consistently, all estimates are generally within the range of the benchmark models.

Tab. A9. Alternative models – Berlin

	(1) Log (Land Value / Land Area)		(2) Log (Capital / Land Ratio)		(3) Log (Floor Space / Land Area)	
log Employment Potential	0.785***	(0.070)	0.886***	(0.164)	0.384***	(0.097)
log photos (residents)	0.048***	(0.007)	0.054***	(0.016)	0.022**	(0.009)
log Area	-0.195***	(0.017)	-0.140***	(0.045)	-0.107***	(0.024)
log Population	-0.001	(0.022)	0.093	(0.065)	0.084***	(0.031)
log Population x average age	-0.001	(0.003)	0.001	(0.014)	0.004	(0.008)
log Population x Estimated income	0.000	(0.000)	0.000	(0.000)	-0.000	(0.000)
log Employment	0.031***	(0.008)	-0.009	(0.023)	-0.008	(0.012)
log Dist to school (sign inverted)	0.045***	(0.012)	0.016	(0.031)	-0.008	(0.018)
log Dist to station (sign inverted)	0.077***	(0.018)	0.189***	(0.046)	0.046*	(0.027)
Income	YES		YES		YES	
Average age	YES		YES		YES	
Year Effects	YES		YES		YES	
Year Effects x East Berlin	YES		YES		YES	
r2	0.778		0.465		0.885	
Centrality (γ_E)	0.076		0.086		0.061	
Urbanity (γ_A)	0.019		0.014		0.017	
Urbanity ($\widetilde{\gamma_A}$)	0.011		0.013		0.008	
Lambda (λ)	4.025		2.614		4.873	
N	897		890		897	

Notes: Standard errors in parentheses. Robust standard errors.. * p<0.1, ** p<0.05, *** p<0.01

Robustness checks

Table A10 below complements the results presented in Table 3 of the main paper and Table A9 in this document by providing a number of variations of the Berlin models to evaluate their robustness. Columns (1-3) add hedonic controls to the models where housing features are not a component of the theoretical equilibrium conditions. Not surprisingly given that these features are part of housing services, the introduction of these controls lowers the estimated centrality and urbanity effects. The effects are, however, still positive and significant. In the preferred specification (1), the indirect elasticities of utility with respect to centrality and urbanity still are around 4.5% and 1%.

Column (4) adds neighborhood controls capturing the purchasing power and the average age of the adult population. While prices tend to be higher in more affluent neighborhoods the estimated centrality and urbanity effects remain virtually unaffected. Similarly the results are robust to the inclusion of spatial trends (6), which should capture unobserved location components that are correlated with either geographical dimension (x- or y- coordinates). Column (5) presents the result of a Tobit variant of the pure quantity regression (floor area ratio, Table 3, column 4 in the main paper) to account for the fact that values beyond 2.5, even if potentially profitable, are generally not observed due to building height regulations. The estimates of interest (urbanity and centrality effects), if at all, slightly increase compared to the benchmark results in Table 3 (main paper).

Throughout all stages of the analyses I have used only a subset of photos, namely those presumably taken by residents (users taking photos for 30 days or more in the same city without taking pictures anywhere else). The rationale is that I intend to merge the perception of places (via photos) and the valuation of places (via property prices) based on a coherent population group (presumably residents). One could, however, argue that prices in a globalized world are equivalently driven by foreign buyers and that these may have similar perceptions as tourists. Columns (7) and (8) therefore present the results using photo measures based on all photos and those that where presumably taken by tourists. I define users that took pictures in the respective study city over less than one month and over a longer period in another city as tourists. The results turn out to be fairly close to the benchmark results.

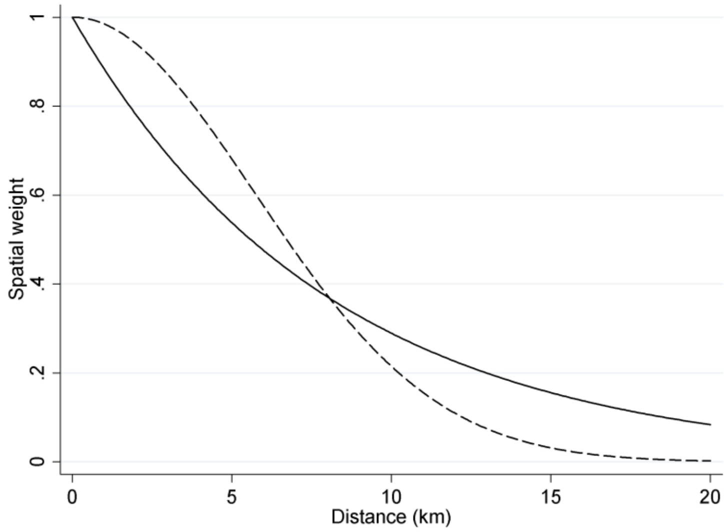
Finally, I experiment with different centrality measures in columns (9-11). Column (9) uses the arguably broadest and most popular centrality measure applied in the urban economics literature: Distance to the CBD. The variable is rescaled so that positive values indicate positive effects. The centrality effect remains positive and statistically significant indicating that the city features a monocentric structure. The distance measure presumably captures a broad range of centrality effects related to concentrations of jobs, but also retail and other services that tend to concentrate in the center.[4] The centrality elasticity is smaller than with the employment potentiality definition, presumably reflecting higher variation in the distance compared to the potentiality measure. The urbanity effect slightly increases using this centrality measure. As noted in the empirical strategy section, the exponential weight function used to construct the employment potentiality measure (12) is based on consistent evidence from different empirical settings and, over the entire distribution of commuting trips, also well aligned with observable commuting patterns

