The price for subway access: Spatial modelling of office rental rates in London

Katarzyna Kopczewska (corresponding author)
kkopczewska@wne.uw.edu.pl
Faculty of Economic Sciences, University of Warsaw, Poland
Ul. Dluga 44/50, 00-241 Warszawa, www.wne.uw.edu.pl
ORCID: http://orcid.org/0000-0003-1065-1790

Anna Lewandowska
anna.lewandowska88@gmail.com
Faculty of Economic Sciences, University of Warsaw, Poland
Ul. Dluga 44/50, 00-241 Warszawa, www.wne.uw.edu.pl

Abstract: The econometric estimation of rental prices for business real estate may help in its proper valuation. As this paper shows, a-spatial hedonic valuation methods are not as efficient as spatial ones. For point geo-located business properties, one can construct neighbourhood relations as well as give the distances to public transport stations and use this spatial information in valuation estimation. Spatial estimation with the Durbin component diminishes the impact of hedonic / random terms and captures the features of neighbourhoods. The study of rental transitions for offices in London in 2015 show that every next 100 m to metro costs an extra 0.5 £ per ft^2 per year.

Keywords: spatial microeconometrics, office real estate, rental price valuation

JEL Code: R33, C21

Introduction

The rental price of property depends on many factors such as the general condition of the building and equipment premises, and the location, and neighbourhood in which the property is found. Another factor may also be the price of similar neighbouring properties due to the fact that while renting premises, owners and brokers estimate the value of the property before issuing an offer by comparing the prices of similar properties and taking into account the conditions prevailing in the local market. Consequently, spatial relationships exists for prices in a given area.

The precise valuation of real estate is particularly important for investors, developers, corporate offices and corporations seeking to locate their employees, as well as for economists. This is even more important because of the size of the commercial real estate market, which in the UK amounted to 5.4% of GDP in 2014, and accounted for 1/5 of the total net assets of the country (BPF, 2016). Despite this, there are still few studies that exhaustively describe the part of the economy related to the rental of office space (Liang, 2010, 2011). The main reason for this is the difficulty in accessing the data because companies involved in commercial real estate rarely provide information on property (e.g.

office space, shopping malls, warehouses, etc.) and their transaction prices due to the high profits associated with the use of this information[1].

This paper explores the spatial relationships in the commercial real estate market in London. It analyses the factors affecting the differences in rental prices of office space. In particular, it investigates if the distance to the nearest metro station from an office, which is considered an important factor defining rental fees, is indeed statistically significant.

Hitherto, most econometric models have been applied to transaction data aggregated by areas (e.g. districts). This paper goes beyond this and uses individual point geo-located data for which one can create a spatial weights matrix of neighbourhood relations to determine the distance to the subway station, as well estimate the characteristics of the transaction, estimate the impact of location and the neighbourhood of the metro station on the transaction price, controlling for the quality of the office. This paper illustrates the robustness of spatial estimation by comparing the models of two spatial weights matrices and different spatial specifications.

1. Literature on the significance of location for the real estate prices

Despite the rich econometric literature available on real estate, the studies on commercial real estate does not give clear answers regarding the factors determining the market prices of offices. The limited available studies are very diverse in terms of variables used, the methodology of estimation, as well as the conclusions on similar phenomena.

In the early publications in this field, office prices were estimated using so-called hedonic models (e.g. Clapp, 1980; Sivitanidou, 1996; Nagai et al., 2000). This concept is based on the assumption that the price of heterogeneous goods depend on their characteristics and is the sum of utility from the features of the explanatory variables and factors included in the random component. Such a model may take a linear or log linear form and usually is estimated with Ordinary Least Squares (OLS). Clapp (1980) analysed the impact of building characteristics and spatial factors on the offer price of renting a square metre of office space on the data of 105 office buildings in Los Angeles. The localisation variables were the distance of the building to the so-called Central Business District (CBD), and thus to major corporations, and trading and service companies, the average travel time of employees to the workplace and the size of the office space. Clapp (1980) showed that the distance to the CBD has a significant positive impact on the rental fee of office space. This indicates that companies are willing to pay more for the opportunity to set up an office in a location where employees and customers have easy access. The positive impact of distance from the CBD was explained by the benefits to the companies resulting from the ease of organising direct meetings with specialists from other companies. Today, technological progress enables teleconferences and easy communication at a distance, so this argument applies particularly to the works from the 1990s and earlier, as summarised by Chegut (2014) and Bollinger et al. (1998). Clapp (1992), following Goddard (1973), also pointed out the phenomenon of "regional specialisation", which suggests that companies with similar business interests locate their offices in the same neighbourhoods, which was confirmed empirically by Chalermpong and Wattana (2009).

Another factor which may diversify the rental prices of office space is tax. Wheaton (1984) examined the impact of various tax policies in the metropolitan area of Boston (the so-called *Greater Boston)* on the rental price of office real estate. A regression model was employed and used data relating to the characteristics of the building, the property tax and the

[1] The exception is the United States, as well as China and other Asian countries (Liang, 2011), where the data on commercial real estate are more readily available. Data quality was tested by Devaney and Martinez (2011) for the Investment Property Databank (IPD).

number of public transport lines available within a mile from the building. Other variables included the number of highways leading to the city, the percentage of households with people who completed high school and the number of inhabitants in the nearest six cities. Wheaton (1984) demonstrated that access to employees, as measured by the above factors, including the distance to the nearest railway station had a significant impact on the rental fee for offices. He showed also that the different tax policies of the towns belonging to the metropolitan area had an insignificant effect on the differentiation of rental prices. Due to the very high price elasticity of rental properties, even a slight increase in prices caused the outflow of capital from the region. This meant that property owners in locations where property tax was higher could not raise rental prices despite higher taxes in the region. In turn, by estimating the rental price of office space, Bollinger et al. (1998) used the information on the tax mortgage rate, salaries and the availability of employees, customers and other stakeholders. In their study they took into account the building characteristics, type of tenancy agreement (for example, whether the agreement includes the possibility to cancel the lease) and the distance from the train station and CBD. They showed, like Clapp (1980), that the distance from the CBD has a statistically significant positive impact on office prices. More research using hedonic models can be found in the paper by Paez (2009).

