# Transaction Based London Commercial Property Indices

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#### **Abstract**

Of the top ten global commercial property markets, London's has the highest transaction turnover price levels in the world. Its prime real estate is part of every major institutional investor's portfolio, has four "appraisal" based indices and has the most developed commercial property derivatives market outside of the US. Yet, London's commercial property sector lacks one critical indicator of market trends that other major commercial real estate markets have, a "transaction based" price index. The aim of this study is to fill that information gap by testing multiple ex-post transaction based index methods from the first quarter of 1998 to the fourth quarter of 2009. Using market data from Estates Gazette Interactive, we aggregate a cross-section of 1,451 transactions and 255 repeat transactions to estimate London's transaction based index. The estimation strategy covers four methods in the literature: repeat sales, hedonic, hybrid and spatial models.

The analysis has three main results. First, that the four models estimate the same value trends for the London commercial property sector. However, their timing of peaks and troughs, magnitude and volatility of price levels and time series properties differ. Second, each estimation style offers different pieces of information on the nature of the London Index market. In retrospect, the repeat sales index displays a distinct pricing bubble and collapse well before the other indices. Moreover, the spatial index suggests the prices paid for scarce, highly desirable and illiquid space is rather large relative to non-spatially weighted indices. Finally, comparing all four indices, the realized gains and losses mimic the price levels in IPD's London Capital Gains Commercial Property Yearly appraisal based index, but the transaction-based index offers insight into price volatility on London's commercial property market over the last decade.

### 1. Introduction

As the most significant commercial real estate market in Europe, London is missing a significant tool for tracking turnover trends and managing risk, an independent 'transaction based' commercial property index. In general, transaction based indices are useful tools for detecting real market behavior, visualizing price changes and depicting the capital valuation that real investors in the property markets face (Fisher, Geltner, and Webb, 1994; Geltner and Bokhari, 2008). For London's institutional investors, transaction based metrics are important for risk management and developing hedging instruments, like property derivatives or valuing commercial mortgage backed securities (Fabozzi, Shiller, and Tunaru, 2010). For private investors, these metrics are important as they represent an independent benchmark of financial performance. In aggregate, transaction based indices provide, at minimum, an invaluable resource for real estate market information.

London's commercial property sector is no stranger to price indices. However, they are mainly appraisal based due to two features of the UK real estate industry. First, robust aggregated transaction data

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was absent until about the middle 1990s. The search costs within London's commercial property sector are significant and markets can be closed to those that are not deal stakeholders. Second, the 'appraisal' is the foundation of real estate valuation and decision making. It is a trusted part of the transaction process, can be frequently updated and is an alternative when transaction or data environments are dry. In the former case, data is less of an impediment as independent agencies are increasingly collecting transaction information from the market. For the latter, appraisals are an instrumental tool for valuation and transactions themselves, but may not be the best tools for detecting aggregate volatility and market dynamics in a timely manner.

Given that transaction based data, data providers and competition for capturing market information has increased since 1990, we are interested in identifying the aggregate transaction prices of London commercial property over time through creating an index. Fisher, Geltner, and Webb (1994) examine alternative price indices in the US commercial property markets. After an empirical look at unsmoothed appraisal based indices, ex-post transaction based indices and unlevered REIT share indices, they conclude that each index method can provide different insights and uses for investors and academics alike. More recent developments in the US transaction-based indices, suggests that these indices can be complementary to appraisal-based indices (Geltner and Fisher, 2007). In turn, we aim to utilize the strengthening data collection process within the UK commercial property sector coupled with recent advances in the real estate literature on commercial property index analysis to gain insight into London's commercial property sector with a transaction-based index.

We view the production of a transaction-based index as an enhancement to market information, decision making and new financial insturments that can be used as a metric of transaction activity and volatility. However, there is not one so-called "true" index. Each style of index, e.g., repeat-sales, hedonic, hybrid, spatial, offers different insights into the market. Thus, we review multiple techniques for index construction, which provides a empirical lens to see various index methods side by side. In the first stage, we can examine one of the oldest estimation techniques in the literature, a repeat sales method. In the second, a hedonic methodology and finally, we can incorporate spatial modeling techniques.

To provide a market index we will identify the ex-post transaction history of London and the macro-economic trends for that period. Studies on commercial property indices in Hong Kong, New York and Chicago have catered mainly to the data available within their markets and localized knowledge. Today, the information markets are looking brighter, allowing for a realized path towards a robust transaction based index. For our analysis, we use a proprietary database of commercial real estate transactions provided by Estates Gazette Interactive (EGi). Their London property database has transactions stretching from 1976 to 2010. Coverage of transactions and building specific characteristics enhanced over the last decade culminating in the London Building Reports database. Starting from a database of 10,251 properties, with strong coverage in core London City, its fringe areas, Midtown and the West End, and ending with a complete hedonic sample of 1,451 transactions and 480 repeat sales transactions, 1,193 and 255 buildings, respectively.

After comparing index methods, the three-stage least squares Goetzmann repeat-sales estimation method yielded the highest mean returns and the spatial index indicated the lowest. The greatest volatility came from the ordinary least squares repeat-sales estimation and the lowest from the hedonic estimation. Lastly, the highest positive first-order autocorrelation came again from the three-stage least squares Goetzmann repeat-sales estimation method. Interestingly, in this sample, repeat-sales indices lead hedonic and spatial indices. However, in terms of absolute price levels, repeat-sales indices depict substantially higher returns during the real-estate "bubble" period, than for the hedonic and spatial indices. In summary, we gain market insights from the various index estimation methods.

However, by shedding light on these different index styles we can reflect on the purpose of indices themselves. Indices reflect price level trends, and can be used as a benchmark for portfolio estimation, marking assets to market and even derivatives trading for hedging risk in appraisal valuation or transactions. Arguably, transaction-based indices could be a clear basis for a benchmark, especially when tracking transaction events or hedging price risk, but there is not a single index to rule them all. Each index method provides a different story on gains or losses, fundamental value or the potential for new financial instruments. However, for policy and future instruments, the recent light shed on data collection, market infor-

mation and transparency in the commercial real estate markets must continue. If investors want to expand their investments and potentially reduce risk, then improving the fundamental market performance data will be the only way as the loss of information and future financial performance could be too great.

The remainder of the paper is outlined as follows. In Section 2, we present a review of the literature on commercial property index construction methods, including repeat-sales, hedonic, hybrid and spatial temporal techniques. In Section 3, we present our estimation strategy for each method. In Section 4, we introduce our data and report results for the frozen repeat-sales, hedonic, hybrid and spatial indices. In Section 5, we contextualize our results. In Section 6, we provide a discussion on the policy relevance of transaction-based indices for the London market.

#### 2. Commercial Indices

The development of transaction based indices has been limited mainly by a lack of data on commercial property transactions (Miles, Hartzell, Guilkey, and Shears, 1991), an ubiquitous problem in real estate. Data on transactions in the UK tends to be proprietary and information is mainly owned by property managers, brokers and client based firms such as Jones Lang LaSalle (JLL), CB Richard Ellis (CBRE) and the Investor Property Databank (IPD). Yet, the main return series reported by these groups is appraisalbased. Currently, there are two main categories of appraisal based indices available within the UK, client driven and market based. Within the field of client based indices there are three main providers, JLL, CBRE and IPD. JLL houses the oldest appraisal based index for the UK. Starting in 1978, the Jones Lang Wootton Index began reporting quarterly property valuations dating back to 1967. CBRE's index started reporting the quarterly valuation performance of their managed properties in the 1980's. IPD's UK series starts in 1980. JLL and CBRE's indices are based on data provided by their client base, whose property they manage and the indices are directly linked to their clients buy and sell strategies (Lee, Lizieri, and Ward, 2000). IPD's business model is different, in agreement with real estate investors, pension funds and developers IPD aggregates property data on a confidential basis. Their valuation index, starting in 1985, covers approximately 75-80 percent of the market. Moreover, starting in 2005, property derivatives trading commenced based on the IPD index with £24.2 bln in notional trade volume as of the 3rd quarter of 2011. FTSE The Index Company, started reporting the daily valuation of their property database in 2006. FTSE produces quarterly indices and categorical appraisal based indices and includes daily updates of valuations in their property portfolio.