[4] The center is chosen to as the underground station “Stadtmitte” (city center) following Ahlfeldt & Wendland (2011).

(Ahlfeldt, 2011, in press; Osland & Thorsen, 2008). It might be criticized, though, on the grounds that it significantly discounts surrounding locations even if they are very close-by, which is somewhat inconsistent with a relatively large number of commuters at intermediate distances and travel times (Office for National Statistics, 2011). To address this concern I build an alternative potentiality measure taking the decay parameter and the distance measure into squares $\left(e^{-\tau^2 dist_{id}^2}\right)$. The resulting spatial weights function generally follows the standard exponential weights function, but attaches relatively higher weights to locations very nearby and somewhat lower weights to locations further away. Both decay functions are illustrated in Figure A4. Columns (10-11) use an employment and a population potentiality measure using these alternative spatial weights. The population potentiality defines centrality as determined by proximity to other residents rather than employment opportunities and as such puts a higher weight on consumption amenities that can be found in denser areas. The results for both alternative potentiality measures are relatively close to the benchmark results. If anything, the urbanity effect slightly comes up at the expense of the centrality effect.

Table A11 replicates most of the robustness checks from Table A10 for London (except those related to models that cannot be replicated due to data limitations). All models are variants of the benchmark model in column (3) of Table 3 in the main paper. The results are generally robust and the pattern of results similar to Table A10. Omitting controls (1-3) hardly changes the outcome as does the use of different photos measures. Using different centrality measures similarly leaves the urbanity estimates largely unaffected. The notable exception is the population potential, which leads to a significantly larger urbanity effect.

Fig A4.Spatial weight function



Notes: Solid line shows the standard exponential weights function $\left(e^{-\tau dist_{id}}\right)$. Dotted line shows the squared distance exponential weights function $\left(e^{-\tau^2 dist_{id}^2}\right)$.

Tab. A10. One-stage robustness checks (Berlin)

