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SPATIAL DEPENDENCE IN COMMERCIAL PROPERTY PRICES

MICRO EVIDENCE FROM THE NETHERLANDS

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In 2014 all ECB publications feature a motif taken from the €20 banknote.

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Abstract

Following a hedonic framework, this paper constructs various transaction-based commercial property price indicators for the Netherlands. Using quarterly data from the Investment Property Databank (IPD)[2], the analysis covers a total of 10,000 listed properties over the period 2001-2011. The study contributes to the empirical literature by introducing a spatial econometric methodology into a hedonic framework, via a spatially lagged explanatory variable (spatially lagged valuations per square metre).

The results provide significant evidence of the presence of spatial dependence in unit valuations in all sub-sectors of the commercial property market, namely retail, office, industrial and residential. Accordingly, high (low) priced commercial properties tend to be geographically clustered rather than randomly distributed over space.

The comparison of the alternative transaction-based indices shows a systematic upward bias in the baseline transaction-based indicator that relies solely on prior appraisals. In addition, compared to the baseline indicator, the spatially augmented transaction-based price indicator appears to fluctuate less and is more robust to small sample sizes. These results are robust for alternative spatial weights matrix specifications.

Keywords: Real estate Economics, Commercial Property Prices, Spatial Econometrics, Spatial dependence.

JEL codes: R30, C31, C21, R12

Non-Technical Summary

Commercial property markets interact significantly with the financial systems and macroeconomic activity. Over the last decade, banks' balance sheets in the EU have been increasingly depending on commercial property loans. In addition, commercial real estate assets have been extensively used as collateral for other types of loans. Risk management in banks is highly reliant on information coming from commercial property markets as commercial property loans generally constitute the most volatile component of the bank portfolios. Adjustments in commercial property prices are also likely to affect the developments in the real economy and vice-versa, in particular in countries where construction and real estate activities significantly contribute to economic growth. Taking these interactions into account, the close monitoring of price developments in the commercial property markets becomes crucial for financial regulation, risk management and monetary policy design.

Tracking price developments in commercial property markets can be very challenging due to the nature of the market. In fact, real estate assets are highly heterogeneous and dispersed in space. A centralised market in which prices and cash flows of properties can easily be observed does not exist. Moreover, the commercial properties are traded on an irregular basis and market liquidity can be extremely low in periods of financial and economic stress in particular. Because of the scarcity of information on property transactions, available commercial property price indicators tend to rely on appraisal information that is broadly available. Yet, appraisals may not always reflect the accurate market value of a property and fail to fulfil the requirements for a price index. The appraisal-based indices have been largely criticised for understating volatility and lagging market turning points. In this study, we construct several model-based commercial property price indicators that use information on transactions.

It is widely accepted that location is one of the most significant determinants of a property's price. However, traditional real estate analyses do not explicitly translate the impact of locational factors on real estate prices. This study fills this gap by explicitly incorporating spatial interactions into the real estate price models. Another distinguishing characteristic of this study is its reliance on a large quarterly data set that covers roughly 10,000 properties over the period 2001-2011 in the Netherlands.

The empirical outcomes provide strong evidence for the presence of spatial interactions in commercial real estate prices. Accordingly, in each market segment, high/low priced properties seem to be clustered over space rather than being randomly distributed. The comparison of the alternative transaction-based commercial property price indices shows a systematic upward bias in the price indicators that ignore spatial interactions. To summarise, our findings give encouraging evidence for the explicit inclusion of spatial interactions in real estate models in order to track price developments in an accurate manner.

I INTRODUCTION

Real estate markets show significant interaction with macroeconomic activity and the soundness of financial institutions. Over the last decade, bank's balance sheets have been increasingly depending on commercial property assets. In addition, investment decisions and risk management of financial market participants have been significantly supported by developments in commercial property markets.

The developments in the commercial property sector may significantly affect the banking sector in various ways[3]. First, commercial property loans constitute an important component of bank assets. In the euro area, real estate activities account for the largest share (34% in 2012[4]) of total lending to non-financial corporations in monetary and financial institutions (MFIs). Second, the MFIs' exposure to the commercial real estate sector tends to be even larger, due to the use of the commercial real estate assets as collateral for other types of loans. Risk management in banks is highly reliant on information coming from commercial property markets, since commercial property loans generally constitute the most volatile component of the bank portfolios (Zhu 2011).

Disorderly adjustments in commercial property markets can have a significant impact on the soundness of financial institutions. Sharp downward movements in the commercial property sector can drive financial institutions into distress (Davis and Zhu 2009). Falling property prices may deteriorate the balance sheets of corporate borrowers that rely on real estate as collateral. Therefore, the close monitoring of price developments in commercial property markets is crucial to help predicting banking crises. Commercial property markets tend to be more volatile than their residential counterpart. Compared to residential property, commercial property is found to be more reactive to business cycles, hence more subject to asset price bubbles (Kan et al. 2004). Commercial real estate assets are highly responsive to macroeconomic conditions because of their lower intrinsic value (as they rarely serve as accommodation to their owners) and their higher maintenance costs compared to residential properties (Davis and Zhu 2009).