Importance of public transportation

Intuitively, buildings located closer to public transportation such as rail or subway, should have a higher value and price than those located further away. This has been confirmed in many studies (such as Brinckerhoff, 2001 and Debrezion, 2003). Chegut (2014) also argues that the introduction of a variable for localisation and / or the neighbourhood (for example, the distance from the business district) significantly improves the fit of the model.

The impact of being next to public transport has been extensively studied for the housing market. There are many studies that show that this distance significantly increases the price of private property. This is due to faster connections between locations in the city and its surroundings, and the reduced travel time to offices, shopping malls etc.

It also cannot be ignored that being located too close to public transport may have a negative impact on the value of property because of noise or air pollution. This relationship, however, has little impact. As Kim (2007) showed, already at a distance of 200 feet (60 m) from a station, the difference between the benefit and discomfort stemming from this distance is at its greatest. Other studies (see Kim, 2007) indicate a ca. 6-7 % positive impact on the price of flats and apartments from being nearby to a train / subway station.

However, till now there have been few studies that deal with the relation of the price of commercial real estate to the distance from the train station / underground. Moreover, the results, more often than in the case of residential property, differ even for the same research area (Debrezion, 2003). The reason for this may be due to differences in the data and methodology used by the researchers, as well as local factors specific to the surveyed cities. Nelson (1999) and Mathur and Ferrell (2009) show in a study on commercial real estate in Atlanta the significant positive impact of distance from a transit station on the value of commercial real estate. Cervero and Landis (1997) studied the effect of distance from a train station on the rental rates of offices in Washington and Atlanta. They compared the prices of offices located close to and far away from stations and confirmed that there is a positive correlation between price and station proximity. However, unlike Nelson (1999), they showed that the benefits of being located close to a station are negligible.

Bollinger et al. (1998) investigated the real estate market in Atlanta and showed that offices within one mile (1.6 km) of train stations have lower rental fees than those further away. The author explained that due to insufficient development of the metro in the area, these were not the most favourable locations for the construction of office buildings. Similar results were obtained by Ryan (2005), indicated that the distance between the railway station and the offices in San Diego had little effect for most of the study area, while in some other regions the impact is significant but negative.

Statistically significant and positive impact of distance from the nearest subway station on the rental price of offices was proven by Kim (2007). He indicated that the most favourable distance from a station to an office is 500 m. He took into account the number of people traveling by subway from the station as an approximation of information on the spatial development of areas around metro stations. This information also proved to be statistically significant. Kim (2007) also showed that location in relation to the Central Business District correlates with the higher rental prices of offices.

Chalermpong and Wattana (2009) studied the capitalisation of profits from the location of offices in relation to distance from railway stations in Bangkok. They took into account the distance calculated "on the pavement" for 85 office properties and showed that the distance to the nodes of public transport has a statistically significant effect on the price of the lease of offices and corresponding to 19 baht, or about 0.4 pound sterling. The study used a simple OLS model as well as the spatial lag and error models, using the spatial matrix of distances between offices. These results confirm that the distance from a train station raises the price of offices and is statistically significant.

In fact, many studies often use the OLS method, with spatial information being included as one of the variables. In the case of data containing spatial information, such as locations or neighbourhoods (Anselin, 1988, LeSage & Pace, 2009), one should examine it closely. This factor is usually included in the spatial error term and biases the results of hedonic models. This can be identified with Moran's I test for residues from OLS. The existence of spatial dependence means that in the studied phenomenon there is the propagation of certain effects on neighbouring properties, which cannot be recognized in simple regression models (Chegut, 2014). Spatial methods were justified and recommended for real estate market analysis by Pace, Barry and Sirmans (1998).

Kim (2007) also confirmed that the use of spatial models for spatially auto-correlated data, for example geo-located data on commercial real estate, improves OLS estimates. Kim (2003, 2007), however used models only with one spatial component and should have been modelled in more advanced way (Pace & LeSage, 2009; Elhorst, 2010). Tu et *al.* (2004) indicated that the spatial relationship between office buildings has a positive and significant impact on prices on the property market in Singapore, similar to results obtained Nappi-Choulet and Maury (2007, 2009). Chegut (2014) also showed the existence of spatial relationships of office real estate markets in the six largest cities in the world, which, however, only had a slight impact on the transaction prices of offices. Chegut (2014) states that this may be related to the global financial crisis that has destabilized real estate markets around the world (he analysed data from 2007 to 2013, which covers the period of the crisis and the years immediately thereafter) and that for stable economies the characteristics of buildings adjacent to the given property could be valuable information in determining its value.

The above confirms that there exists a spatial relation between observations on the commercial real estate market and that its inclusion improves the fit of the model. It was also confirmed that rental office price is influenced by, amongst other things, location, distance to the Central Business District, and the characteristics of the building. On the other hand, studies on the effect of distance to public transportation do not provide clear conclusions, both in terms of the significance and magnitude of this phenomenon. Therefore the goal is to investigate the importance of the role public transport plays in the movement of workers.