	(1) Log (Price / Land Area)	(2) Log (Land Value / Land Area)	(3) Log (Capital / Land Ratio)	(4) Log (Price / Land Area)	(5) Log (Floor Space / Land Area)	(6) Log (Price / Land Area)	(7) Log (Price / Land Area)	(8) Log (Price / Land Area)	(9) Log (Price / Land Area)	(10) Log (Price / Land Area)	(11) Log (Price / Land Area)
	OLS	OLS	OLS	OLS	Tobit	OLS	OLS	OLS	OLS	OLS	OLS
log Centrality	0.457***	0.569***	0.539***	0.822***	0.388***	0.766***	0.826***	0.897***	0.461***	0.372***	0.392***
	(0.111)	(0.068)	(0.139)	(0.121)	(0.100)	(0.124)	(0.123)	(0.114)	(0.089)	(0.065)	(0.087)
log photos	0.037***	0.038***	0.033**	0.063***	0.033***	0.051***	0.056***	0.052***	0.061***	0.070***	0.076***
	(0.010)	(0.006)	(0.015)	(0.012)	(0.010)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
log Area	-0.131***	-0.135***	-0.119***	-0.167***	-0.135***	-0.140***	-0.167***	-0.161***	-0.198***	-0.186***	-0.203***
	(0.025)	(0.016)	(0.037)	(0.030)	(0.025)	(0.030)	(0.031)	(0.030)	(0.029)	(0.029)	(0.029)
log Population	0.021	-0.002	0.080	0.003	0.107***	-0.001	-0.008	0.008	-0.004	0.001	-0.008
	(0.038)	(0.020)	(0.058)	(0.047)	(0.034)	(0.047)	(0.047)	(0.046)	(0.047)	(0.047)	(0.048)
log Population x	-0.003***	-0.001**	-0.004***	-0.003	-0.005***	-0.004***	-0.004***	-0.004***	-0.003***	-0.004***	-0.003***
average age	(0.001)	(0.000)	(0.001)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log Population x	0.034***	0.060***	0.020***	-0.106*	-0.007	0.025***	0.044***	0.045***	0.045***	0.042***	0.045***
Estimated income	(0.005)	(0.004)	(0.008)	(0.058)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
log Employment	-0.000	0.016**	-0.013	0.002	-0.006	0.004	0.003	0.008	0.012	0.008	0.012
	(0.013)	(0.007)	(0.020)	(0.015)	(0.013)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
log Dist to school	0.030	0.028**	-0.007	0.051**	-0.017	0.088***	0.039*	0.018	0.071***	0.068***	0.108***
(sign inverted)	(0.020)	(0.012)	(0.029)	(0.022)	(0.024)	(0.029)	(0.022)	(0.022)	(0.023)	(0.022)	(0.021)
log Dist to station	0.083***	0.036**	0.118***	0.136***	0.052*	0.142***	0.146***	0.141***	0.143***	0.148***	0.155***
(sign inverted)	(0.029)	(0.017)	(0.041)	(0.034)	(0.028)	(0.034)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)
log Estimated purchasing power				5.303**							
				(2.081)							
log Average age				-0.289							
				(2.203)							
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects x East	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hedonics	Yes	Yes	Yes	No	Yes	No	No	No	No	No	No
Spatial Trends	No	No	No	No	No	Yes	No	No	No	No	No
Photos	Residents	Residents	Residents	Residents	Residents	Residents	All	Tourists	Residents	Residents	Residents
Centrality measure	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Distance to CBD	Emp. pot (dist. sq.)	Emp. pot (dist. sq.)
r2	0.738	0.828	0.619	0.607		0.613	0.600	0.601	0.592	0.630	0.599
Centrality (γ_E)	0.044	0.054	0.051	0.078	0.060	0.073	0.079	0.086	0.044	0.035	0.037
Urbanity (γ_A)	0.012	0.013	0.011	0.016	0.021	0.013	0.016	0.015	0.019	0.018	0.019
Urbanity ($\widetilde{\gamma_A}$)	0.009	0.009	0.008	0.015	0.012	0.012	0.013	0.012	0.014	0.016	0.017
Lambda (λ)	3.510	3.520	3.551	2.638	4.045	2.758	2.975	3.105	3.255	2.664	2.681
N	897	897	890	897	897	897	897	897	897	897	897

Notes: Standard errors in parentheses Robust standard errors. * p<0.1, ** p<0.05, *** p<0.01. Lin. dist.. (dist. sq.) denotes linear (squared) distance in potentiality weight.

Tab. A11. One-stage robustness checks (London)

	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price	(5) Log Price	(6) Log Price	(7) Log Price	(8) Log Price
log Employment Potential	0.490***	0.502***	0.545***	0.473***	0.466***	0.226***	0.259***	0.306***
	(0.021)	(0.022)	(0.021)	(0.021)	(0.020)	(0.011)	(0.012)	(0.025)
log photos (residents)	0.016***	0.016***	0.016***	0.021***	0.026***	0.016***	0.018***	0.027***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log Area	-0.032***	-0.028***	-0.027***	-0.033***	-0.032***	-0.022***	-0.038***	-0.067***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
log Employment	0.038***	0.027***	0.034***	0.025***	0.021***	0.012***	0.032***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
log Population	-0.090***	-0.083***	-0.094***	-0.087***	-0.064***	-0.032**	-0.080***	-0.081***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)	(0.016)
log Population x average age	0.001*** (0.000)	0.009*** (0.002)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
log Population x Estimated income	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
log Distance to metro station (inverted sign)	0.025*** (0.004)	0.031*** (0.004)	0.007* (0.004)	0.028*** (0.004)	0.024*** (0.004)	0.045*** (0.004)	0.031*** (0.004)	0.048*** (0.004)
Log average key stage 2 score	0.453*** (0.035)	0.351*** (0.031)	0.388*** (0.033)	0.356*** (0.031)	0.350*** (0.030)	0.287*** (0.030)	0.357*** (0.032)	0.282*** (0.034)
Log average household income		0.661*** (0.140)						
Log average age of adult population		-2.389*** (0.652)						
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hedonics	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Floor space	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial trends	No	No	Yes	No	No	No	No	No
Photos	Residents	Residents	Residents	All	Tourists	Residents	Residents	Residents
Centrality measure	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Emp. pot (lin. dist.)	Distance to CBD	Emp. pot (dist. sq.)	Emp. pot (dist. sq.)
r2	0.794	0.834	0.811	0.834	0.837	0.831	0.828	0.806
Centrality (γ_E)	0.123	0.126	0.136	0.118	0.116	0.057	0.065	0.076
Urbanity (γ_A)	0.008	0.007	0.007	0.008	0.008	0.006	0.009	0.017
Urbanity ($\widetilde{\gamma_A}$)	0.008	0.008	0.009	0.011	0.014	0.008	0.009	0.014
Lambda (λ)	2.054	1.758	1.679	1.562	1.240	1.405	2.143	2.493
N	2639	2639	2639	2639	2639	2639	2639	2639