The boom-bust nature of commercial property markets tend to magnify the upside and downside movements of economic activity. Adjustments in commercial property prices can have strong impact on the real economy and vice-versa, in particular in countries where construction and real estate activities significantly contribute to economic growth. During the boom phases, key macroeconomic aggregates, such as consumer demand or employment may drive demand for additional production facilities, storage space, retail shops and offices. This may stimulate the construction activity and drive up commercial property prices. Moreover, new construction activity may generate new demand for other industries as well as for bank credit. On the other hand, in times of economic downturns, weak macroeconomic conditions and slowed down business activity may decrease demand for

[3] For an extensive assessment of the EU commercial property markets from a financial stability perspective see ECB (2008).

[4] Data source: ECB

commercial property. As a result, vacancy rates would rise and rental and sales prices of commercial properties would decline.

Davis and Zhu (2011) underline the importance of commercial property prices as a key macro-prudential indicator and a relevant component of the monetary transmission mechanism. Developments on commercial property markets have important implications in terms of financial regulation, risk management and monetary policy design. The close monitoring of price developments on commercial property markets might provide information relevant for the early warning of crises by identifying asset price imbalances and real estate bubbles in order to formulate appropriate policy responses.

Tracking price developments in commercial property markets can be extremely challenging due to the nature of the market. Commercial real estate markets have certain characteristics that make it difficult to monitor pure price developments and identify the formulation of price bubbles. For instance, real estate assets are highly heterogeneous and dispersed in space. The properties are traded on an irregular basis and market liquidity can be extremely low in periods of financial and economic stress in particular. A centralised market in which prices and cash flows of properties can easily be observed does not exist (Devaney and Martinez Diaz 2011).

Because of the scarcity of information on property transactions, available commercial property price or performance indices generally rely on appraisal[5] information that is broadly available mainly for tax purposes. Yet, the appraisal-based indices may have some shortcomings such as understating volatility, lagging turning points and for possibly being influenced by clients[6] (Devaney and Martinez Diaz 2011, Geltner et al. 2003). Empirical evidence shows that appraisal-based indicators may fail to capture actual market developments in a timely manner. In addition, appraisal data are generally collected at low frequency (annual for the majority of EU countries), as most properties may not be independently and fully appraised each quarter. Appraisal regimes may also vary considerably between countries (Crosby and Devaney 2011).

Appraisal-based commercial property price indices may not systematically fulfil the requirements of a price indicator suitable for macro-prudential purposes and economic policy design. Transaction-based indices (TBIs) could be good candidates to overcome the issues that emerge with the mere use of appraisal information. Recent studies find that the TBIs show higher volatility and less autocorrelation compared to their appraisal-based counterparts (Fisher et al. 2007, Devaney and Martinez Diaz 2011). Nevertheless, the TBIs also have some shortcomings that are mostly data related; in fact, it is believed that in periods of financial and economic stress market liquidity can be exceptionally low. Owing to

[5] In this paper, we use the terms 'appraisal' and 'valuation' interchangeably.

[6] The investment agents acting for a purchaser receive an income fee depending upon completion of the transaction. Thus, these agents may have an incentive to provide a confirmatory valuation of the clients. In addition, as the valuations are used in the measurement of performance, fund managers could also have an interest in influencing them. For a detailed discussion on client influence please see Baum et al. (2000).

data limitations, this study uses the "assessed value" approach proposed by Clapp (1990) rather than the 'traditional' hedonic transaction-based approach.

In real estate economics it is widely accepted that location is one of the most significant determinants of a property's price. However, traditional real estate analyses do not explicitly translate the impact of locational factors on real estate prices. Spatial interactions are rarely included in applied real estate studies, mainly because of the technical complexity and interpretation difficulties they imply. This study fills this gap by explicitly incorporating a spatial component into the empirical investigation through adequate techniques. Spatial econometric models address spatial relationships in order to provide more reliable statistical inferences, better predictions and more efficient parameter estimations.

Recent empirical literature shows that the incorporation of the observed spatial relationship may significantly improve the performance of property price indicators. To this end, hedonic models with an explicit spatial component are found to explain more of the price variation than traditional model specifications[7].

This paper constructs alternative transaction-based indices, based on quarterly sales data of commercial real estate in the Netherlands. It applies recently developed state of art econometric techniques to construct a commercial property price indicator that explicitly accounts for the influence of space. To the best of our knowledge, this is the first study that applies spatial econometric methodology in a hedonic framework via spatially lagged explanatory variables. Another distinguishing characteristic of this study is its reliance on a large set of micro data that covers roughly 10,000 properties over the period 2001-2011.