From an index construction standpoint, the extant literature on indices has shown that appraisal-based indices may have some drawbacks. First, a valuation is a property's price, given that the real estate markets are in equilibrium. This assumption does not always hold. Secondly, individual appraisals can introduce measurement error into an index through potentially subjective evaluations on behalf of appraisers. Thirdly, when the appraisal is used for an index, index smoothing can arise from the the valuation updating process, i.e., updated appraisals are based on a mixture of previous appraisals, "new" comparable property information and current market conditions. Lee, Lizieri, and Ward (2000) found that the IPD and Jones Lang LaSalle annual and categorical appraisal based indices display consistent and statistically significant autocorrelation for lags up to 13 months. For an index this indicates that the relationship in values from one period to the next contains marginally new information, which can have the drawback of drowning out market volatility. Lastly, Chau, Wong, Yiu, and Leung (2005) find that the frequency of appraisal updates can further compound the index smoothing problem, i.e., updates every three months or daily are not likely to possess "new" information, which causes temporal aggregation effects at the index level.

However, information markets are changing. Since the early 1990s, there has been an increased effort by the markets to track and capture pertinent real estate information at the transaction level. Perhaps, this is a result of the investigation of appraisal indices in the commercial real estate literature. Concurrently, transaction based indices started being developed in the real estate literature, where various techniques aimed at coping with scarce and illiquid data environments. An assessment of the extant literature on transaction based index construction methods indicates that there are four viable models for developing an ex-post transaction based commercial property index: repeat sales, hedonic, hybrid and spatial-temporal

applied models. Given that these models have been applied in both the residential and commercial sector, we will restrict our review to the commercial property literature where possible.

Each model has been shown to display 'relative' strengths and weaknesses. The primary strength of the repeat sales indices reflect capital gains or depreciation in the market. Essentially, this type of index is a reflection of what the market faces in any given period (Geltner and Pollakowski, 2007). However, the repeat sales index method has several drawbacks. First, repeat sales only capture the set of properties that are transacting in multiple since the beginning of index construction. Second, there is an inefficient use of data. Chau, Wong, Yiu, and Leung (2005) compared 11 studies on repeat sales and found that out of total transactions available in the population there was at most 32 percent of data used in repeat sales. Third, there are periods of higher turnover that can influence the index. Dorsey, Hu, Mayer, and Wang (2010) find that 20 percent of transactions in Los Angeles County between 2003 and 2006 were repeat sales and in this case the sample was catching mostly 'flips'. Lastly, indices based on repeat sales can have long lags between transactions, which may reflect new capital expenditures or changes in building techniques. If this is expansive, it may introduce a bias into the index regardless of any weighting correction (Quigley, 1995).

As an alternative, hedonic methods offer a different pricing mechanism. The regression based technique utilizes the full cross section of data to parse the individual components of value. In addition, if the data is qualitatively rich, then quality changes in the property are observed over time. However, it does not communicate to investors the capital gains or losses of investments. To resolve the hedonic model's shortcomings, but retain its inherent data qualities, there was the introduction of the hybrid repeat sales methods. However, this model has yet to be fully adopted by the real estate literature or adopted within the commercial property literature. In addition, the standard hedonic framework, may be be a misspecification in the context of real estate as prior empirical work did not take into account the spatial and temporal dependence of contemporaneous and lagged real estate transactions. More recently, there has been more development around spatial temporal index construction techniques in the commercial property sector in Asia and Europe. Initial findings, indicate that these methods improve upon the standard hedonic estimation strategies through decreased standard errors and improved model fits.

The repeat sales method is the search for multiple transacted observations for the same object. Bailey, Muth, and Nourse (1963) and Case and Shiller (1987) were the first to employ the repeat sales methodology in residential real estate. These models are mainly applied in housing indices, such as The US Office of Federal Housing Enterprise and Oversight. Gatzlaff and Geltner (1998) constructed a repeat sales analysis of Florida commercial properties from 1975 to 1997. They found that the repeat sales index registers more price movements than the NCREIF appraisal based index. Chau, Wong, Yiu, and Leung (2005) constructed a repeat sales analysis for Hong Kong over the 1992 to 2001 period. The index takes advantage of the substantial data available for repeat sales analysis in Hong Kong due to transaction transparency in the city. More recently, in an effort to create a commercial property index for tradable property derivatives in the US, Geltner and Pollakowski (2007) and Geltner and Bokhari (2008) created a national index for the US and 15 sub-regions, estimated from 2001 to the present. Wheaton, Baranski, and Templeton (2009) constructed a repeat sales index of 86 properties in Manhattan over a 100 year period. This study found that for any given decade properties appreciated by 20 to 50 percent, but then faced the same decline. Ultimately, in real terms, real estate in the late 2000s is worth what it was at the turn of the 19th century.

The hedonic model, originally employed by Rosen (1974), was created for the purpose of creating a constant-quality price index for products. The method relates the price of a product to the product's individual components. As it applies to real estate, the price of a transacted building relates to the individual building characteristics, the building's neighborhood characteristics and time. In its first application to commercial real estate, Fisher, Geltner, and Webb (1994) compare commercial property index construction methods through three methods: unsmoothing the US Russell-NCREIF Index, generating an ex-post transaction-based cap rates hedonic index and an index based on unlevered REIT shares. Results indicated that the ex-post transaction-based indices lag behind the other series in time, and are consistent with the idea that institutional investors attempt to hold onto properties until they can sell them for a price at least equal to the current appraised value, in effect trading off liquidity for reduced volatility. Colwell, Munneke, and Trefzger (1998) apply a hedonic model to Chicago office property utilizing 427 observations over the

1986 to 1993 period. The index includes building characteristics, e.g., age, lot area, size and height, and many aspects of neighborhood characteristics, e.g. distances to airport, rail and road facilities, parks and golf course access, as explanatory variables. The results depict a contrary result to general market belief that there was a nominal expansion in Chicago office transaction prices over the course of the 1980s. In an additional study on commercial property markets, Fisher, Geltner, and Pollakowski (2007) constructed a quarterly transactions based index of property level investment performance for US institutional real estate, which indicates that investment periodic returns and capital appreciation or price changes for the major property types included in the NCK Property Index.

To enhance the hedonic specification Case and Quigley (1991) related the repeat sales and hedonic approaches to generate a hybrid model. The estimation strategy consists of a two stage generalized least squares procedure, first, regressing prices on the full hedonic characteristics and a property index, then weighting the first stage with the building specific factor and inter-temporal discrete residuals from the repeat sales sub sample. (Quigley, 1995) estimated returns for a 12 year sample of Los Angeles condominium units and found that the incorporation of cross-sectional observations that take into consideration the repeat sales component of the analysis substantially reduces the standard errors and confidence interval of the price index. Currently, there are no studies available on hybrid indices of commercial property assets.