Notes: Standard errors in parentheses. Standard errors are robust. * p<0.1, ** p<0.05, *** p<0.01. Lin. dist.. (dist. sq.) denotes linear (squared) distance in potentiality weight.

3.5 Two-stage estimates

Section 2.3 has outlined an alternative two-stage estimation approach that allows separating the effects of employment and population densities operating through the photo production process from the direct effects on house prices (and quantities). The two-stage approach also allows for an evaluation of potential correlations of the neighborhood land area and unobserved determinates of house prices that could cause identification problems in the one-stage regressions. Table A12 shows the results of this alternative estimation procedure. The baseline (1-5, 11) estimates are generally close to the one-stage results presented in Table 3 of the main paper and Table A9 of the appendix. A notable exception is the Berlin floor area ratio quantity regression (4). The urbanity effect disappears in the model, likely due multicollinearity of housing quantities, population densities and urbanity. While population density has negative effects on prices in most price models (Berlin and London) it, unsurprisingly, enters the quantity model with positive sign. In the other models a higher population density net of urbanity seems to be perceived as a disamenity. Employment densities, in contrast, consistently enter the models with a positive sign. The variable ether captures a residual labor market effect not captured by the centrality measure or some correlated local services. Columns (6-10, 12) replicate the models form (1-5, 11) adding a control for neighborhood land area. Given that photos, employment and population are expressed in densities, the resulting coefficient captures the (conditional) correlation of the variable with unobserved housing and location attributes. The inclusion of the variable, if anything, increases the urbanity effect, which alleviates concerns about correlations of the neighborhood area variable with unobserved location features in the one-stage regressions. These interpretations consistently apply to Berlin and London.

Tab. A12. Two-stage regressions

	(1) Log (Price / Land Area)	(2) Log (Land Value / Land Area)	(3) Log (Capi-tal / Land Ratio)	(4) Log (Floor Space / Land Area)	(5) Log Price	(6) Log (Price / Land Area)	(7) Log (Land Value / Land Area)	(8) Log (Capi-tal / Land Ratio)	(9) Log (Floor Space / Land Area)	(10) Log Price	(11) Log Price	(12) Log Price
	Berlin	Berlin	Berlin	Berlin	Berlin	Berlin	Berlin	Berlin	Berlin	Berlin	London	London
log Employment	0.668***	0.516***	0.921***	0.444***	-0.034	0.652***	0.526***	0.864***	0.427***	-0.022	0.480***	0.472***
Potential	(0.114)	(0.068)	(0.156)	(0.095)	(0.083)	(0.118)	(0.067)	(0.160)	(0.095)	(0.087)	(0.025)	(0.025)
Amenity index	0.160***	0.164***	0.084***	0.007	0.075***	0.173***	0.155***	0.134***	0.025	0.062***	0.033***	0.037***
(residual)	(0.024)	(0.014)	(0.033)	(0.019)	(0.015)	(0.029)	(0.018)	(0.039)	(0.023)	(0.020)	(0.005)	(0.005)
Log population	-0.029	-0.055***	0.060	0.112***	-0.064***	-0.010	-0.068***	0.132**	0.139***	-0.082***	-0.076***	-0.039**
density	(0.034)	(0.021)	(0.045)	(0.023)	(0.020)	(0.045)	(0.025)	(0.062)	(0.032)	(0.027)	(0.008)	(0.018)
Log employment	0.066***	0.085***	0.041*	0.003	0.040***	0.067***	0.084***	0.043*	0.004	0.039***	0.042***	0.042***
density	(0.017)	(0.009)	(0.025)	(0.013)	(0.012)	(0.017)	(0.009)	(0.025)	(0.013)	(0.012)	(0.005)	(0.005)
log school (dist.	0.058**	0.024	0.035	0.017	0.009	0.060**	0.023	0.040	0.019	0.007	0.036***	0.037***
or quality)	(0.024)	(0.015)	(0.032)	(0.020)	(0.017)	(0.023)	(0.015)	(0.032)	(0.019)	(0.017)	(0.005)	(0.005)
log Dist to station	0.138***	0.059***	0.197***	0.053**	0.039	0.137***	0.060***	0.193***	0.053**	0.040*	0.838***	0.838***
(sign inverted)	(0.036)	(0.021)	(0.046)	(0.027)	(0.024)	(0.036)	(0.021)	(0.046)	(0.027)	(0.024)	(0.033)	(0.033)
log Neighborhood						0.033	-0.023	0.127**	0.046	-0.032		0.044**
Area						(0.045)	(0.029)	(0.065)	(0.033)	(0.029)		(0.020)
Year Effects (YE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YE x East	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Hedonics	No	No	No	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes
Log Floorspace	No	No	No	No	Yes	No	No	No	No	Yes	No	Yes
r2	0.556	0.694	0.439	0.872	0.913	0.556	0.694	0.442	0.872	0.914	0.746	0.746
Centrality (γ_E)	0.064	0.049	0.088	0.068	-0.009	0.062	0.050	0.082	0.066	-0.006	0.120	0.118
Urbanity ($\widetilde{\gamma_A}$)	0.015	0.016	0.008	0.001	0.019	0.017	0.015	0.013	0.004	0.016	0.008	0.009
N	897.000	897.000	890.000	897.000	897.000	897.000	897.000	890.000	897.000	897.000	2639	2639

