A Spatial Analysis of the Central London Office Market

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Context

There have been many studies that have examined the operation of the Central London office market.

Many of these have tended to use valuation based rental indices and have constructed rental adjustment models that have been time series based.

Some authors have explicitly used office submarkets as a basis for time series analysis recognising imperfect substitutability across locations.

Stevenson (2007) constructs an ECM for London office submarkets and permits interaction between submarkets to be captured by the error correction term.

As the error correction terms represent the deviation of observed rent from its long run equilibrium, this deviation is then used to capture submarket interaction. If the deviation in one submarket is statistically significant in another submarket, it would suggest that there is some connection between the two submarkets.

He found that the EC term for the City of London affected rental change in other submarkets.

Spatial Concentration

However office markets are highly spatially concentrated in a few urban areas (Byrne & Lee 2006)

Office investment is also geographically concentrated (Hoesli *et al*., 1997; Key *et al*., 1998; Andrew *et al*., 2003)

Byrne and Lee (2006) find that 56% of local authorities in England and Wales have no institutional office holdings and 89% of LAs had 20 or fewer office holdings.

However, spatial studies of office markets have been more limited, even of London where the market is much larger.

Spatial Models I

We begin by testing for spatial autocorrelation using Moran's I statistic. This is an extension of Pearson's correlation coefficient and can be written as:

$$I = \frac{n}{S_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2}, \text{ for } i \neq j \qquad (1)$$

where z_i is the deviation of the ith attribute from its mean $(x_i - \mu)$, $w_{i,j}$ is the spatial weight between 'feature' i and j, n is the total number of features and S_o is the aggregate of all spatial weights:

$$S_o = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j \qquad (2)$$

Moran's I Statistic for Spatial Autocorrelation

	Observed	Expected	Std Deviation	P-value
Central London	0.322	0.157	0.018	0.000
West End	0.416	0.187	0.019	0.000
City of London	0.391	0.182	0.017	0.000
Docklands	0.443	0.202	0.025	0.000

We can reject the null hypothesis of no spatial autocorrelation as the observed and expected values are statistically significantly different.

Thus there is evidence of spatial autocorrelation across central London and within each office submarket.

Spatial connections

If rental values in one office submarket depend upon demand in its own and another submarkets we can estimate a spatial Durbin model of the form:

$$y=X\beta+WX\theta+\mu \qquad (3)$$

μ being the stochastic disturbance term, X, a vector of explanatory variables, y the dependent variable, and β a vector of coefficients and where average neighbouring values of the independent variables are added

Spatial Models II

If however rents or capital values (as dependent variable) in one submarket are affected by those in another then we could use a spatial autoregressive model

$$y = \lambda W y + X\beta + \mu \tag{4}$$

This has y on both sides of the equation. Collecting the dependent variable on the left hand side and rearranging gives:

$$y = (I - \lambda W)^{-1} X\beta + (I - \lambda W)^{-1} \mu \tag{5}$$

where I is the identity matrix of dimension n x n. In this case the error term is no longer homoscedastic and the model is not linear in parameters due to unknown λ. The autoregressive nature of rents has been noted in time-series literature and temporal lags and spillovers may therefore be possible.

Spatial Lag Model for CV

	Estimate	z value	Pr (> |z|)
Intercept	16.255	26.101	0.000
Size	0.002	9.384	0.000
$Size^2$	-2.05E-7	-7.085	0.000
Investor	-0.028	-6.658	0.000
Distance	-0.077	-4.533	0.000
Rho	0.3771	LR Test P value	0.000
Log Likelihood	7.11329	ML Residual Variance	0.03889
AIC	-188.35		

Rho reflects spatial dependence and is statistically significant. It suggests that neighbouring properties have a significantly positive influence on the building's capital value.

Spatial Analyses of Property Markets

Tu et al. (2004) examine spatial dependence in the Singapore office market. They adopt a spatial-temporal autoregressive model and find a significant spatial dependence effect.

Nappi-Choulet and Maury (2009) examine the Paris office market and also find significant spatial effects.

However Geltner and Bokhari (2008) argue that spatial dependence may not be significant in commercial property markets due to segmentation.

Variation over Time and Space

Anselin (1999) considers four related models where: a) dependence relates to neighbouring locations in different time periods; b) dependence relates to the same and neighbouring locations in different time periods; c) with both a time and spatially lagged dependent variable; and d) where all forms of dependence are possible:

$$y_{it} = \lambda y_{it-1} + \rho[Wy_t]_i + \gamma[Wy_{t-1}]_i + f(z) + \mu_{it} \qquad (6)$$

where *f(z)* includes regressors that can be lagged over both time and space, $[Wy_{t-1}]$ is the ith element of the spatial lag vector applied to observations on the dependent variable in the last time period, and $[Wy_t]_i$ is the ith element of the spatial lag vector in the current time period.

Spatial-Temporal Autoregressive (STAR) Model

Price setting in real estate may use past selling prices of similar properties in the same location as an anchor and consequently there tends to be an autoregressive nature to CV and rents.

We extend our initial model to include its time dimension as well as considering spatial effects.

We use our transactions database from 2006 to 2014 and have 304 transactions across London office submarkets mainly in City and West End markets with very few in Docklands.

STAR Model

Based upon equation (6) above

Following Pace et al. (1998), Tu et al. (2004), and Nappi-Choulet and Maury (2009) elements in the spatial weight matrix equal the inverse distance in km between two objects.

Weights to future transactions are set to zero.

Weights to capture the time dimension are set equal to inverse distance in time measured by the number of days.

As spatial dependence might reasonably be expected to decline with distance and time, only nearest 10 neighbours are set not equal to zero.

Building Statistics

Using data from 2006 the median capital value per square foot was:

- City - £561
- West End - £862
- Docklands - £375

Skewed value distributions

Median building size:

- City – 64,930 sqft
- West End – 21,263 sqft
- Docklands – 71,843 sqft

STAR Model Estimates – CV sqft Dep Var

	Coefficient	Std Error
Constant	437.652***	(29.544)
Ln Size	-0.033***	(0.006)
Ln Size^2	0.001**	(0.000)
Investor – Institution	-3.277	(2.925)
Investor – Overseas	-8.401***	(1.893)
Years (relative to 2006)		
2007	-18.332***	(3.661)
2008	-22.396***	(3.446)
2009	-9.212***	(3.014)
2010	-11.382***	(4.004)
2011	-8.268***	(3.019)
2012	-12.232***	(4.156)
2013	-8.742***	(2.969)
2014	-4.322	(3.101)
Spatial	0.385***	(0.078)
Temporal	0.025***	(0.009)
Space & Time	0.004	(0.012)
Spatial Error	1.585***	(0.465)
Adjusted R^2	0.412	
No. Observations	304	

Discussion

Results above indicate statistical significance for spatial and temporal effects.

But these seem quite small with respect to their overall size.

Time fixed effects seem, in contrast, to be larger.

Foreign investors as a whole seem to buy cheaper offices per sqft than institutional investors, interesting given than London has been an important destination for foreign investment.

Currently the variables on characteristics are quite limited hence this heterogeneity is hard to capture

Transactions data for Docklands is also limited over this period in the dataset.

Thank You