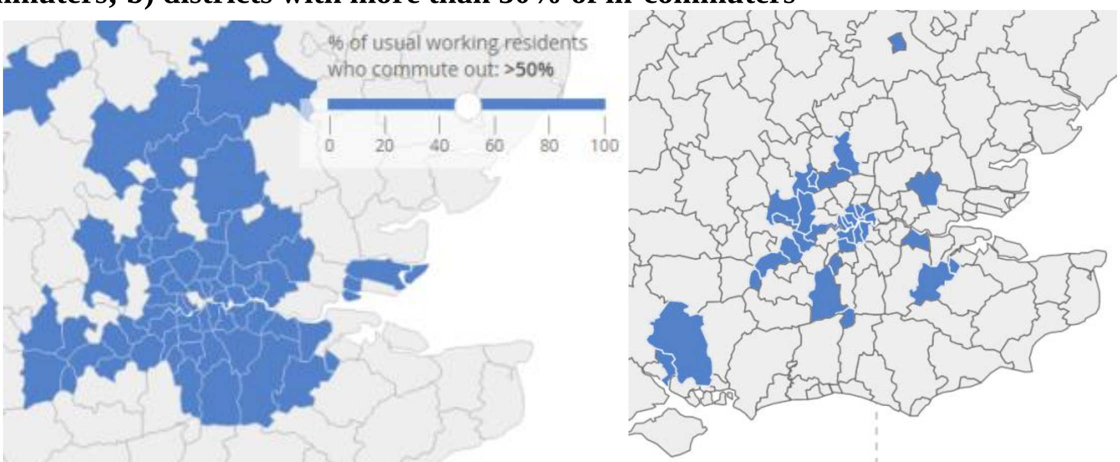
2. The commercial real estate market in London

Along with New York, London is the largest financial centre in the world, and hosts the offices of hundreds of banks, insurance companies and investment funds. It also hosts Europe's largest stock market. London's commercial property market is well developed and attracts investment capital from investors from around the world. According to NESTA rankings, it is the best city in Europe in which to establish digital start-ups and has the highest degree of digitisation as measured by the European Index Digitization (DigitalCityIndex, 2015). The business activity of companies in London is constantly growing (expressed by the ratio of financial activity *purchasing managers index,* PMI) and has been increasing in terms of the number of new orders for goods and services (GLA, 2015a).

According to Eurostat, in London there are more than 8.5 million inhabitants and more than 14 million in the whole metropolitan area. The total number of people employed by mid-2015 was 5,645,000 and this figure has been steadily growing by 2% per annum (GLA, 2015b). The unemployment rate (6.3% in 2015) remains at the level of the natural rate of unemployment. The majority of working people in London use public transport to commute to work (O'Sullivan, 2016). Overall, an average of more than 10 million passengers a day use public transport in London, including almost 4 million who ride the subway (GLA, 2015a).

A report published by the UK statistical office shows that in the majority of districts in London, more than 50% of employees are commuters from a different district than the one in which they work (data from Office for National Statistics). Employees commuting from the 19 districts of the metropolis of London to so-called Greater London account for 20% of working people, while ca.10% of people commutes to work from the remaining 23 districts (see Figure 1).

Figure 1: Commuter districts in London in 2011: a) districts with more than 50% of out-commuters; b) districts with more than 50% of in-commuters



Source: Office for National Statistics, *http://www.neighbourhood.statistics.gov.uk/HTMLDocs/dvc193/*

A report by the *Bank of England* (2015) has indicated a steadily growing demand for commercial real estate in London. Due to the slight increase in newly built offices in recent years, the supply of A class (the highest quality) buildings is relatively low, increasing rental fees and sales prices in better locations. However, this also affects new investment in less prestigious locations.

These arguments are the reason why the author chose London as an interesting area to study the effect of distance from public transport to offices on rental prices, as well as the analysis of spatial relationships between the prices of renting office space in London in 2015.

This paper uses data on rental transactions of office space in London from the CoStar database. Data were collected for the first three quarters of 2015[2] for offices located in the Central Business District (*CBD*) and further districts of London *(London Fringe).* All data in the survey are expressed in pounds sterling and British measurement units. An overview of determinants of office rental process by Higgins (2015) indicated the groups of determinants of supply and demand on the commercial real estate market used in equilibrium models. These are GDP, unemployment rate, and office employment as the spatial determinants (demand), office floor stock, construction orders and vacancy rate as the property factors, (supply) and interest rates as the capital factors. Financial and economic variables are justified especially in the case of inter-city or inter-temporal comparisons of markets. Importantly, location factors, transportation accessibility and spatial components are rarely mentioned in the literature, as very few studies have included these elements.

The determinants of the rental price described below were derived from existing studies (e.g. Chegut, 2014; Kim, 2007; Clapp, 1980), and were complemented with spatial information and transport accessibility. The econometric model is employed to explain the fees that owners charge per square foot on an annual basis (variable *rent)*, which is the dependent variable. The model is expected to be dependent on the **structural characteristics** of the property: total space leased *(sqft*) and highest floor rented (*MAXFloor*); **transaction characteristics**: terms of rental contract (*term*), additional insurances or the cost of repairs *(service)*, and the promotion period of free rental at the beginning of the contract (*rent.free*); **location and neighbourhood characteristics:** location in Central Business District (*CBD*), distance to the subway in a straight line *(d.metro)*, number of metro stations within 500 meters of the office building *(how.many.stations)*, and a set of dummies for dominating sectors in the neighbourhood of the building (*I.Health, I.Professional.scientific.tech, I.Financial.insurance, I.Retail, I.IT.communication*) and density of surroundings (*passengers.density*). The latter was obtained by multiplying the number of passengers departing from the subway / train station (divided by 1000 and the number of days in the year) by the Euclidean distance between the office building and the station. This variable was driven by the theory, according to which the number of passengers may be an approximation of the level density development area in the vicinity of the metro station (Kim, 2007). Location variables were obtained on the basis of the geographical coordinates of offices analysed and stations of public transport in London, with calculations done in R software. The coordinates of the metro and city trains were obtained from OpenStreetMap (2016). More details on the variables used are listed in Table 1.