Notes: Standard errors in parentheses. Robust standard errors. * p<0.1, ** p<0.05, *** p<0.01. School indicates distance to the nearest school in Berlin and local average key-stage test scores in London. Distance to station refers to U- and S-Bahn stations in Berlin and underground and dock land light railway stations in London. Standard errors in parentheses. Robust standard errors.

3.6 Preference heterogeneity

The models considered so far have assumed identical individuals with homogenous preferences for urbanity and centrality. Table A13 shows the result of specifications (A31) and (A32), which allow for preference heterogeneity by means of interaction terms of the three variables of interest (employment potential, photos and neighborhood land area) and (demeaned) average age and income. The results indicate little evidence for preference heterogeneity along these observable household characteristics in Berlin. For London, there is some evidence that urbanity preferences are negatively correlated with income, i.e. as income increases the consumption of urbanity increases at a lower rate than the consumption of housing services and tradable consumption goods.

Tab. A13. Heterogeneous preferences (models with interaction terms)

	(1) Log (Price / Land Area)		(1) Log Price	
	Berlin		London	
log Employment Potential	0.784***	(0.124)	0.494***	(0.022)
log photos (residents)	0.065***	(0.012)	0.016***	(0.002)
log Area	-0.169***	(0.030)	-0.031***	(0.008)
log Population	-0.004	(0.045)	-0.082***	(0.016)
log Population x average age	-0.002	(0.009)	0.001	(0.004)
log Population x Estimated income	0.012	(0.081)	0.000***	(0.000)
log Employment	0.000	(0.016)	0.027***	(0.004)
log school (dist. or quality)	0.056**	(0.022)	0.030***	(0.004)
log Dist to station (sign inverted)	0.141***	(0.034)	0.347***	(0.031)
log Emp. pot x income	0.065	(0.049)	-0.000	(0.000)
log Emp. pot x average age	-0.000	(0.006)	-0.004*	(0.002)
log photos x income	0.019	(0.020)	-0.000***	(0.000)
log photos x average age	0.002	(0.003)	0.000	(0.000)
log Neighborhood area x income	-0.047	(0.048)	-0.000**	(0.000)
log Neighborhood area x average age	-0.001	(0.006)	0.004***	(0.001)
Year Effects	Yes		Yes	
Year Effects x East	Yes		No	
Hedonics	No		Yes	
Log Floorspace	No		Yes	
r2	0.602		0.835	
Centrality (γ_E)	0.075		0.123	
Urbanity (γ_A)	0.016		0.008	
Urbanity ($\widetilde{\gamma_A}$)	0.015		0.009	
Lambda (λ)	2.609		1.902	
N	897		2639	