The empirical results provide strong evidence for the presence of spatial interaction in commercial real estate prices. In each market segment, high/low priced properties seem to be clustered over space rather than being randomly distributed. The comparison of the alternative transaction-based indices suggests a systematic upward bias in the baseline transaction-based indicator that relies solely on prior appraisals. Furthermore, compared to the standard TBI, the spatially-augmented TBI appears to fluctuate less and is more robust to small sample sizes. As expected, the official valuation-based Commercial Property Price Indicator (CPPI) has an extremely smooth pattern and fails to capture the market turmoil in the second half of 2009.

The remainder of the paper is organised as follows. The next section provides an overview of the data. Section three introduces the basic theory and methodology underlying the baseline TBI model. Section four discusses the spatial econometric methodology and presents the spatial extension of the TBI model.

[7] For an extensive review of the empirical real estate studies using spatial econometric techniques please see Wilhelmsson (2002), Pace et al. (1998).

II DATA DESCRIPTION

National Statistical Institutes of EU Member States do not systematically publish data series on the commercial property sector. Thus, existing data on commercial property extensively relies on private sources. This study uses quarterly data from the Investment Property Databank (IPD) and covers roughly 10,000 listed properties in the Netherlands over the period 2001-2011. IPD (a subsidiary of MSCI inc.) is a private company based in London which provides performance benchmarking services and appraisal based performance indices to the institutionally invested commercial property markets in 25 countries. Real assets listed in the database are in majority owned by institutional investors, such as insurance companies, pension funds, open-ended funds, publicly listed property companies and Real Estate Investment Trusts. The IPD dataset excludes owner-occupied commercial property, so that it covers only a part of the commercial property market held by institutional investors. The IPD market coverage for the Netherlands is estimated at 28 per cent of the total institutionally invested market at the end of 2011.

The database is rich in terms of cash-flow information, whereas information on the characteristics of individual assets remains relatively scarce. Data are provided for four main commercial property sectors of the EU countries, namely retail, office, industrial and residential[8]. At this stage, using data from the Netherlands appeared optimal because of the good geographic data coverage and the large number of listed properties available for the country. In the future, the research is planned to be extended to other EU countries for which quarterly appraisal data are or will become available.

The main statistical challenge for this analysis is the small amount of transaction information which is collected in each quarter. Therefore, we adopt the approach of Devaney (2013), which uses a six months rolling sample of sales evidence to obtain quarterly price indicators. That is to say, each quarter's sample of sold properties includes sales completed in the current quarter as well as in the preceding one. We are fully aware that this approach represents some shortcomings as prior sale information may cause artificial smoothness of the TBI.

The composition of real estate markets changes continuously over time. Therefore, applied real estate studies are generally subject to a trade-off between a large number of listed properties and compositional stability of the database. As expected, the IPD database reports highly heterogeneous assets with a changing composition over time. In order to ensure a satisfactory level of stability, this analysis uses continuous coverage series, so that only properties held for at least one year as a standing investment are included in the sample. The database is also filtered for anomalous cases (regarding sale price and mark-ups)[9] that are likely to distort estimations.

Based on an econometric approach, we model the sale price for properties that have traded in the reference quarter. The parameters obtained from this econometric relationship are then used to

[8] Residential commercial property is developed for commercial purposes rather than being owner occupied.

[9] Following Devaney and Martinez Diaz 2011 we exclude sales related to development investment operations , the properties with valuation or sale price less than €12,500 or above €1 billion, and cases are where the mark up on prior appraisal lies outside the range -50% to +50.

conduct a mass appraisal of the not traded properties. Figure 1 shows the ratio of the number of sold assets to the number of total assets in the reference quarters[10]. Over the entire period of study, which consists of 44 quarters in total, the number of properties sold out of the IPD database corresponds on average to 3 per cent of the total number of held assets in the reference period. This rate often ranges from a low of 1 per cent between 2004 and 2011 (see Table 1 the last column). The highest share of the number of properties sold out of the database is 7 per cent and was recorded in March 2008.