Finally, Pace, Barry, Clapp, and Rodriquez (1998) were the first to apply the spatial temporal model to the US residential real estate sector, using a 22 year period of transaction prices. The prices were a function of building hedonic characteristics, an auto-regressive process, spatial dependencies between transacted observations, and the time horizon between transactions. Tu, Yu, and Sun (2004) conducted a similar spatial temporal analysis of Singapore's commercial property sector. Their analysis made two contributions. First, the study controlled for spatial dependence within and between transacted observations in buildings and for neighborhood buildings. Secondly, they corrected for heteroskedasticity, with a bayesian estimation procedure. More recently, spatial temporal techniques have been applied in the European commercial sector. In a study of the Paris office market, Nappi-Choulet and Maury (2009) find that spatial and temporal dependence are statistically significant for the Paris office market over the 1991 to 2005 period, indicating that Parisian commercial property models should correct for spatial auto-correlation in their analysis and that spatial autocorrelation is a potential in European real estate markets.

In summary, each method has its advantages and drawbacks. Clearly from a data perspective, repeat sales methodologies are highly contingent upon the existence of multiple transaction events, quantity and flushness of data, and the number of transactions across all time cohorts. Hedonic models, on the other hand, have the benefits of incorporating more data, but losing the added benefit of repeated transaction representation. A hybrid model may be of benefit, by incorporating both repeat and hedonic models. However, spatial temporal modeling suggests that hedonic indices may be misspecified due to a general omission of spatial dependence. Thus, our estimation strategy will be to empirically assess the information content of each methodology for the London office market, whilst considering the drawbacks of each estimation strategy.

### 3. Methodology

#### 3.1. Repeat Sales Analysis

From our review of the academic literature on commercial property indices we can start by applying a repeat sales estimation strategy. The method does not use multi-variate controls for hedonic, location or neighborhood characteristics in a transaction event. Instead, a repeat sale measure specifies the periodic returns. The periodic return captures the capital gain or loss between two transaction events. Given the criteria that the hedonic, location or neighborhood characteristics remain constant from one transaction to the next. Otherwise, the model is misspecified and can result in upward bias (Case, Pollakowski, and Wachter, 1991).

Following Geltner and Pollakowski (2007), we employ an ex-post transaction based repeat sales model to estimate our periodic returns. The original repeat sales model by Bailey, Muth, and Nourse (1963) forms the basis of the analysis. The empirical model is specified as follows:

$$\frac{P_{i,(t+\tau)}}{P_{i,t}} = \sum_{t=1}^{T} d_{i,t} \beta_t + \epsilon_i \tag{1}$$

where  $P_{i,(t+\tau)}$  and  $P_{i,t}$ , are transaction prices for the same object observed at  $t+\tau$  and t, respectively. The parameter estimates  $(\beta_t)$  give the average periodic return.  $d_{i,t}$  is a dummy variable taking on values of unity during the investor holding period, but the holding period's first and last year of ownership in  $d_{i,t}$  is the fraction of time owned within that year.  $\epsilon_i$  denotes a stochastic error term. We denote by y the  $N \times 1$  vector that collects all observed repeat sales transactions, X denotes a  $N \times T$  matrix that collects all dummies  $d_{i,t}$  and the  $T \times 1$  vector  $\beta$  collects all parameter estimates. We denote by N the number of observed repeat sales and by T the number of years. Given the above variable definitions, we can rewrite Equation (1) as follows:

$$y = X\beta + \epsilon \tag{2}$$

Different estimation procedures have been proposed in the literature. These procedures take into account different assumptions concerning the distribution of the error term or the ability to incorporate prior information. For the base case, we assume that the error term is independently and identically distributed, which results in an error covariance matrix given by  $\Omega = \sigma^2 I_N$ , where  $I_N$  denotes the identity matrix of dimension N. The resulting OLS estimator is given by:

$$\beta_{OLS} = \left(X'X\right)^{-1} X'y \tag{3}$$

However, the error term,  $\epsilon_i$  is generally found to be heteroskedastic. Heteroskedasticity in this context arises because of the varying holding periods for investors, which can have the effect of over or under weighting the return series. In the case of heteroskedastic errors the error covariance matrix is given by  $\Omega = \text{diag}\{\omega_i\}$ , i.e., a diagonal matrix with elements  $\omega_i$  on the main diagonal. The resulting optimal estimator is given by the weighted least squares estimator:

$$\beta_{WLS} = \left(X'\Omega^{-1}X\right)^{-1}X'\Omega^{-1}y\tag{4}$$

In order to make this estimator feasible, two assumptions have been proposed in the literature. First, the variance of each observation is proportional to the holding period, and second, the variance grows linearly with the holding period but contains an unrelated constant term. For the first case, we set the  $\omega_i$  equal to the holding period of the observation  $I_i$ . In the second case, we employ a three stage estimation procedure. First, the errors are estimated from a OLS regression, i.e.,  $\hat{\epsilon} = Y - X\hat{\beta}$ . Second, the squared errors are regressed on a constant and the holding period, i.e.,  $\hat{\epsilon}_i^2 = \alpha + I_i \gamma + \eta_i$ , where  $\eta_i$  is the i.i.d. error term for this regression. Third, the estimated squared errors  $(\hat{\epsilon}_i^2 = \hat{\alpha} + I_i \hat{\gamma})$  are used as weight  $\omega_i$ .

Goetzmann (1992) proposes to incorporate prior information concerning the distribution of the vector  $\beta$  into the estimation. Since this parameter vector represents a time series of asset returns, it should be uncorrelated if the market efficiency hypothesis holds. In order to incorporate this prior belief into the estimation, Goetzmann (1992) augments the likelihood function by a prior distribution concerning the  $\beta$  vector, specifically this prior distribution is a product of univariate normals for each  $\beta_i$ . The resulting maximization of this likelihood function gives (in case the prior is centred at zero):

$$\beta_{GOETZ} = \{I + k(X'\Omega^{-1}X)^{-1}\}^{-1}\beta_{WLS}$$
(5)

where  $\kappa = \sigma^2/\sigma_\beta^2$ , i.e., the ratio of the prior and posterior variances. The estimation of the parameter  $\kappa$  employed in this paper follows the two stage procedure proposed in Section 2.6.1 in Goetzmann (1992), i.e., we estimate  $\sigma^2$  and  $\sigma_\beta^2$  from a first stage WLS regression.

Finally, to generate the index we calculate the exponential value of the return series. 1998 is used as the base period and the index is estimated as:

$$I_t = I_{t-1} * e^{\beta_t} \tag{6}$$

where *I* is the index value in period *t* and t - 1.

### 3.2. Hedonic Analysis

The hedonic technique is a multi-variate cross-sectional analysis of transaction prices, which relates prices of goods to their bundle of components. For commercial real estate prices, a buildings fundamental characteristics and the services it provides, e.g., size, age, location, etc.. It is also customary to add controls for time and neighborhood effects that can accrue cross-sectionally. The standard hedonic framework as originally specified by Rosen (1974) is as follows:

$$\log P_{i,t} = X_{i,t}\beta + T_t\delta_t + \epsilon_{i,t} \tag{7}$$

where P is an nx1 vector of logged property transaction prices,  $X_i$  is an nxk matrix of (exogenous) hedonic property characteristics;  $\beta_i$  is a kx1 parameter vector;  $\epsilon_i$  is the nx1 vector of regression disturbances. Antiloged parameter estimates from the time effect dummies are used to form the base of the index values.