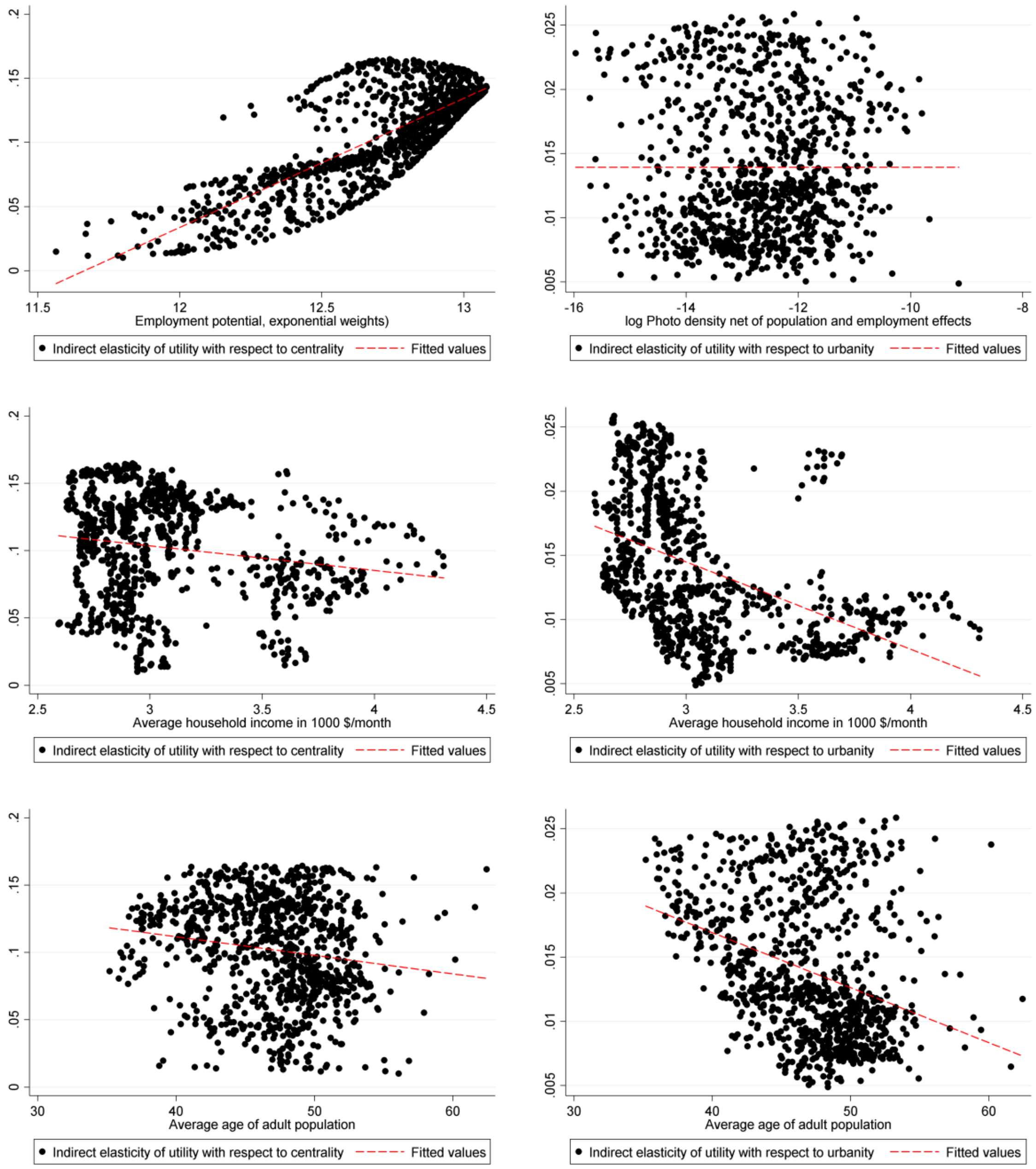
Notes: School indicates distance to the nearest school in Berlin and local average key-stage test scores in London. Distance to station refers to U- and S-Bahn stations in Berlin and underground and dock land light railway stations in London. Standard errors in parentheses. Robust standard errors.. Standard errors in parentheses. Robust standard errors. * p<0.1, ** p<0.05, *** p<0.01

To the extent that residents with similar characteristics sort into neighborhoods that are geographically near to each other the locally weighted regression approach allows for a more flexible account of preference heterogeneity. It provides a full set of neighborhood specific preference parameters that can be compared to observable features of the locations and characteristics of residents living in the areas. Figure 4 in the main paper plots the estimated indirect elasticities of utility with respect to centrality and urbanity against centrality and urbanity measures. Figures A5 and A6 extend the comparison to a number of additional location characteristics. The most notable finding, which is in line with the interpretations based on Table 4 and Figure 4, is that the results suggest preference based sorting with respect to centrality, but not, or to a significantly lesser extent, with respect to urbanity. The estimated centrality effects are clearly higher in more central areas. Despite significant dispersion in the estimated urbanity effects, there is hardly any correlation apparent between the willingness to pay for urbanity and the local levels of urbanity (approximated by the photo residual from the first-stage of the two-stage models). To some extent the results further indicate that urbanity, and to some degree, centrality preferences are higher among younger adults in Berlin. In London such a negative correlation is more evident for centrality effects.