Figure 1: Number of held and sold assets per quarter

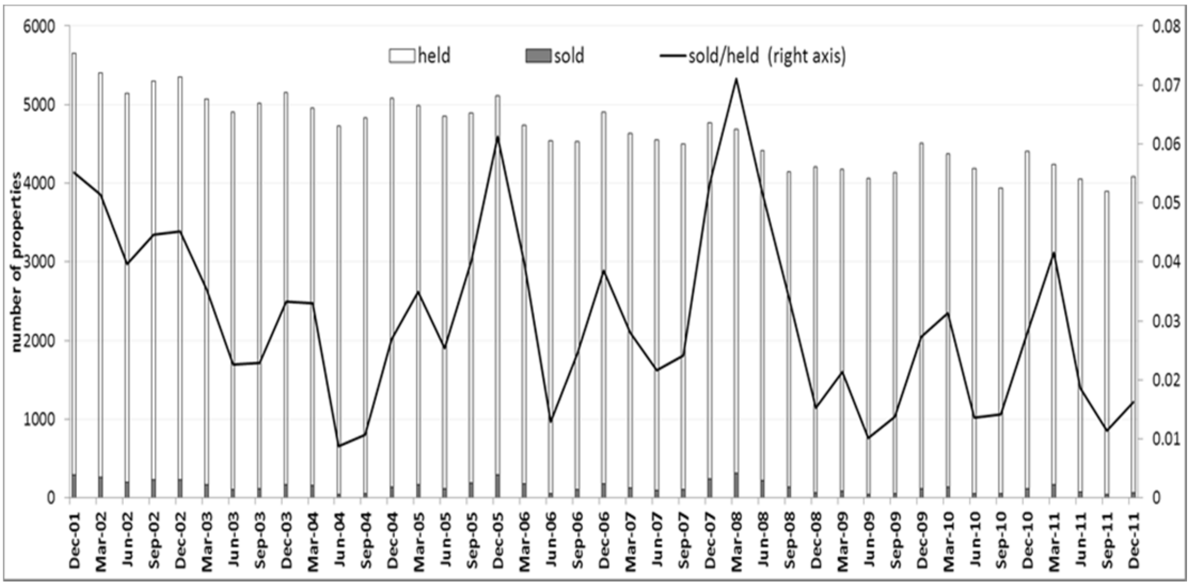

Table 1 reports the number of sold and held properties by sector. It can easily be observed that whilst the number of listed assets in the database remained fairly constant, the number of sales fluctuated remarkably throughout the period of study. Dramatic drops in the total number of sold properties occurred particularly in the second half of 2004, 2009 and 2010[11]. An interesting finding from Table 1 is that the highest numbers of sales were recorded in the years 2001-2002, 2005 and 2007-2008; these periods are generally characterised by weak or falling conditions in the real estate markets. Devaney and Martinez Diaz (2011) also use the IPD data and observe the same phenomenon for the United Kingdom. It should be borne in mind that the IPD data cover only the institutionally invested segment of the commercial property market. In fact, in the institutionally invested segment, the portfolio decisions to buy and sell might show a different pattern from the owner-occupied segment of the market. Furthermore, properties that are sold during market downturns may essentially belong to a certain category of buildings (e.g. regarding size or quality) without being representative for the entire commercial property market.

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[10] For sold assets in quarter (t) the held assets represent all properties listed in the database in quarter (t-2).

[11] These large drops in sales occur in the same period of the year; therefore the seasonality of the quarterly commercial property market activity is worth investigating in the future.

Table 1 reports the composition of the baseline sample used for the econometric analysis in the next section. Since the actual size and sectoral composition of the commercial property market of the Netherlands (also of many other European countries) are unknown, it is impossible to assess to what extent our data set reflects the actual sectoral composition. Our 'all property' aggregate is database weighted by construction and these weights may differ from the observed sectoral composition. In order to obtain a reliable aggregate picture of the commercial property markets, the availability of these sectoral weights is crucial.

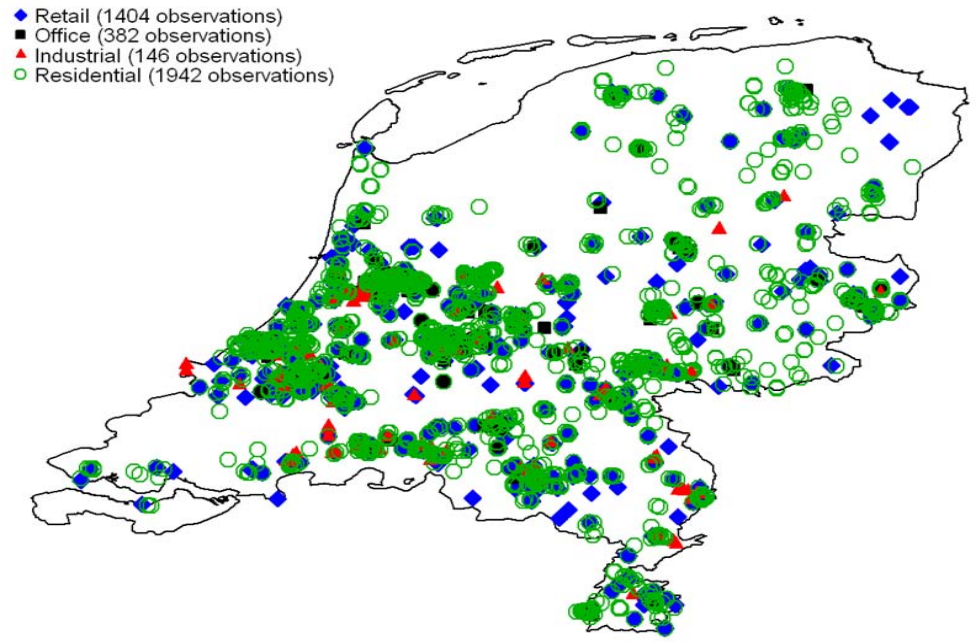
According to Table 1 the retail sector has the largest share in the dataset, whereas the industrial sector accounts for the smallest share. This appears intuitive since retail and office sectors also tend to dominate the aggregate European commercial property markets. The regional economic specialisation pattern in Europe is characterised by the expansion of the service industries at the expense of manufacturing. In addition, industrial property is generally found to be weakly represented in institutionally invested commercial property markets, as it tends to be tailor made for a specific company and therefore often owner-occupied (ECB 2008).