# 3.3. Hybrid Analysis

The hybrid technique is also a multi-variate cross-sectional analysis of transaction prices, but is a tool for creating more efficient estimates by incorporating the information gained from the repeat-sales component of the data set through a generalized least squares estimation procedure. The hybrid estimation strategy as espoused by Quigley (1995) is based on three steps, outlined as follows:

$$\log P_{i,t} = X_{i,t}\beta + T_t\delta_t + \xi_i + \epsilon_{i,t} \tag{8}$$

where, first for the repeat sales sample, P is an nx1 vector of logged property transaction prices,  $X_i$  is an nxk matrix of (exogenous) hedonic property characteristics;  $\beta_i$  is a kx1 parameter vector;  $\xi_i$  is a fixed effect measure for the individual buildings and  $\epsilon_i$  is the nx1 vector of regression disturbances. In a second step, Equation (8) is estimated without the building fixed effect  $\xi_i$ . The results yield the significant components for estimating the new error term,  $\widehat{\sigma_{\epsilon}^2}$ ,  $\widehat{\sigma_{\delta}^2}$  and  $\epsilon_{i,t}$ . In the last step, the full hedonic mode is estimated from Equation (7) via GLS. Similar to the hedonic model, anti-loged parameter estimates from the time effect dummies are used to form the base of the index values.

#### 3.4. Spatial Analysis

The spatial approach is a multi-variate cross-sectional analysis of transaction prices. Unlike the standard hedonic approach, the spatial temporal function also incorporates a spatial and temporal weights matrix into a standard multi-variate analysis of transaction prices. Thus, the transaction prices are a function of building hedonic characteristics, spatial dependence within a neighborhood and the time between transactions. There is a simple breakdown relating to the spatial autoregressive process to correct for spatial autocorrelation of the error term. The standard spatial autoregressive (SAR(1)) model is specified as follows:

$$\log P_{i,t} = \alpha + X_{i,t}\beta + \lambda \sum_{i=1}^{n} W_{i,j} P_{i,t} + \epsilon_{i,t}$$

$$\epsilon_{i,t} = \rho \sum_{i=1}^{n} W_{i,j} \epsilon_{i,t} + \gamma_{i,t}$$
(9)

where P is an nx1 vector of logged property transaction prices, X is an nxk matrix of (exogenous) hedonic property characteristics; and  $\beta$  is a kx1 vector of parameters; W is an nxn spatial weight matrices with nonnegative spatial characteristics on the off diagonal and zero elements on the diagonal and W=W;  $\epsilon$  is the nx1 of regression disturbances,  $\gamma$  is vector of innovations;  $\lambda$  and  $\rho$  are the spatial autoregressive parameters.

The spatial weight matrices are specified using an inverse distance decay weighting scheme, with eigenvalue row normalization. Then,  $W_i$  is constructed as follows:

$$W_{i,j} = \frac{((1/D_{i,j}))}{\max(\min_{r,c})}$$
 (10)

where  $D_{ij}$  is the distance between transaction i and earlier transaction j and the expression in the numerator is the normalization factor proposed in (Kelejian and Prucha, 1999). Furthermore, we set the weight to zero in case the transaction j occurs after the transaction i.

Different estimation strategies have been proposed in the spatial literature. Pace, Barry, Clapp, and Rodriquez (1998) employ a maximum-likelihood procedure and due to their sparse matrices technique the procedure becomes feasible for even large sample sizes. Others, e.g., Tu, Yu, and Sun (2004) and Nappi-Choulet and Maury (2009) employ a bayesian estimation procedure. In this case, (Chegut, Eichholtz, and Kok, 2011) found heteroskedaticity in the EGi London building sample, i.e., building size, and no correction would make for invalid confidence intervals and t statistics. Thus, we employ a so-called Generalized Spatial Two Stage Least Squares (GS2SLS) estimation procedure, with corrections for autoregressive and heteroskedastic disturbances (Kelejian and Prucha, 2010). The procedure has three steps: the model is first estimated by two stage least squares using the instruments  $H_n$ , which are a subset of the linearaly independent columns of (X,WX, $W^2X^2$ ,....), in the second step a GM estimator for the autoregressive parameter  $\rho_i$  is estimated using the 2SLS residuals  $\epsilon_i$  from the first step, and lastly the regression model is re-estimated by 2SLS after transforming the model through a Cochrane-Orcutt procedure to account for spatial correlation. Similar to the hedonic estimation, antiloged parameter estimates from the time effect dummies are used to form the base of the index values.

### 4. Data, Descriptive Statistics and Expectations

For our analysis, we use data provided by Estates Gazette Interactive (EGi) London Offices dataset. EGi is a commercial property database covering news, building reports, deals, auction, availability and occupier data, and ratable value analysis. For this analysis, we accessed the Building Reports database to collect detailed building information. EGi began covering market information in 1976, but their coverage of transactions substantially increased in the last decade. The starting cross-section of data is 10,251 observations. The total cross-section of observations available with information on price, transaction date, hedonic characteristics, location and erroneous data characteristics is 1,451 observations, 1,193 buildings and on average 120 transactions in every year.

From the hedonic sample, we can gather a repeat sales sample. Geltner and Pollakowski (2007) outline and motivate the removal of more transaction events for a repeat sales analysis. For example, flips, buildings that transact within six quarters, are removed from the sample so as not to bias the sample with speculative activity. For sample comparability and transparency, we employ the same filters across all estimation strategies. However, we have further exclusion due to erroneous data. Appendix A outlines all filters to the data. The resulting repeat sales sample is 480 multiple observations, culminating in 255 buildings.

Table (1) highlights the descriptive statistics of the repeat and full sales sample. Starting with the hedonic sample, the average price achieved is £25.4 mln with about twice the variation. The average building size is 4,344 square meters with high variation; average building age is 28 years; the average building height is seven stories; and more than half of buildings have amenities present. There are two dominant markets in the sample, London City and West End, followed closely by Midtown and the City Fringe. The

first quarter has the highest number of transactions and transactions mainly accrue in the sample from 2004 to 2007.

Table 1: Descriptive Statistics

(a) Hedonic and Spatial Sample

(b) Repeat Sales Sample

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Variable	Mean	(Std. Dev.	) N	Variable		(Std. Dev.)	
				Return	0.37	(0.56)	255
				Yearly Return	0.1	(0.16)	255
Price Achieved (GBP mlns)	25.4	(53.0)	1451	Price Achieved (GBP mlns)	48.6	(70.0)	255
Size (Net Square M)	4,333.4	(7,661.4)	1451	Size (Net Square M)	6,830.08	(8,589.20)	255
Building Age	38.67	(30.82)	1451	Building Age	28.89	(27.09)	255
Stories	6.81	(3.15)	1451	Stories	7.76	(3.65)	255
Amenities Present	0.69	(0.46)	1451	Amenities Present	0.78	(0.41)	255
Market				Market			
London City	0.21	(0.41)	1451	London City	0.32	(0.47)	255
City Fringe	0.13	(0.34)	1451	City Fringe	0.11	(0.31)	255
Docklands	0.02	(0.12)	1451	Docklands	0	(0)	255
Midtown	0.16	(0.37)	1451	Midtown	0.17	(0.38)	255
North Central	0.03	(0.18)	1451	North Central	0.02	(0.14)	255
Outer London	0	(0.03)	1451	Outer London	0	(0)	255
South Central	0.03	(0.18)	1451	South Central	0.04	(0.18)	255
Southern Fringe	0.04	(0.21)	1451	Southern Fringe	0.04	(0.18)	255
West Central	0.03	(0.18)	1451	West Central	0.03	(0.17)	255
West End	0.34	(0.47)	1451	West End	0.28	(0.45)	255
Time				Time			
Quarter 1	0.27	(0.44)	1451	Quarter 1	0.21	(0.41)	255
Quarter 2	0.26	(0.44)	1451	Quarter 2	0.27	(0.45)	255
Quarter 3	0.24	(0.43)	1451	Quarter 3	0.27	(0.45)	255
Quarter 4	0.23	(0.42)	1451	Quarter 4	0.24	(0.43)	255
1998	0.05	(0.22)	1451	1998	0	(0)	255
1999	0.06	(0.23)	1451	1999	0	(0)	255
2000	0.08	(0.26)	1451	2000	0.02	(0.12)	255
2001	0.09	(0.28)	1451	2001	0.02	(0.15)	255
2002	0.08	(0.28)	1451	2002	0.07	(0.25)	255
2003	0.08	(0.27)	1451	2003	0.07	(0.25)	255
2004	0.12	(0.32)	1451	2004	0.14	(0.35)	255
2005	0.10	(0.31)	1451	2005	0.13	(0.33)	255
2006	0.12	(0.32)	1451	2006	0.18	(0.38)	255
2007	0.11	(0.31)	1451	2007	0.17	(0.38)	255
2008	0.07	(0.25)	1451	2008	0.09	(0.29)	255
2009	0.05	(0.23)	1451	2009	0.12	(0.33)	255