Figure A7, finally, correlates the local preference parameters for urbanity and centrality. The relationship between the two is evidently negative in both cities, suggesting that centrality and urbanity are distinct urban phenomena that appeal to different population groups. Tables 14 and 15 provide the results of an econometric 2nd stage analysis of the recovered local preference parameters that shares some similarities with (Bajari & Kahn, 2005; Koster, Van Ommeren, & Rietveld, 2012). The results are in line with the Figures 5-7. There appears to be strong spatial sorting with respect to centrality in both cities. Older and higher income groups have lower preferences for centrality. For urbanity the picture is less evident. While the valuation of urbanity seems to increase in income, it appears that lower income groups in Berlin are primarily attracted to urbanity. This is in line with many of the central amenity districts in Berlin being at a relatively early stage of gentrification, while similar areas in London have reached some maturity.

Fig A5.FIG WTP Berlin

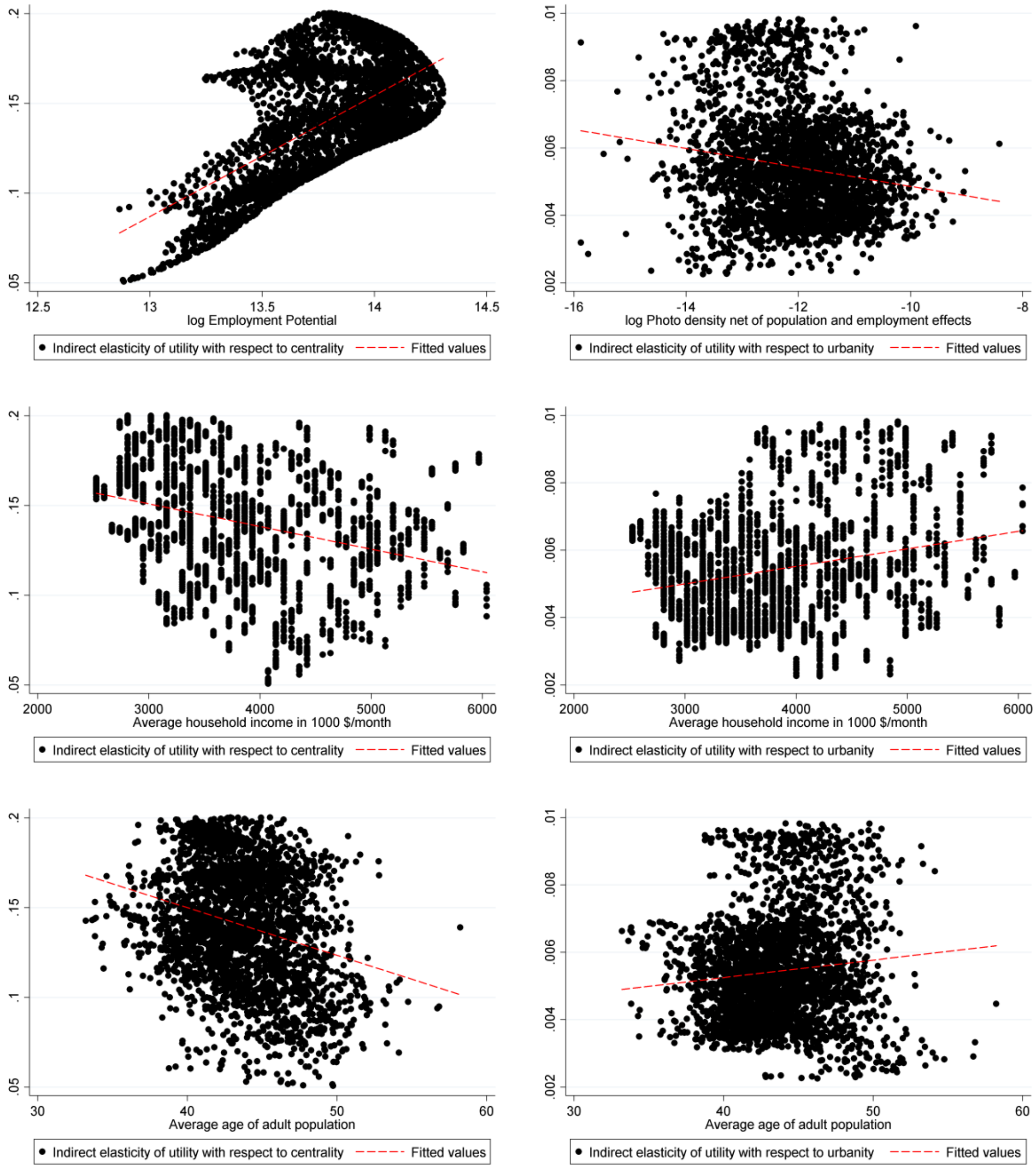
Centrality **Urbanity**



Notes: Neighbourhood specific parameters estimated using geographically weighted regressions. See section 2.3.2 for details.