As an overview, in 2015 the office space in London was 6.3 million square feet. Rental fees for offices in the Central Business District were on average 65 ₤ per square foot per year in the most prestigious neighbourhoods and ca. 42.5 ₤ in other districts (JLL, 2015). In the data set used in this work (see Table 1) the average rental fee was 42.6 ₤. The most expensive office cost 135.23 ₤ per ft^2, while the cheapest was 4.24 ₤ per ft^2. The average surface rented was ca. 11.5 thousand square feet (1060,3 square meters) and was located on average on the 3rd and 4th floor. Contracts were signed on average for 7.7 years (the longest contract was for more than 25 years). More than half of the contracts included additional payable services and about 1/3 of contracts included a free rental period. The average distance of the analysed offices from the subway or urban railway was 491.7 metres. The best located office had six different stations at a distance of 500 metres. Offices in the Central Business District comprised 38% of the entire data set. Most transactions were made in neighbourhoods dominated by companies from areas related to science and technology*(I.Professional.*

[2] CoStar is a company that collects data on buildings and transactions and conducts market research in the area of commercial real estate. Its data are used by property companies, brokers, sellers, and buyers of office space, warehouses, shopping centers and similar types of property.

scientific.tech) with 49% of transactions, followed by financial districts *(I.Financial. insurance)* with 28%, retail trade districts *(I.Retail)* with 11%, health services *(I.Health)* with 9%, and districts in the area of IT and communications *(I.IT.communication)* with 3%.

Table 1: Variables used in this study

Category	Variable	Expected Sign	Unit	Description	Source	Min	Q1	Median	Average	Q3	Max
Dependent	*rent*	N / D	Pound / square foot / year	The price of renting a square foot in pounds	CoStar Database	4.24	28.70	42.00	**42.61**	53.17	135.23
Structure	*sqft*	-	Square feet	The area rented property / premises, the natural logarithm of the surface, value is summed if the offices are located on different floors	CoStar Database	126.00	1 854.00	6 437.00	**11 413.00**	12 092.00	275 204.00
	MAXFloor	+	Natural number	Floor, which is rented office space. When renting affects more than 1 floor, number expresses the max	CoStar Database	-1	1	2	**3.71**	4	44
Transaction	*term*	-	Years	The length of the lease in years	CoStar Database	0.67	5	9.17	**7.67**	10	25.17
	service	+	1 or 0	Dummy, equals 1 if the rental agreement was signed with additional services, such as repair costs and building insurance	CoStar Database	0	0	1	**0.62**	1	1
	rent.free	+	1 or 0	Dummy, equals 1 if the rental agreement was signed with the option of free rental for a specified period	CoStar Database	0	0	0	**0.36**	1	1
Location/ Neighbour-hood	*CBD*	+	1 or 0	Dummy, equals 1 if the building is located in the Central Business District, which is in the City of London or Westminster (GLA, 2008)	CoStar Database	0	0	0	**0.38**	1	1
	d.metro	-	m	Distance from office to the nearest metro / city train station; included as a logarithm	Calculated using R CRAN	14.80	212.70	348.00	**491.70**	557.30	4 780.80
	how.many. stations	+		The number of stations within a radius of 500 metres from the building	Calculated using R CRAN	0	0	1	**1.12**	2	6
	I.Health		1 or 0	Dummy, equals 1 if the office is located in a district	Office for National	0	0	0	**0.09**	0	1

				dominated by health sector employment	Statistics London DataStore (2016)						
	I.Professional. scientific.tech		1 or 0	Dummy, equals 1 if the office is located in a district dominated by professional scientific or technical sector employment	As above	0	0	0	**0.49**	1	1
	I.Financial. insurance		1 or 0	Dummy, equals 1 if the office is located in a district dominated by finance and insurance sector employment	As above	0	0	0	**0.28**	1	1
	I.Retail		1 or 0	Dummy, equals 1 if the office is located in a district dominated by retail sector employment	As above	0	0	0	**0.11**	0	1
	I.IT. communication		1 or 0	Dummy, equals 1 if the office is located in a district dominated by IT or communication sector employment	As above	0	0	0	**0.03**	0	1
Other	*passengers. density*	+		Number of people per year leaving the nearest station multiplied by the distance of the building from the station	Office of Rail and Road (ORR, 2015)	48.30	1 250.00	2 958.00	**5 962.00**	5 824.00	92 410.00

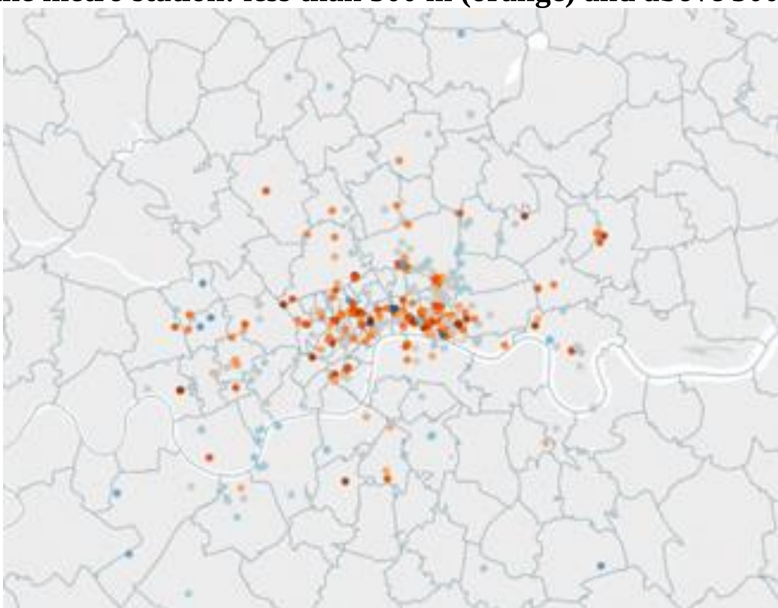
Source: Own work

We analysed 431 transactions involving the lease of office space in the buildings of the highest class (A). Almost 40% of transactions (162 transactions) were completed in the Central Business District of London. Figure 1 shows a map of the public transport network in London. Figure 2 presents the location of the buildings analysed in this study. The orange colour denotes the locations where the distance from the nearest subway station is less than 500m, while blue indicates that the distance of the office building from the nearest subway station is in the range of 500 - 9000 m.