For the repeats sample, the average return is about 37 percent with a standard deviation of approximately 56 percent, but the average yearly return is about 1 percent with a standard deviation of 16 percent. The average price of the properties is approximately £48.6 mln with high variation. The average building size is 6,830 square meters with high variation; average building age is 39 years; the average building height is eight stories; and more than three quarters of buildings have amenities present. The repeats sample has a larger proportion of returns accruing in London City than in West End, which is the opposite for the hedonic sample. Moreover, there is a higher percentage of transactions that occur in years 2004 to 2009.

Whilst comparing the two samples, there are multiple differences that suggest the repeat sales sample picks up a different market segment. Repeat sample properties are mainly younger, taller, larger and renovated properties lining the Thames River running through London. Moreover, these properties are the actively traded segment of the London commercial property district, 92 of the buildings have been traded more than twice over the sample period. Noticeably, the repeat sales sample is weakest at the start of the time period as multiples do not yet exist for the sample.

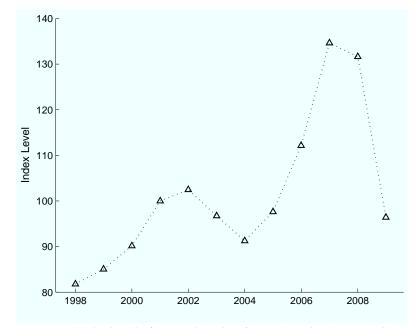


Figure 1: IPD London Commercial Property Annual Capital Growth Index

*Notes*: Figure (1) displays the frozen index values for IPD's London Commercial Property Annual Capital Growth Index over the 1998 to 2009 period (the index stretches back to 1980 and is current to year end 2010). The left vertical axis is the index level. 2001 is the base index period.

(Fisher, Geltner, and Webb, 1994) find that the levels produced by the appraisal based indices are smoothed, but should generally reflect the trends in the market. *Ex-ante* we can turn to IPD's Yearly Capital Growth London Property Index to get an idea of the general index levels over the 1998 to 2009 period. IPD measures capital growth as follows:

$$CVG_{t} = \frac{(CV_{t} - CV_{t-1} - CExp_{t} + CRpt_{t})}{(CV_{t-1} + CExp_{t})} * 100$$
(11)

where CVG is capital value growth in period t and t + 1; CExp is the capital expenditure, including purchases and developments in month t; and CRpt is the capital receipts (including sales) in month t (Cullen,

Clacy-Jones, and Pedersen, 2011).

Although our dataset does not have measures of capital expenditure and receipts (other than sales), we can see price movements that could be anticipated in the markets over the period. The IPD index displays that returns average 1.5 percent over the 1998 to 2009 period, with low volatility. Figure (1) displays IPD's index values over the 1998 to 2009 period, with 2001 as the base year. The index indicates that from 1998 to 2001, there was a recovery in commercial property values and then a slight decline before a surge to their highest levels in 2007. The index averages the appraisal values of approximately 1,700 properties in any given year over this time period with similarly high proportions coming from London City, West End and Midtown.

Table 2: Repeat Sales Estimation

	R-OLS	R-WLS	R-WLS2	R-Goet.
1998	0.39	0.27	0.31	0.07
-,,,	(0.27)	(0.30)	(0.28)	(0.11)
1999	-0.22	-0.19	-0.21	-0.00
	(0.20)	(0.21)	(0.21)	(0.09)
2000	0.34*	0.45**	0.40**	0.31***
	(0.19)	(0.18)	(0.18)	(0.09)
2001	0.30*	0.22	0.26	0.22**
	(0.18)	(0.17)	(0.17)	(0.09)
2002	-0.08	-0.05	-0.06	-0.02
	(0.19)	(0.17)	(0.18)	(0.09)
2003	-0.07	-0.06	-0.07	-0.07
	(0.18)	(0.16)	(0.17)	(0.08)
2004	0.08	0.03	0.07	0.04
	(0.17)	(0.16)	(0.16)	(0.09)
2005	0.04	0.12	0.08	0.14*
	(0.15)	(0.14)	(0.14)	(0.08)
2006	0.37**	0.35**	0.35**	0.32***
	(0.15)	(0.14)	(0.15)	(0.08)
2007	0.18	0.11	0.15	0.07
	(0.18)	(0.17)	(0.18)	(0.09)
2008	-0.41*	-0.35*	-0.37*	-0.25***
	(0.21)	(0.20)	(0.21)	(0.09)
2009	-0.13	-0.02	-0.08	-0.08
	(0.26)	(0.27)	(0.27)	(0.11)
$R^2$	0.16	0.15	0.15	0.14
MAE	0.25	0.24	0.25	0.23
SSE	67.61	68.44	67.84	69.01
No. of Obs.	255	255	255	255

*Notes*: This table reports the estimates of Equation (1) for time weighted dummies over the period 1998 to 2009. This table also reports the  $R^2$ , median absolute error (MAE) and sum of squared error (SSE). The dependent variable is the logarithmic returns. \*p value is 10%; \*\*p value is 5%; and \*\*\* p value is 1%

Furthermore, we have expectations regarding the volatility and time-series properties, i.e., noise and lag, of the indices *ex-ante*. (Geltner and Fisher, 2007) suggest that index noise is signaled by short-run volatility and negative autocorrelation, where as a lag is generally denoted by low-volatility and positive autocorrelation. (Fisher, Geltner, and Pollakowski, 2007) do not find substantial noise or lag in their hedonic

index of US commercial property over the 1984-2007 period, where the index has autocorrelation in the returns of about 35 percent and advances the appraisal based index by 1 to 3 years. However, there are distinct differences as the index covers the whole US and utilizes appraisals (just prior to transactions) as the primary independent variables in the specifications.

### 5. Results

### 5.1. Repeat Sales

Table (2) presents the results for the repeat sales empirical model in Equation (1), relating the logarithmic returns of commercial property to weighted time dummies. Results are presented for ordinary least squares, weighted least squares, three stage weighted least squares and Goetzmann estimation procedures. Not all years are statistically significant, but 2000, 2001, 2006 and 2008 are. The estimated coefficients are the smallest for the Goetzmann estimation. The time weighted dummies explain 13 to 16 percent of the variation in logarithmic returns. The mean absolute error is on average 24 percent and the sum of squared errors is highest with the Goetzman procedure, but not substantially.

Figure (2) depicts the frozen index values for the London commercial property repeat sales index over the 1998 to 2009 period. On the left axis, index levels are reported with 2001 as the base year. Index levels in general over the 1998 to 2009 period have substantially risen. From 2001 to 2005, there is a distinct trough in realized returns. From 2005 to 2007, index values increased by 80 percent. From 2007 to 2009, there is a sharp decline in value and observed transactions.