The spatial extension of the transaction-based model (in Section 4) requires locational information of commercial properties. The recently developed geographic information system (GIS) makes it possible to locate these observations on a coordinate system from which the distances can be calculated. Here we used a web-based application called "GPS visualizer" [12] to geocode a total number of 10,000 properties. The IPD database provides information on street names, street numbers and postal codes. Yet, for a large number of properties address information is not systematically reported. In some cases the information is incomplete or recorded in an inconsistent format. Hence, we had to use a manual procedure to extract the maximum amount of usable address information for each property. A large number of properties (around 30 per cent of the dataset) were dropped from the study due to lack of locational information. Future analysis can benefit from further efforts by the data provider and reporters to standardise the data reporting process and improve data availability.

Figure 2 shows the geographic distribution of properties listed in the IPD database in the period January-March 2011. The geographical coverage of data appears fairly homogenous with some expected clustering in major large cities, namely Rotterdam, the Hague, Amsterdam and Utrecht. This appears also in line with the geographic distribution of economic activity in the Netherlands. Sectoral information shows that retail and residential commercial properties that account for the majority of the data set are geographically spread across all regions.

[12] The web-based software "GPS Visualizer" is freely available from the address http://www.gpsvisualizer.com/geocoder/.

Figure 2: Geographic and sectoral data coverage (January-March 2011)



Note: The map is computed using the Stata software.

III BASELINE SPECIFICATION OF THE TRANSACTION-BASED MODEL

Real estate markets show extreme heterogeneity as every property is different in terms of its physical characteristics and location. Therefore, analysing price developments on these markets represent a significant challenge. Hedonic price models constitute one of the frequently used approaches to analyse price developments on real estate markets. The method consists of modelling the sale price of an asset as a function of its price determining characteristics such as age, size, location, land area and the quality of the building materials. A hedonic regression usually takes the form below where Y is the sale price, X_n is the observed characteristics of the property and ε is a random error term.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon \quad (1)$$

From Equation 1 the price indicator can be estimated either based on a pooled data set that includes time dummies or on cross sectional data via period-by-period estimations. The main difficulty regarding the hedonic approach is that all price determinant attributes of a property may not be directly observable. Yet, the omission of important price influencing factors from the hedonic model specification can lead to biased estimates. This bias is likely to carry over to the hedonic price indicators obtained from the regression coefficients. To overcome the omitted variables, Clapp

(1990) uses appraisals information when attribute variables for land prices are missing. The main advantage of using appraisals is their relatively large availability, as this information is periodically collected for the purpose of tax assessment, portfolio performance measurement or as input to bank's balance sheets, etc. Fisher et al. (2003) qualify appraisal information as a 'catch all' (or composite) variable (that captures age, quality, locational characteristics etc.) and also use it in a hedonic framework.

Theoretically speaking, appraisals represent the prices that an asset is expected to sell at the time of revaluation (excluding taxation and transaction costs). Nevertheless, appraisals may not always reflect the accurate market value of a property. There is a large body of recent academic literature that highlights the shortcomings of the appraisal based-price indices (see Devaney and Martinez Diaz 2011, Clayton et al. 2001, Geltner et al.2003, Baum et al. 2000). It is argued that appraisal-based indices tend to understate the volatility of the markets and fail to capture market turning points in a timely manner due to their strong reliance on past evidence. Cannon and Cole (2011) conduct an empirical analysis using US micro data that cover the period 1984-2010. The results show that appraised value is a biased predictor for subsequent sale prices where the absolute bias is found to be 12% on average. Accordingly, during market downturns appraisals may over-estimate the sale prices.

3.1 Baseline Model Specification

Hedonic price methods express the price of a property as a function of a vector of its key attributes. However, it is almost impossible to directly measure all factors that may influence the price of a real estate asset. The IPD database does not systematically record information on building quality and characteristics, hence it does not allow the use of the traditional hedonic approach. It reports systematically the cash flow and property segment information, and for a fairly large number of properties, information on some key attributes such as property address and floor spaces. Hence, the various model specifications used in this study are tightly conditioned on available information.

For the baseline transaction-based CPPI model we adopt an approach that is similar to Fisher et al. (2007) and which is also used by the Massachusetts Institute of Technology [13] (on National Council of Real Estate Investment Fiduciaries). The baseline model draws largely on Devaney and Martinez Diaz (2011) which also uses the IPD data to analyse the commercial real estate markets in the UK[14]. In the model, sale prices of properties that have been sold in each quarter are based on the preceding valuations (i.e. composite hedonic variable) and sector dummies. In each quarter, the estimated model coefficients are used to predict the (hypothetical) sale price of the held (unsold assets) assets. Thus, the model is estimated separately for each quarter over the entire study period (44 times in total).