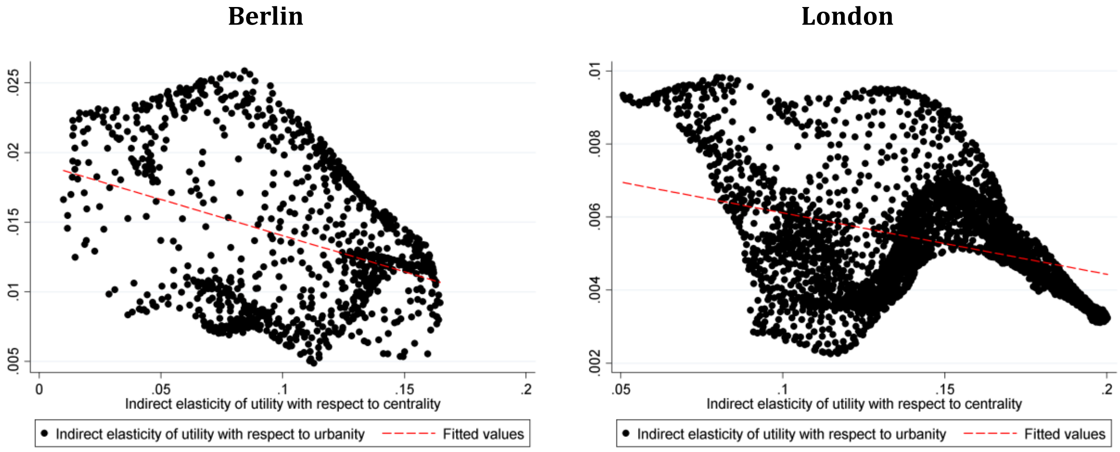
Fig A6.FIG WTP London

Centrality **Urbanity**



Notes: Neighbourhood specific parameters estimated using locally weighted regressions. See section 2.3.2 for details.

Fig A7.WTP for urbanity vs. centrality (Berlin and London)



Notes: Neighbourhood specific parameters estimated using locally weighted regressions. See section 2.3.2 for details.

Tab. A14. Sorting effects – 2nd stage (Berlin)

	(1)	(2)	(3)	(4)	(5)	(6)
	Indirect elasticity of utility with respect to urbanity			Indirect elasticity of utility with respect to centrality		
log Photo density net of pop. and emp. effects	0.000 (0.000)		0.000 (0.000)			
Average household income in 1000 $/month		-0.006*** (0.001)	-0.006*** (0.000)		-0.014*** (0.004)	-0.010*** (0.002)
Average age of adult population		-0.000*** (0.000)	-0.000*** (0.000)		-0.001*** (0.000)	-0.000 (0.000)
Indirect elasticity of utility wrt centrality			-0.069*** (0.004)			
Employment potential, exponential weights)				0.101*** (0.002)		0.094*** (0.002)
Indirect elasticity of utility wrt urbanity						-2.510*** (0.142)
Constant	0.014*** (0.002)	0.041*** (0.001)	0.056*** (0.002)	-1.174*** (0.026)	0.185*** (0.012)	-1.020*** (0.027)
r2	0.000	0.223	0.434	0.612	0.038	0.718
N	969	969	969	969	969	969

Notes: Neighbourhood specific parameters estimated using locally weighted regressions. See section 2.3.2 for details. Standard errors in parentheses and bootstrapped in 500 iterations. * p<0.1, ** p<0.05, *** p<0.01

Tab. A15. Sorting effects – 2nd stage (London)

	(1)	(2)	(3)	(4)	(5)	(6)
	Indirect elasticity of utility with respect to urbanity			Indirect elasticity of utility with respect to centrality		
log Photo density net of pop. and emp. effects	-0.000***		-0.000***			
	(0.000)		(0.000)			
Average household income in 1000 $/month		0.000***	0.000***		-0.000***	-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
Average age of adult population		0.000***	0.000		-0.002***	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Indirect elasticity of utility wrt centrality			-0.014***			
			(0.001)			
log Employment Potential				0.067***		0.060***
				(0.002)		(0.002)
Indirect elasticity of utility wrt urbanity						-3.166***
						(0.304)
Constant	0.002***	0.002***	0.005***	-0.790***	0.286***	-0.635***
	(0.000)	(0.000)	(0.001)	(0.022)	(0.008)	(0.028)
r2	0.029	0.066	0.139	0.363	0.142	0.424
N	2731	2731	2731	2639	2731	2639

Notes: Neighbourhood specific parameters estimated using locally weighted regressions. See section 2.3.2 for details. Standard errors in parentheses and bootstrapped in 500 iterations. * p<0.1, ** p<0.05, *** p<0.01

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