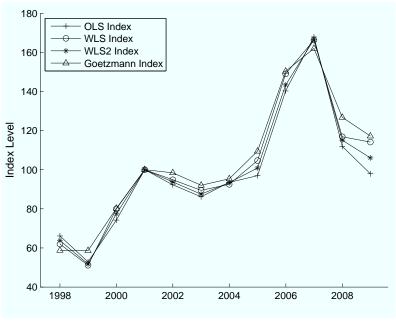


Figure 2: London Repeat Sales Index

*Notes*: Figure (2) displays the frozen index values for London's Repeat Sales Commercial Property Index over the 1998 to 2009 period. The left vertical axis is the index level. 2001 is the base index period for the ordinary least squares, weighted least squares, three stage weighted least squares and Goetzmann indices. The horizontal axis is the time period measured in years. The right vertical axis is the number of properties being held during that investor period.

Table 3: Hedonic, Hybrid and Spatial Estimation

Variables	Hec	lonic	Hy	brid	Spa	atial
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Size	0.89***	(0.02)	0.88***	(0.02)	0.89***	(0.02)
Age	-0.00***	(0.00)	-0.00***	(0.00)	-0.00***	(0.00)
Renovated	-0.07	(0.05)	-0.07	(0.05)	-0.09*	(0.05)
Levels	0.03***	(0.01)	0.03***	(0.01)	0.03***	(0.01)
Amenities	0.09**	(0.04)	0.08**	(0.04)	$0.07^{*}$	(0.04)
City Fringe	-0.57***	(0.06)	-0.55***	(0.06)	-0.51***	(0.08)
Docklands	-0.28	(0.26)	-0.25*	(0.14)	-0.02	(0.27)
Midtown	-0.10**	(0.05)	-0.10	(0.06)	-0.09	(0.07)
North Central	-0.55***	(0.14)	-0.59***	(0.10)	-0.41***	(0.15)
Outer London	-2.91***	(0.07)	-2.87***	(0.63)	-2.75***	(0.08)
South Central	-0.63***	(0.13)	-0.61***	(0.10)	-0.50***	(0.14)
Southern Fringe	-0.51***	(0.07)	-0.51***	(0.09)	-0.43***	(0.09)
West Central	-0.38**	(0.15)	-0.37***	(0.10)	-0.11	(0.18)
West End	0.17***	(0.05)	0.17***	(0.05)	$0.18^{**}$	(0.07)
1998	8.88***	(0.19)	8.93***	(0.16)	8.86***	(0.19)
1999	9.06***	(0.19)	9.11***	(0.16)	8.99***	(0.20)
2000	8.99***	(0.20)	9.02***	(0.16)	8.87***	(0.21)
2001	9.22***	(0.18)	9.27***	(0.15)	9.08***	(0.19)
2002	9.27***	(0.17)	9.30***	(0.16)	9.08***	(0.18)
2003	9.30***	(0.19)	9.34***	(0.16)	9.06***	(0.20)
2004	9.20***	(0.19)	9.20***	(0.15)	8.93***	(0.21)
2005	9.34***	(0.19)	9.36***	(0.16)	9.01***	(0.22)
2006	9.45***	(0.18)	9.47***	(0.16)	9.07***	(0.23)
2007	9.58***	(0.19)	9.60***	(0.16)	9.16***	(0.24)
2008	9.64***	(0.19)	9.65***	(0.16)	9.20***	(0.25)
2009	9.27***	(0.20)	9.29***	(0.17)	8.77***	(0.27)
$\lambda$					0.08***	(0.03)
ρ					4.04***	(1.15)
$\frac{\rho}{R^2}$		0.82		0.80		0.82
MAE		0.34		0.35		0.34
SSE		597.93		599.28		592.12
No. of Obs.		1451		1451		1451

*Notes*: This table reports the estimates of Equations (7) and (9 relating hedonic characteristics, location, time and space effects over the period 1998 to 2009. This table also reports the  $R^2$ , median absolute error (MAE) and sum of squared error (SSE). The dependent variable is the logarithm of the achieved price on the given transaction date. \*p value is 10%; \*p value is 5%; and \*p value is 1%.

## 5.2. Hedonic, Hybrid and Spatial Indices

Table (3) presents the results for the hedonic empirical model in Equation (7), relating the logarithmic prices of commercial property to a vector of hedonic characteristics, time and location dummies. In the first two columns, results are presented for White (1980) heteroskedastically robust ordinary least squares estimation procedure. The hedonics, location and time weighted dummies explain 82 percent of the variation in logarithmic prices. Size, age, stories and amenities have the expected signs and significance levels. Increments to location are measured relative to, London City. As expected all locations relative to London City are negative and significant with one exception, the West End neighborhood. All time factors are positive and significant at the one percent level.

In the second two columns, the hybrid estimation is presented, whereby Equation (7) is estimated via GLS corrected for known heteroskedasticity. The end results suggest that the standard errors decreased as expected and the index returns slightly decreased. However, the fit of the model decreased and there was a minor increase in the model's error. In the third two columns, results are presented for the for the spatial autoregressive empirical model in Equation (9), relating the logarithmic prices of commercial property to a vector of hedonic characteristics, time and location dummies via a GMM estimator with autoregressive and heteroskedastic disturbances. The hedonics, location, time and spatially weighted independent variables explain 82 percent of the variation in logarithmic prices. Similar to the hedonic specification, size, age, stories and amenities have the expected signs and significance levels, but have increased in magnitude. However, the location and time dummies have undergone substantial modification with the addition of the spatial weighting matrix. Increments to location relative to London City, are no longer all significant as the positive and significant increments to value in Midtown and West Central lost their significance. Moreover, the magnitude of the coefficients has moderated across both specifications, despite the fit of the model, median absolute error and sum of squared errors remaining similar, but decreasing by .3 and .9 percent, respectively.

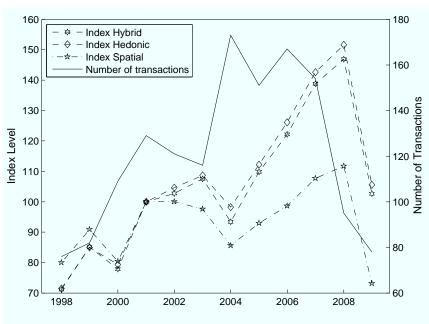


Figure 3: London Hedonic, Hybrid and Spatial Index

*Notes*: Figure (3) displays the frozen index values for London's Hedonic, Hybrid and Spatial Commercial Property Index over the 1998 to 2009 period. The left vertical axis is the index level. 2001 is the base index period for the heteroskedastic robust ordinary least squares index estimation and the generalized spatial two stage least squares estimation. The right vertical axis is the number of transactions over the index period.

Figure (3) depicts the frozen index values for the London commercial property hedonic and spatial index values over the 1998 to 2009 period. On the left axis, index levels are reported with 2001 as the base year. On the right axis is the number of transactions supporting the index over the period. For the hedonic results (depicted in dashes), index levels in general over the 1998 to 2009 period have substantially risen. From 1998 to 2009, index values range between 100 and 155 points. Between 1998 and 2003 there was a recovery in commercial-property values, but with a slight decline in 2000. Between 2003 and 2005, there was a small trough and from 2005 until 2008, index values increase. On the right axis, the yearly observation density

over the 1998 to 2009 period is reported. Yearly observation density gives insight into the liquidity of the market. In 2003, when the market is at a local maximum, the number of transactions is at a local minimum, indicating that buyers are aware of increasing price levels. This is also evident at the peak of the market in 2008, where transactions drop to their lowest. On the contrary, when index levels are at a local minimum, there is a surge in transactions. Perhaps an indication, the investors are realizing deals in the market.