In hedonic real-estate price models, using appraisals that refer to two periods prior to sales have become common practice (see Fisher et al. 2007, Devaney and Martinez Diaz 2011, Crosby et al.

[13] The research by Fisher et al. (2007) underlies the transaction based series for the US real estate market that used to be published by the MIT Centre for Real Estate in collaboration with NCREIF .

[14] Devaney (2013) employs value weighting in contrast to equal weighting in Fisher et al. (2007).

2003, Cannon and Cole 2011). This time lag ensures that the appraisals are independent of sale price so that valuations are not contaminated by the appraiser's knowledge of negotiated sale price[15]. In addition, the date of sale recorded in the database is the official completion date; however, it is highly likely that prices have been agreed upon between buyer and seller prior to this date[16].

$$\ln SaleP_t = \beta_0 + \beta_1 \ln Val_{t-2} + \beta_2 retail + \beta_3 industrial + \beta_4 residential + \varepsilon \quad (2)$$

In the baseline transaction-based model above *SaleP* is the sale price in euros, *Val* is the appraised capital value in euros two quarters prior to the sale, and sector is the sector dummies for the retail, industrial and residential sectors. ε is the random error term which is assumed to be independently and identically distributed. The intercept β_0 captures the common factors across all properties in a given quarter. Sectoral dummies are included, since different types of commercial properties may have varying price dynamics. The β_1 coefficient, associated with the valuations captures the extent to which prior valuations differ from actual sale prices. The coefficient can be interpreted as a systematic bias in valuations relative to prices (i.e. between high and low value assets).

Equation 2 is estimated using the quantile regression that minimizes the sum of absolute deviations from the median. As an estimate of central tendency, the median is affected by outliers generally to a lesser extent than the mean. The quantile regression technique is more suitable for our data set, as it contains a large number of outliers and shows skewed distribution. In addition, the tentative OLS estimations we performed yielded residuals with a strong presence of outliers[17].

The methodology of Devaney and Martinez Diaz (2011) generates the transaction-based Commercial Property Price Indicator in the following way: As a first step, and in a given quarter, all assets that do not trade during that quarter are identified. Second, using the regression coefficients of Equation 2, the predicted sale price of these unsold properties is estimated. For each quarter, two different predictions of sales price are generated, namely a start price (based on the preceding quarter's parameter estimates) and an end price (based on the current quarter's parameter estimates). To illustrate, in December 2009, the start prices are based on the regression on June and September sales, while end prices are predicted based on sales in September and December. After the exponential transformation, the estimated start and end prices are separately summed for all assets and also for each sector[18]. The ratio of the total start and end values represent a value-weighted capital return rate

[15] In this case we can expect that the appraisal value will be very close to sale price (if it is not the same as the sale price). This could be problematic as the information derived from the sold properties will be used to predict the sale price of the non-traded assets for which the appraiser's will not have such information.

[16] For institutional grade properties in the UK, Crosby et McAllister (2004) find a median time of 62 days between price agreement and exchange of contracts and 19 days from exchange of contract to completion of sales.

[17] These results and statistical analysis are available from the author upon request. For an applied discussion on quantile regression techniques please refer to Koenker and Hallock (2001).

[18] The IPD database is organised in a way that for each quarter the number of properties may be different. In this way, new assets are allowed to enter the database reflecting the composition changes of the real estate markets. Properties start being listed in the database when they are acquired or when their portfolio manager joins IPD. In the same way an asset can leave the database if it is sold to another portfolio which is managed by another company outside IPD.