Figure 2: Map of the public transport network in London.

Source: OpenStreetMap screen

Figure 3: Location of office buildings – analysed transactions in 2015, colour coded with the distance to the metro station: less than 500 m (orange) and above 500 m (blue).



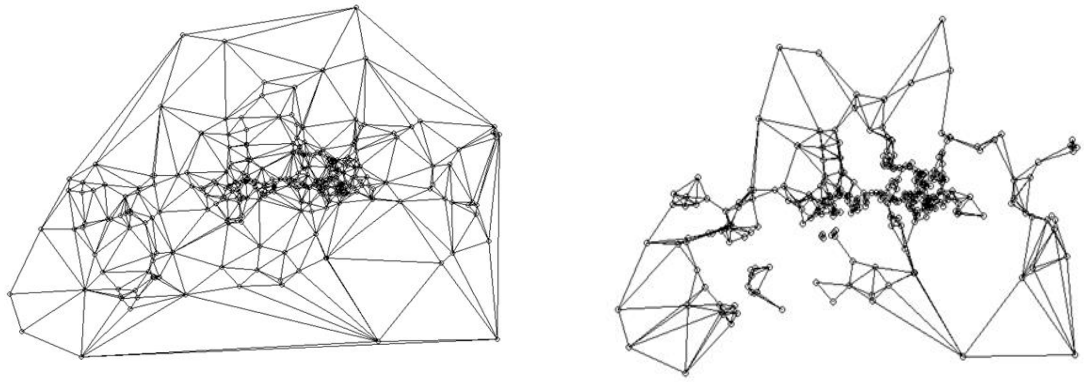
Source: Own work

3. Spatial estimation method

The spatial estimation techniques applied in this study can cover several spatial effects that are expected to exist, as shown in the previous section. Firstly, one can include information on the characteristics of offices located in different neighbourhoods, which can determine the price of property. Market valuation, which is commonly used in the process of price setting, is intrinsically based on the spatial correlation of different phenomena. As a consequence, one can get spillover estimates, which indicate the magnitude of the impact of the characteristics of neighbours on the rental price. Secondly, it relates the office location to the public transport network and provides information on the distance to the station or number of stations in a given radius[3]. This relative location is of core interest in this study, and as a proxy of centrality and connectivity, is of value added the analysis undertaken.

The novelty in this study is the spatial micro-data approach presented. Most of the cited studies aggregate the individual transaction data to districts, which limits the information as the variance becomes unknown. In this study, classic spatial estimation techniques are applied to geo-located point data. Atypically, a spatial weights matrix is calculated for individual points rather than polygons and their centroids, as is the case in most studies. We used two different spatial weights matrices to determine the neighbourhood structure and to evaluate the stability of the estimation results. The first spatial weights matrix W_1 includes the inverse squared distances between all buildings therefore all the buildings are neighbours but to a different degree. In the second spatial weights matrix $W_{2,}$ the neighbours were defined as the five closest offices situated in relation to a given office (see Figure 4). It is also possible in this situation to apply a standard contiguity matrix, which is feasible on the basis of the tessellation method. The selection of the matrix could be crucial for modelling, as a poorly chosen W matrix may lead to incorrect estimates of the coefficients (Stakhovych & Bijmolt, 2009; Elhorst, 2010).

Figure 4: Map of the neighbourhood for connections between two office buildings; a) contiguity based on triangulation and spatial separation measured with inverse squared distance, b) five nearest neighbours.



Source: Own work

It should be noted that spatial weights matrices can be significantly different because of smaller distances in city centres than in further away locations. However, this allows one to check if the type of matrix used in the model affects the values and significance of variables and their lags.

[3] All spatial issues were solved in R CRAN software with *spdep* (Bivand, 2013), *sp* (Pebesma & Bivand, 2005), and *rgdal* (Bivand, Keitt & Rowlingson, 2015) packages, enabling the easy calculation of distances and points in a given radius for geo-located data and GIS maps.

The general form[4] of the model considered here is as follows:

$$Y = \rho WY + \alpha\iota_N + X\beta + WX\theta + u \quad and \quad u = \lambda Wu + \varepsilon$$

where Y is the vector of individual rental transactions (dependent variable), ρWY is the average rental fee in a neighbourhood defined with spatial weights matrix W (spatial lag of dependent variable), $\alpha\iota_N$ is a constant term, $X\beta$ is the set of explanatory variables for a given transaction, $WX\theta$ is the set of average values (weighted with W) of explanatory variables in a neighbourhood, and u is an error term, which includes spatial autoregressive component λWu and standardised error term ε. The above is the Mansky model (GNS model), which is simplified in this study.

As the goal of the study was to find the determinants of office price, with special regard to location and the distance to the subway and city train, the estimated model is as follows:

$$\begin{gathered}\Delta rent_i = \\ \alpha\iota_N + \rho W\Delta rent + \beta_1 sqft + \beta_2 MAXfloor + \beta_3 term + \beta_4 service + \beta_5 rent.free + \\ \beta_6 CBD + \beta_7 d.metro + \beta_8 how.many.stations + \beta_9 I.Health + \\ \beta_{10} I.Professional.scientific.tech + \beta_{11} I.Financial.insurance + \beta_{12} I.Retail + \\ \beta_{13} I.IT.communication + \beta_{14} passengers.density + W\theta_1 sqft + W\theta_2 MAXfloor + \\ W\theta_3 term + W\theta_4 service + W\theta_5 rent.free + W\theta_6 CBD + W\theta_7 d.metro + \\ W\theta_8 how.many.stations + W\theta_9 I.Health + W\theta_{10} I.Professional.scientific.tech + \\ W\theta_{11} I.Financial.insurance + W\theta_{12} I.Retail + W\theta_{13} I.IT.communication + \\ W\theta_{14} passengers.density + u\end{gathered}$$

$$\text{and } u = \lambda Wu + \varepsilon$$

In the process of estimation zero-restrictions were imposed on the spatial components to find the best-fitting model[5]. With the Moran's I test for residuals from the OLS model we confirmed the existence of spatial autocorrelation and the spatial nature of the data, which justifies the necessity of spatial modelling. We estimated two sets with seven models for inverse squared distance W and for five nearest neighbours W. This follows the Elhorst (2010) classification and includes the GNS, SDM, SDEM, SAC, SAR, SEM and SLX models[6]. All spatial specifications are compared with the OLS model. The best model was considered to be that with the best AIC, BIC information criteria and LogLik and with the highest number of significant variables. Estimation results are detailed in Table 2. After final