In contrast, the frozen index values for the London commercial property spatial index value over the 1998 to 2009 period do not depict similar gains in property value. Despite the spatial dependence parameter  $\rho$  not being large, the addition of the spatial weights matrix has a moderating impact on location and time dummies. Therefore, the decline in index levels from 2001 to 2004, indicates a nominal loss for the market, and the surge from 2004 to 2008 indicates a recovery in value. The spatial parameter dampens the gains and losses in the market, but it is uncertain whether the parameter modification indicates a loss in premiums for key city locations.

#### 6. Discussion

In the previous section, we presented and estimated repeat-sales, hedonic, hybrid and spatial methods for an ex-post transaction based London commercial property index over the 1998- 2009 period. Table (4) and Figure (4) visually and quantifiably summarize this comparison. We compare the indices to IPD's London Commercial Property Annual Capital Growth Index and the FTSE Equity Index. Conforming to the literature on repeat sales and hedonic regression methodology, Fisher, Geltner, and Webb (1994) and Fisher, Geltner, and Pollakowski (2007) compare indices on the basis of appreciation returns ( geometric mean, standard deviation, first-order autocorrelation). Contemporaneous cross correlation, covariance and variance with other index methods and other financial price indices. Nominal Property Value Levels ( percent rise trough to peak, fall to peak, year of first and 2nd troughs and peaks).

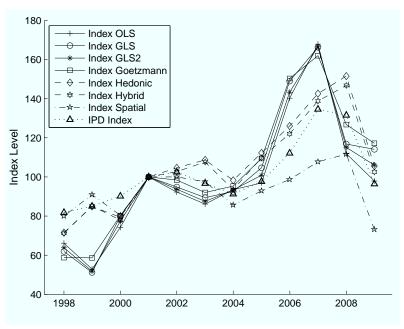


Figure 4: London Commercial Property Transaction Indices 1998-2009 period

*Notes*: Figure (4) displays the frozen index values for the estimated London Repeat-Sales, Hedonic and Spatial Commercial Property Indices and the IPD London Commercial Property Annual Capital Growth Index over the 1998 to 2009 period. The left vertical axis is the index level. 2001 is the base index period.

Figure (4) summarizes all indices, which displays that there are general transaction events that all index estimation methods depict. There is an overall historical pattern of commercial property value in London's commercial property districts. All indices suggest that values were rising from 1998 to 2001. However, there is significant variation in when the rise began. The repeat-sales index suggests that the local trough occurred in 1999, but the hedonic, hybrid and spatial indices suggest in 2000. The IPD index does not decipher this local minimum. From 2001 to 2005, there was a local trough in the market. For the repeat-sale indices the market decline to local minimum in 2003, the Hedonic, Hybrid, Spatial and IPD Indices suggest that the minimum occurred in 2004. From 2005 to 2009, the indices suggest a local maximum, a so-called "bubble" in commercial property values. In 2007, repeat-sale and IPD indices indicate a local maximum, but the hedonic and spatial indices realize the local maximum a year later. In general, the repeat-sales consistently leads the IPD index by one year and the hedonic, hybrid and spatial are consistently lagged by one year or on target.

Table (4) compares and contrasts the return characteristics of the indices, where some interesting differences are apparent. All of the indices display higher geometric mean returns, with the exception of the spatially weighted index series, than the appraisal-based index. The highest returns are attributable to the repeat-sales indices by far, but this is variable across specifications. The lowest returns arise in the spatial specification where mostly gains originally seen in the hedonic specification were modified by the addition of a spatial weight matrix. The annualized geometric returns decreased by 1.81 percent.

*Ex-Ante* we anticipated that the transaction indices would be noisier and more timely. Aggregate results are mixed on this front. All transaction-based indices display greater volatility than the appraisal-based index. Mainly, the standard deviation of the indices is higher in the repeat-sales specifications than for the hedonic and spatial specifications. The repeat-sales specification has a small number of repeat-sale transactions, which suggests a small-sample problem mainly characteristic of repeat-sale indices for cities. However, the over-all volatility of the hedonic and spatial indices is closer to that of the IPD index, but this largely due to aggregation. First-order autocorrelation, is highest for the IPD Index, approximately 40 percent, followed by the repeat-sales Goetzmann estimator at 30 percent. The other repeat-sales indices have low positive autocorrelation. In contrast, the hedonic and spatial indices indicate strongly negative autocorrelation. Thus, hedonic and spatial transaction based-indices would be considered noisier than an appraisal-based index, but given the comparable volatility levels and similar turning points also lagged in this sample.

The IPD index is highly correlated with the hedonic and spatial indices at about 85 percent, but also exhibits some correlation with the repeat-sales indices ranging from 40 to 56 percent. The repeat-sales, hedonic and spatial indices have very low correlation, ranging from two to 26 percent. The highest correlation is with the Goetzmann estimation. Positive and high correlations with the appraisal based index are a surprising result. Anecdotally, it is suggested that IPD's market coverage of London is unmatched, but these results suggest otherwise.

### 7. Conclusion

In summary, the results indicate that their is a clear trade-off between volatility and information staleness. Different types of index estimation techniques command different results. Most similar to appraisal-based indices are transaction-based indices, regardless of the controls for spatial correlation. However, least like appraisal-based indices are repeat-sales indices, but this is to be expected as a repeat-sale index is an aggregation of tradable assets and not necessarily of buy and hold assets. Overall, this analysis points to one significant finding, there is not one true index to rule them all as each index methodology brings different information to the table. Moreover, each index technique has its own set of benefits and drawbacks in terms of noise and lag.

This analysis is the first ex-post transaction based commercial property index for the London market. Commercial property indices have been produced in the literature for Chicago, New York, Hong Kong, Paris and Singapore. London is globally the most expensive commercial property market. However, it

Table 4: All Index

	R-OLS	R-WLS	R-WLS2	R-Goet.	Hedonic	Hybrid	Spatial	IPD	FTSE
Return Characteristics:									
Mean Return	3.58	5.57	4.63	6.29	3.55	3.32	-0.81	1.50	-0.76
Std. Deviation	24.72	23.18	23.58	17.38	16.38	17.28	17.18	13.23	19.89
Autocorrelation	5.81	1.59	3.91	29.15	-21.84	-29.22	-26.38	40.23	-12.39
Nominal Property Value Lev	vels:								
% Fall 1st Peak to Trough	-15.00	-11.14	-13.40	-8.34	-10.08	-14.10	-15.63	-11.61	-56.60
% Rise 1st Trough to Peak	63.76	67.13	65.86	53.51	31.42	32.34	21.85	38.91	49.58
Year of penultimate Peak	2001	2001	2001	2001	2003	2003	2002	2002	1999
Year of Jast Peak	2007	2007	2007	2007	2008	2008	2008	2007	2002
Year of penultimate Trough	1999	1999	1999	1999	2000	2000	2000	2004	2002
Year of last Trough	2003	2003	2003	2003	2004	2004	2004	0	2008
Correlations and Covariance	es:								
R-OLS	0.0611	0.0552	0.0578	0.0403	0.0072	0.0067	0.0071	0.0170	0.0075
R-WLS	0.9625	0.0537	0.0541	0.0384	0.0016	0.0012	0.0009	0.0125	0.0085
R-WLS2	0.9907	0.9898	0.0556	0.0390	0.0042	0.0038	0.0039	0.0148	0.0074
R-Goet.	0.9382	0.9522	0.9521	0.0302	0.0076	0.0076	0.0073	0.0129	0.0065
Hedonic	0.1777	0.0422	0.1097	0.2675	0.0268	0.0282	0.0281	0.0185	-0.0077
Hybrid	0.1577	0.0306	0.0921	0.2520	0.9946	0.0298	0.0294	0.0188	-0.0068
Spatial	0.1673	0.0215	0.0953	0.2457	0.9965	0.9892	0.0295	0.0192	-0.0096
IPD	0.5208	0.4076	0.4742	0.5626	0.8511	0.8216	0.8440	0.0175	-0.0059
FTSE	0.1534	0.1851	0.1569	0.1887	-0.2377	-0.1989	-0.2811	-0.2241	0.0396

Notes: Table (4 outlines the return characteristics, nominal property value levels and correlations and covariances of the transaction-based indices, IPD's appraisal-based index and the FTSE over the 1998 to 2009 period.)

lacks a significant metric for analysis, an ex-post transaction based commercial property index. Using a proprietary dataset from EGi, we estimate three styles of transaction based indices, repeat-sales, hedonic and hedonic-spatial over the 1998 to 2009 period.