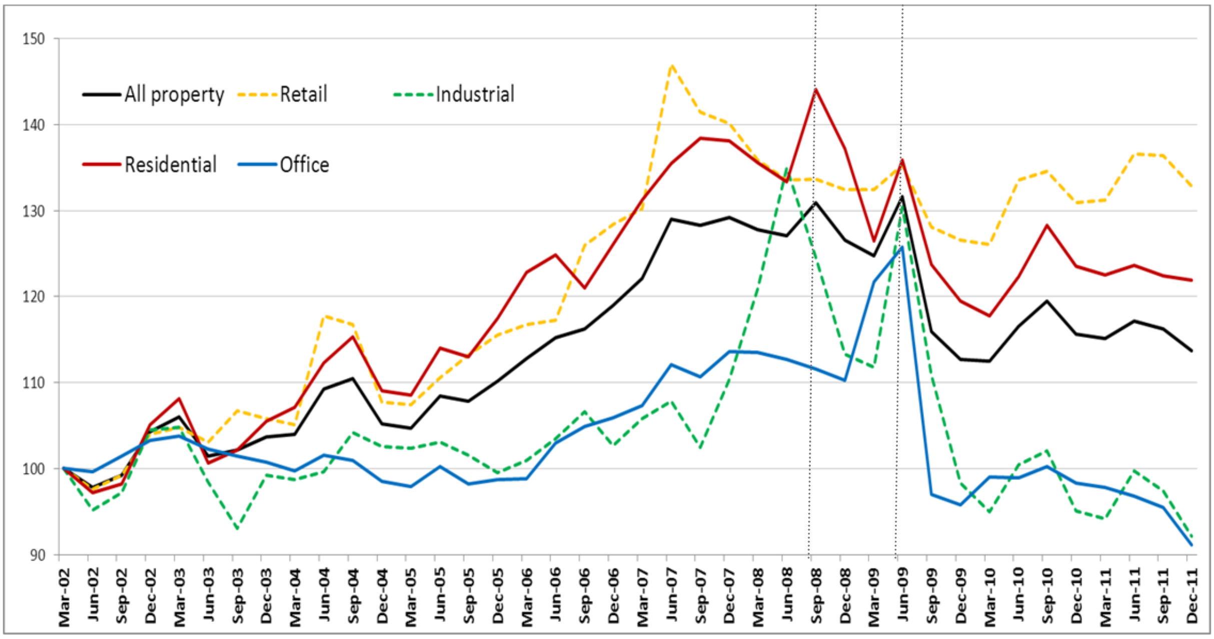
for each quarter. These quarterly percentage changes are then chain-linked to build longer time series. This methodology ensures a very large data coverage by allowing for the market composition change over time, so that, the underlying property samples for individual intervals (start and end of a quarter) remain constant, but may change between intervals (between quarters).

3.2 Baseline model results

Table 2 shows the first set of results for the coefficient estimations and their significance levels (based on the t-test) and summary statistics for the baseline model (Equation 2). The model is estimated for each quarter separately, using the quantile regression technique. The coefficients β_1 associated with ln*Val* capture the relationship between sale prices and appraisals from two quarters prior. As expected, this variable is highly significant (at the 1 per cent level) for all quarters. In addition, pseudo R-squared is above 0.90 showing a good fit of the model. Tests for the joint significance of the sector dummies are reported in the second column of Table 2. The dummies capture the systematic differences in the relationship between sale prices and prior appraisals among different types of properties. The sector dummies generally appear significant (27 out of 44 quarters at the 5 per cent confidence level), supporting the inclusion of sectoral dummy variables.

Figure 3 illustrates the CPPIs obtained from the mass appraisal procedure by chain-linking the quarterly growth rates (Equation 2). The indicators are computed at the 'all property' aggregate level as well as for four distinct sub-sectors, using the sectoral dummy coefficients from the pooled model.

Figure 3: The transaction-based Commercial Property Indicator from the baseline model

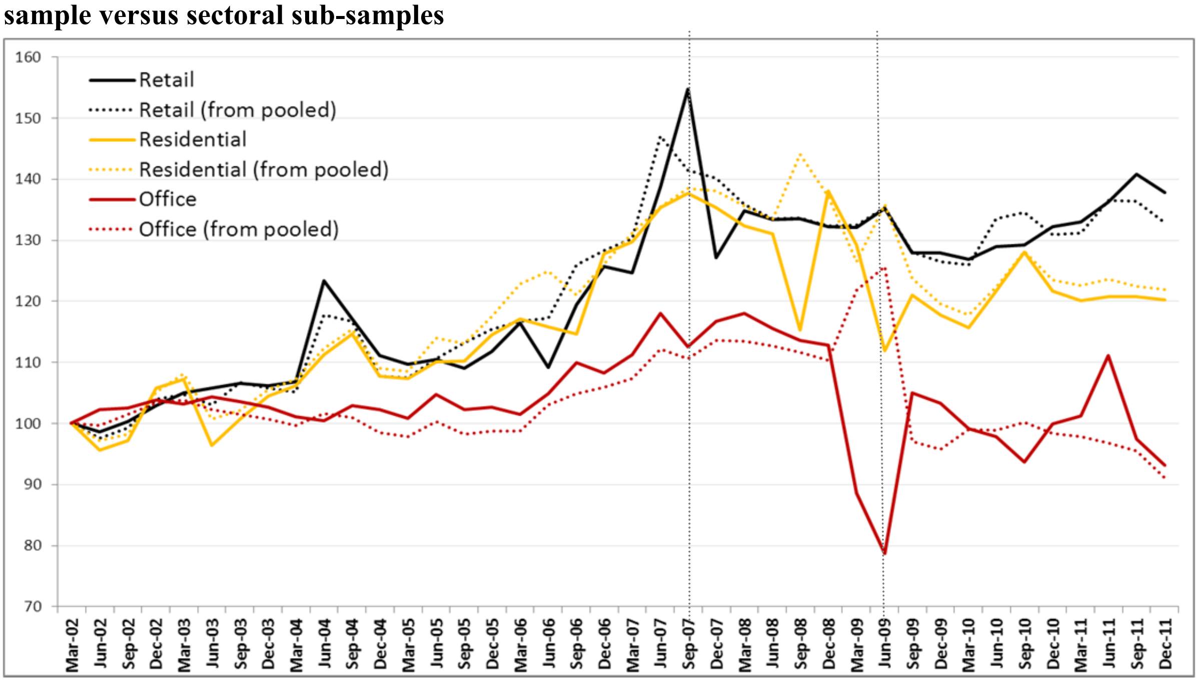


The CPPI movements in the residential and office (which is the omitted 'base case') sectors show a very similar pattern to the aggregated 'all property' indicator. Following the same trend as in other