[4] Overview of specification methods for the real estate market can be found in Chrostek and Kopczewska (2013).
[5] The basic model explains 46% of the variance of the dependent variable. This result is similar to results obtained by Ryan (2005): R^2 ~ 31.4-51.8%, or Sivitanidou (1996) and Chalermpong and Wattana, 2009: R^2 ~ 44%-59%, or Chegut (2014): R^2 ~ 44%
[6] There are three spatial components: the spatially lagged dependent variable (rho), explanatory variables (theta) and the error term (lambda), that occur as three components together (the so-called Manski model, GNS), as two components together (rho and lambda in the SAC model, rho and theta in the SDM model, theta, and lambda in the SDEM model), or one component (rho in the SAR model, theta in the SLX model, lambda in the SEM model).

selection, we choose SDM for inverse squared distance W_1 and SDEM for five nearest neighbours W_2.

Following the work of LeSage and Pace (2009) and Elhorst (2010), in order to eliminate the problem of simultaneity in models with a spatially lagged dependent variable (as dependent variable *y* appears on both sides of the equation), one operates on direct and indirect effects instead of traditional beta. Direct effects measure the impact of explanatory variables in the studied location on the value in studied location. Indirect effects measure the impact of explanatory variables in the studied location on the values in neighbouring locations. The share of indirect impact in the total is interpreted as spillover. Direct and indirect impacts are presented in Table 3.

The study assumes that there are both local and global effects, resulting from the fact that the rental price for a given property is correlated with the rental prices of other offices in adjacent areas and their (office and district) characteristics. Global effects are associated with factors not covered in the model, which affect all office properties in London. These may be the current economic conditions, the amount of property tax, unemployment rate, employment rate, etc. They are reflected in the inverse squared distance W, which links all offices with all offices and results in a global spillover measured by the indirect impact. Local effects are typically considered as being similar for closest neighbourhoods and different with reference to other, further-located properties; thus, they give the characteristics of local surroundings such as prestige, history etc.

4. What determines and differentiates the rental fees for offices in London?

The specification of models involved a few groups of variables expected to have had an impact on the pricing of office rental space in London in 2015.

Structural variables include the office surface area (*sqft*) and highest floor of rented offices (*MAXfloor*). For both spatial weights matrices W, the results are similar: a significant and positive impact of ***MAXfloor*** and an insignificant impact of ***sqft*.** The size of the office space leased turns out to be irrelevant in the process of determining the price for its rent. Chegut (2014) obtained a similar result in the model, but only for the CBD in London. For the other cities examined, as well for the whole of London, the size of the office space was significant. *MAXfloor* with a coefficient ca. 0.4-0.5 indicates that every floor up increases the price by ca. 0.5 ₤ per sqft per year.

Transaction variables include the length of lease contract (*term*), inclusion of extra payable costs in the agreement (*service*), and the inclusion of a rent-free period (*rent.free*). For both spatial weights matrices W, the results are similar: a significant and positive impact of **length of lease** and a significant negative impact of **rent-free period**. It is uncertain as to the effect of **additional payable services** included in the agreement, as significance among the models varies (sometimes significant for global effects and never significant for local effects). The duration of the rental contract in in agreement with the study by Caduff (2013), who also obtained a positive and statistically significant effect of this variable on the rental price. *Term,* with a coefficient of ca. 0.8-1.0, indicates that long-term contracts are more expensive than short-term contracts, and each extra year costs up to 1 ₤ per sqft per year. Offices with a rent-free period are in general cheaper by ca. 1-3 ₤ per sqft per year. Extra payable services in general lower the fee, but the high variance in the sample, resulting from different pricing strategies, makes it insignificant.

Location and neighbourhood variables included the location in the Central Business District (*CBD*), distance to the closest subway station (*d.metro*), number of subway stations within a radius of 500 metres from the office (*how.many.stations*) and main economic activity of the district where the office is located for 5 sectors (*I.Health*, *I.Professional.scientific.tech,* *I.Financial.insurance, I.Retail, I.IT.communication)*. Again, for both spatial weights matrices W, the results are similar. ***CBD*** is positive and significant, with coefficients of ca. 15-20 for inverse distance and ca. 11-18 for the five nearest neighbours proving that centrally located offices cost more by ca. 15-20 ₤ per sqft per year in comparison to the other offices analysed. Local effects are naturally weaker as they refer to similarly located offices. This coincides with other studies on commercial real estate (see Clapp, 1992; Kim, 2007; Caduff, 2013; Chegut, 2014). **Distance to the closest subway station** is also a statistically significant factor in all models and has a positive but limited impact on the rental fee, which, again, coincides with the conclusions made by Chegut (2014). It is interesting that the OLS models significantly overestimate this coefficient; compare β_{OLS}=-3,4 and $\beta_{spatial}$=-0.005±0.002, with a difference of 1000 times. Every one hundred metres to a subway station lowers the price by 0.5 ₤ per sqft per year. A similar result was obtained by Chalermpong and Wattana (2009). **Number of subway stations within a radius of 500 meters** from an office is surprisingly negatively significant, meaning that every next station in surrounding lowers the rental fee by ca. 2 ₤ per sqft per year. **The main economic activity of the district where the office is located,** measured by the number of employees in the industry, tends to vary. Compared with the IT and communication neighbours, only the professional scientific and technical neighbourhood is more expensive, while between the rest, no difference was found. The difference in price is ca. 20 ₤ per sqft per year, suggesting the existence of very prestigious streets / quarters where prices are significantly higher. The **density of surroundings** (*passengers.density*), which was obtained by multiplying the number of passengers departing from the subway / train station (divided by 1000 and the number of days in the year) by the Euclidean distance from the office building to the station is significant in all models. This coincides with a study by Kim (2007), who estimated the figure to be 0.0013 $, or about 0.0006 ₤. The results are in line with studies for the Tokyo CBD, where transport nodes impact the process less than the agglomeration of offices and surroundings (Nagai et al., 2000).