#### References

- Bailey, Martin J., Richard F. Muth, and Hugh O. Nourse, 1963, A Regression Method for Real Estate Price Index Construction, *Journal of the American Statistical Association* 58, 933–942.
- Case, Bradford, Henry O. Pollakowski, and Susan M. Wachter, 1991, On Choosing Among House Price Index Methodologies, *Real Estate Economics* 19, 286–307.
- Case, B., and J.M. Quigley, 1991, The dynamics of real estate prices, The Review of Economics and Statistics pp. 50-58.
- Case, K.E., and R.J. Shiller, 1987, Prices of single family homes since 1970: New indexes for four cities, in (National Bureau of Economic Research Cambridge, Mass., USA, ).
- Chau, K., S. Wong, C. Yiu, and H. Leung, 2005, Real Estate Price Indices in Hong Kong, Journal of Real Estate Literature 13, 337–356.
- Chegut, A., P. Eichholtz, and N. Kok, 2011, Supply, Demand, and the Value of Green Buildings, AREUEA 2012 Annual Proceedings.
- Colwell, Peter F., Henry J. Munneke, and Joseph W. Trefzger, 1998, Chicago's Office Market: Price Indices, Location and Time, *Real Estate Economics* 26, 83–106.
- Cullen, Ian, Mark Clacy-Jones, and Kate Pedersen, 2011, IPD Index GuideIPD seven edn.
- Dorsey, R.E., H. Hu, W.J. Mayer, and H. Wang, 2010, Hedonic versus repeat-sales housing price indexes for measuring the recent boom-bust cycle, *Journal of Housing Economics* 19, 75–93.
- Fabozzi, Frank J., Robert J. Shiller, and Radu S. Tunaru, 2010, Property Derivatives for Managing European Real-Estate Risk, European Financial Management 16, 8–26.
- Fisher, Jeff, David Geltner, and Henry Pollakowski, 2007, A Quarterly Transactions-based Index of Institutional Real Estate Investment Performance and Movements in Supply and Demand, *The Journal of Real Estate Finance and Economics* 34, 5–33.
- Fisher, Jeffrey D., David M. Geltner, and R. Brian Webb, 1994, Value indices of commercial real estate: A comparison of index construction methods, *The Journal of Real Estate Finance and Economics* 9, 137–164.
- Gatzlaff, D., and D. Geltner, 1998, A repeat-sales transaction-based index of commercial property, A study for the real estate research institute
- Geltner, D, and S Bokhari, 2008, A Technical Note on Index Methodology Enhancement by Two-stage Regression Estimation, Supplement 1 to: A Set of Indexes for Trading Commercial Real Estate Based on the Real Capital Analytics Transaction Prices Database.
- Geltner, D., and J.D. Fisher, 2007, Pricing and index considerations in commercial real estate derivatives, *The Journal of Portfolio Management* 33, 99–118
- Geltner, D, and H Pollakowski, 2007, A Set of Indexes for Trading Commercial Real Estate Based on the Real Capital Analytics Transaction Prices Database, Release 2.
- Goetzmann, W.N., 1992, The accuracy of real estate indices: Repeat sale estimators, *The Journal of Real Estate Finance and Economics* 5, 5–53
- Kelejian, H.H., and I.R. Prucha, 1999, A generalized moments estimator for the autoregressive parameter in a spatial model, *International economic review* 40, 509–533
- Kelejian, H.H., and I.R. Prucha, 2010, Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances, *Journal of Econometrics* 157, 53–67 0304–4076.
- Lee, S., C. Lizieri, and C. Ward, 2000, The time series performance of UK real estate indices, RERI report 31, 140-387.
- Miles, M., D. Hartzell, D. Guilkey, and D. Shears, 1991, A transactions-based real estate index: is it possible?, *Journal of Property Research* 8, 203–217.
- Nappi-Choulet, Ingrid, and Tristan-Pierre Maury, 2009, A Spatiotemporal Autoregressive Price Index for the Paris Office Property Market, *Real Estate Economics* 37, 305–340.
- Pace, R. Kelley, Ronald Barry, John M. Clapp, and Mauricio Rodriquez, 1998, Spatiotemporal Autoregressive Models of Neighborhood Effects, *The Journal of Real Estate Finance and Economics* 17, 15–33.
- Quigley, John M, 1995, A Simple Hybrid Model for Estimating Real Estate Price Indexes, Journal of Housing Economics 4, 1–12.
- Rosen, S., 1974, Hedonic prices and implicit markets: product differentiation in pure competition, *The Journal of Political Economy* 82, 34–55.
- Tu, Yong, Shi-Ming Yu, and Hua Sun, 2004, Transaction-Based Office Price Indexes: A Spatiotemporal Modeling Approach, Real Estate Economics 32, 297–328.
- Wheaton, William C., Mark S. Baranski, and Cesarina A. Templeton, 2009, 100 Years of Commercial Real Estate Prices in Manhattan, Real Estate Economics 37, 69–83.
- White, H., 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica: Journal of the Econometric Society* pp. 817–838

### **Appendix A Data Restrictions**

Following Geltner and Bokhari (2008) and adapted for our data set, we employ specific controls for data inclusion in the repeat sales or spatial-temporal index. The rules mainly restrict spurious data or speculation in the markets. In addition, employing the rules ensures that the same cross-section of data is comparable to MIT Center for Real Estate's transaction price index. The exact filtering process is difficult to report as a transaction event may belong to one or many of the exclusion criteria. However, we report the exclusion critiera along with the number of observations that were excluded on those grounds.

- 1. "Flips" filter. All properties in the index are held for more than 1.5 years. this filter prevents "flipped" properties from entering the index. The flips filter removed 102 transactions.
- 2. Portfolio transactions. All properties that are a part of portfolio (multiple-property) transactions, 248 in the sample, are discarded.
- 3. Excessively old data. All properties with first transactions prior to 1998 are dropped due to data sparsity. In total 6,818 observations are deleted. Data collection began for EGi's electronic database in 1973. Transactions were sparse over the 1973-1997 period, 96 quarters, for a total deletion of 627 transactions with on average 6.5 transactions per quarter. 6,191 transactions are deleted due to inaccurate date information coded by EGi as January 1, 1900.
- 4. Incomplete information. Properties without hedonic characteristics, location, missing transaction price or date are dropped. Resulting in 536 observations deleted.
- 5. Consistent Usage. Properties must be comparable in terms of use and size from the first sale to the second. Thus, they cannot change property types, i.e., become residential, or if they have been renovated a flag must be included. There was no filtering necessary on the sample due to changes in property type.
- 6. No major change in size. The rentable area must not change between transactions. If so, then the change must be accounted for, but within the repeat sales sample there was no filtering at this stage in this sub-sample.
- 7. Extreme yearly returns or losses are also filtered from the analysis. Transactions that had a higher yearly return than 50 percent within the first 16 holding periods, i.e., 4 years were removed. As well as those that had a yearly loss greater than 50 percent.