The spillover in the model, given by the proportion of indirect impact with regard to the total, differs between variables, and mainly appears in the impact of the main economic activity of surroundings. It is also apparent, that there must be district-specific rules on extra payable costs and relation price-area rented, as the spatial diffusion is valid there.

The estimation results for both spatial weights matrices are in line with LeSage's (2014) theory, which proposes that the choice of the matrix should not have much significance for estimates of spatial models, under the assumption that the models are well specified. The differences in estimates between the models may arise from the nature of the data used in this study. In the case of cross-sectional data on rental fees for offices in only one year, the distribution of observations might be biased. In the model of local spillovers with W for the closest five neighbours, there is a high risk of omissions of closely located observations, for example, from previous years, which could more adequately define the price of rental properties in a given location. This favours the model with global spillover, with squared inverse distance W. The omission of these observations may result in the deterioration of the model fit. On the other hand, LeSage and Pace (2014) state that the sensitivity of the model to the selection of the W matrix may indicate poor model specification. The final comparison of the three models - linear regression by OLS, spatial models with inverse squared distance W and five nearest neighbours W - confirms the hypothesis that in the case of a well-chosen spatial model, the choice of the spatial weights matrix is of secondary importance because the estimated parameters derived from the models are of a similar size. LeSage (2014) does not say, however, that the choice of the matrix does not matter, but merely states that researchers should not apply too much attention to the process of selection of the matrix, and instead focus on the correct model specification.

Summary

The aim of the study was to identify factors influencing the differences in prices for office rental space in London's commercial real estate market in 2015, especially the impact of distance to the nearest public transport station. We used an advanced spatial econometrics modelling technique, which is the first time that individual real estate geo-located point data for rental transactions has been used. The goal of this study from a technical perspective was to apply the spatial individual data model without the necessity to aggregate transaction data by districts and compare the spatial modelling with a-spatial OLS. The research aim was to find a premium for good location, with special regard to the distance to subway stations, while controlling for location in the Central Business District, dominating nearby industries and other characteristics of place and transaction. This study has filled a gap in the literature, as there are few up-to-date studies on the commercial real estate market, especially in London. The study compares the results obtained here with other existing models (for different periods of time, cities, target markets etc.). Most of the econometric results are in line with previous studies, confirming the robustness the of study presented.

The question about the price for subway access can be answered positively. In all estimated models the result was significant and confirms that distance from the subway or urban railway is an important factor, but only has negligible impact on the rental fee of office space, being about 0.5 pounds sterling per year per square foot for every 100 metres distance in a straight line from the station. This result is consistent with the conclusions made by other researchers, for example Chalermpong and Wattana (2009) and Chegut (2014). Favourable location refers not only to being next to the metro, but also primarily being in the Central Business District (CBD). Our study confirms that offices in this part of London cost about 15-20 ₤ per sqft per year more. The results are consistent with studies by Clapp (1992), Kim (2007), Caduff (2013) and Chegut (2014).

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Table 2: Estimation results

						inverse squared distance W					nearest five neighbours W				
Rent (dependent var.)	**OLS**	**GNS**	**SAC**	**SDM**	**SDEM**	**SLX**	**SEM**	**SAR**	**GNS**	**SAC**	**SDM**	**SDEM**	**SLX**	**SEM**	**SAR**
(Intercept)	49,80***	24,818*	28,99***	20,33***	32,28***	33,77***	31,45***	21,77***	56,58***	22,97***	18,87***	34,21***	31,52***	28,20***	17,18***
sqft	0,21	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
MAXfloor	0,964***	0,871***	0,89***	0,88***	0,88***	0,88***	0,88***	0,80***	0,67***	0,82***	0,82***	0,78***	0,84***	0,83***	0,76***
term	0,470***	0,545***	0,5***	0,55***	0,52***	0,500**	0,518***	0,36**	0,48***	0,46***	0,45***	0,45**	0,43**	0,49**	0,40**
service	-1,28	-2,925**	-2,81**	-3,11**	-2,77**	-2,47	-2,91**	-1,76	-0,73	-1,20	-1,10	-0,94	-0,92	-1,38	-0,96
rent.free	-5,46***	-5,99***	-5,88***	-6,14***	-5,91***	-6,18***	-5,97***	-4,93***	-3,69**	-4,99***	-4,67***	-4,35***	-4,92***	-5,10***	-4,0***
CBD	18,69***	19,28***	18,89***	19,48***	19,14***	20,34***	19,99***	14,54***	13,99***	15,13***	12,89***	13,60***	14,12***	17,02***	11,71***
d.metro	-3,4***	-0,007**	-0,005**	-0,007**	-0,007**	-0,007**	-0,006**	-0,004**	-0,005*	-0,004**	-0,004**	-0,004**	-0,005**	-0,004**	-0,003*
how.many.stations	-1,13	-2,231	-1,471	-2,29*	-2,175	-2,074	-1,55	-0,90	-2,13**	-1,23	-2,44**	-2,12**	-2,51**	-1,63	-0,84
I.Health	-10,22**	7,03	-7,20	7,15	7,05	7,57	-6,75	-8,05**	5,23	-4,89	2,73	4,05	2,73	-3,60	-4,97
I.Professional. scientific.tech	4,16	21,591**	5,826	21,67**	21,62**	22,11**	6,98	2,11	19,57**	5,87	19,01***	19,42***	20,14**	9,99**	2,42
I.Financial. insurance	-11,49**	18,895*	-7,131	19,11*	18,90*	20,18*	-6,24	-9,50*	11,58*	-4,66	12,69	12,08	12,35	-0,27	-6,96
I.Retail	-6,018	11,451	-1,627	11,95	11,27	14,80	-0,99	-3,84	5,40	-1,92	5,16	5,39	4,46	-0,16	-2,75
I.IT.communication	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Passengers.density	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***
slag.sqft	---	0,000**	---	0,000**	0,000**	0,000**	---	---	0,000***	---	0,000**	0,000***	0,000*	---	---
slag.MAXfloor	---	-0,292	---	-0,46*	-0,04	-0,08	---	---	-0,31	---	-0,42	-0,44	0,28	---	---
slag.term	---	-0,313	---	-0,36*	-0,20	-0,21	---	---	0,70**	---	-0,15	0,17	-0,02	---	---
slag.service	---	3,175	---	3,64*	2,40	4,41*	---	---	0,79	---	0,75	0,73	0,63	---	---
slag.rent.free	---	3,382	---	4,40*	1,78	2,34	---	---	2,57	---	3,51	3,16	0,65	---	---
slag.CBD	---	-4,718	---	-7,92*	0,55	-2,86	---	---	17,49**	---	-0,77	6,85	6,41	---	---
slag.d.metro	---	0,005	---	0,005	0,005	0,002	---	---	-0,007	---	0,001	-0,003	0,001	---	---
slag.how.many.stations	---	2,343	---	2,44	2,23	2,34	---	---	-1,11	---	2,00	1,19	1,77	---	---
slag.I.Health	---	-14,824	---	-13,60	-16,99	-17,94	---	---	-15,85	---	-7,54	-11,85	-12,67	---	---
slag.I.Professional. scientific.tech	---	-21,08*	---	-21,50**	-20,33*	-21,42*	---	---	-13,01	---	-19,02**	-17,87*	-19,94**	---	---
slag.I.Financial. insurance	---	-33,51**	---	-31,24**	-37,38**	-38,70**	---	---	-29,99**	---	-23,30**	-28,47**	-31,35**	---	---
slag.I.Retail	---	-18,64*	---	-18,24*	-19,61*	-26,71*	---	---	-10,11	---	-9,20	-11,42	-11,41	---	---
slag.I.IT.communication	---	NA	---	NA	NA	NA	---	---	NA	---	NA	NA	NA	---	---
slag.Passengers.density	---	0,000	---	0,000	0,000	0,000	---	---	0,000	---	0,000	0,000	0,000	---	---
ρ	---	0,24	0,08	0,39**	--	---	--	0,34***	-0,65***	0,21*	0,42***	--	--	--	0,42***
λ	---	0,19	0,37***	--	0,39***	---	0,43***	--	0,74***	0,30**	--	0,45***	--	0,50***	--
Moran's I		0,30***	0,015	0,03	0,03	0,03	0,28***	0,09*	0,01	-0,01	-0,01	-0,01	0,23***	-0,02	0,00
AIC		3510	3446,1	3451,6	3446,7	3448,3	3497,5	3450,6	3444,6	3451,4	3452,4	3450,9	3497,8	3449,6	3449,9
BIC		3571	3568,1	3520,7	3564,6	3566,2	3611,3	3515,6	3566,6	3520,6	3570,3	3568,8	3611,6	3514,6	3568,8
LogLik		-1740	-1693	-1708,8	-1694,3	-1695,2	-1720,7	-1709,3	-1692,3	-1708,7	-1697,2	-1696,5	-1720,9	-1708,8	-1708,9

p-value marked as: 0.00000001 *** 0.01 ** 0.05 * 0.1

Source: Own calculations

Table 3: Direct and indirect impacts for final models

	OLS model	SDM model (with inverse squared distance W)			SDEM model (with nearest five neighbours W)		
Rent (dependent variable)	**Direct impact (only)**	**Direct impact**	**Indirect impact**	**Total impact**	**Direct impact**	**Indirect impact**	**Total impact**
	β	**β**	**θ**	**β+ θ**	**β**	**θ**	**β+ θ**
(Intercept)	49,80***	---			34,210***		
sqft	0,21	0,0002**	0,0001*	0,0003**	0,0002	0,0001***	0,0003**
MAXfloor	0,964***	0,526**	-0,217	0,309	0,446***	0,174	0,620
term	0,470***	0,860***	-0,175	0,686	0,785***	-0,437	0,348
service	-1,28	-2,710*	3,564	0,854	-0,938	0,727	-0,211
rent.free	-5,46***	-5,805***	2,971	-2,834	-4,399***	3,162	-1,237
CBD	18,69***	19,419***	-0,577	18,842***	13,583***	6,851	20,434*
d.metro	-3,4***	-0,007***	0,004	-0,003	-0,004**	-0,003	-0,007
how.many.stations	-1,13	-2,037	2,273	0,237	-2,119**	1,193	-0,926
I.Health	-10,22**	5,349	-15,866	-10,517	4,046	-11,851	-7,805
I.Professional.scientific.tech	4,16	19,499**	-19,210*	0,289**	19,425***	-17,867*	1,558**
I.Financial.insurance	-11,49**	15,150*	-34,920***	-19,769***	12,080	-28,468***	-16,388*
I.Retail	-6,018	9,695	-19,942*	-10,246	5,395	-11,422	-6,027
I.IT.communication	NA	---	---	---	---	---	---
Passengers.density	0,000***	0,0003***	0,0001	0,0004	0,0003**	0,0001	0,0004***

p-value marked as: 0.00000001 *** 0.01 ** 0.05 * 0.1
Source: Own calculations