EU countries, the CPPIs in the Netherlands show an upward trend between 2002 and 2008. In the residential sector, the CPPI reached its peak in September 2008 and June 2009, which also represents the peak level of the indicator for the rest of the sectors. The office and industrial sectors appear to be the sectors most dramatically affected by the economic crisis; they recorded the highest decline since June 2009 (that is the common turning point for all sectors). Another interesting finding is that the CPPI movements in the industrial and retail sectors show pretty distinct price patterns with regard to other sectors.

The CPPI estimations in Figure 3 rely on a pooled data set that includes sector dummies. The 'all property' chain-linked series are constructed in a way that the sectoral composition of the underlying data may change from one quarter to another. In order to test the sensitivity of our results to changing composition, Figure 4 compares the TBI series generated by the pooled model (Figure 3) with the ones estimated on sub-groups for office, retail and residential sectors[19]. The TBI estimated from the sectoral sub-groups is expected to give a more accurate picture of sectoral price developments than the estimations based on the pooled data. Except for some quarters, Figure 4 shows broad similarities between the two series (generated from the pooled model and from the sectoral sub-samples). A striking finding is that, when the number of transactions is very low (in these cases lower than 9 transactions per quarter), the TBIs based on the sectoral sub-group estimations are highly volatile and diverge strongly from the series based on the pooled data (i.e. September 2007 for retail, September 2008 for residential and June 2009 for offices).

Figure 4: The transaction-based Commercial Property Indicator estimates from the pooled sample versus sectoral sub-samples



[19] Because of the insufficient number of transactions, it is impossible to estimate a separate cross-sectional model for the industrial sector.

This high volatility and sometimes erratic behaviour of the sectoral series can be problematic. The robustness of sectoral estimations is highly conditioned on a sufficient number of transactions. Therefore, the pooled model appears to have a more plausible profile as it has the advantage of gathering a higher number of transactions. We also found that the pooled model increases the estimation efficiency (due to high degree of freedom) and generates lower standard errors.

IV SPATIAL EXTENTION OF THE TRANSACTION-BASED MODEL

4.1 Why does space matter for commercial property prices?

It is widely-accepted that location is one of the most important price determinants of a real estate asset. Yet, empirical analyses have largely ignored the existence of spatial interactions due to computational complexity and data limitations. Real estate economics systematically employs statistical tools designed for independent observations. However the presence of spatial interactions in the data may generate statistical issues that affect the reliability of the resulting price and performance indicators.

Spatial autocorrelation and spatial heterogeneity[20] are the main statistical problems introduced by the use of cross-sectional data with a geographical dimension. In regional science, spatial autocorrelation (or spatial dependence) refers to the situation where similar values of a random variable tend to cluster in some locations (Anselin and Bera 1998). The concept of spatial dependence is very intuitive and has its origins in Tobler's first law of geography (1970): "Everything is related to everything else, but near things are more related than distant things." Applied to the real estate sector, spatial dependence implies that high (low) priced real estate assets would be geographically clustered.

It is intuitive to assume that real estate prices would not be randomly distributed across space because of theory-driven or statistical reasons (Anselin 2002). In real estate markets, theory driven spatial autocorrelation relates to the intuitive idea that a property surrounded by expensive ones will be worth more than a property surrounded by inexpensive properties**.** In real estate markets, due to herd behaviour of market participants (i.e. buyers, sellers), the value of a property generally signals or guides price expectations in a neighbourhood. In addition, neighbourhoods tend to develop at the same time and may have similar structural (locational) characteristics, such as dwelling size, vintage, interior and exterior design features and so on (Basu and Thibodeau 1998). Nearby buildings tend to share the same amenities like accessibility (e.g. transport and communication), environmental

[20] Spatial heteroscedasticity is another statistical issue introduced by the use of spatial data. It refers to the instability of model coefficients over space. In contrast to spatial dependence, tackling this issue does not always require a specific set of methods (Anselin 2009). On the other hand, treating spatial heterogeneity could be challenging in some cases since it is often difficult to separate from spatial dependence. In this paper we leave the spatial heterogeneity aside and focus exclusively on spatial dependence.

characteristics, and have similar access to labour markets and public facilities (Can 1992). On the other hand, the most common "statistical" sources of spatial autocorrelation in house prices include omitted locational variables, measurement errors, unsuitable functional form and model misspecification. All these factors can result in spatially correlated errors in hedonic models which require a specific statistical approach.

From a statistical point of view, the clustering of the same sign residuals by neighbourhood, along roads, and in business hubs could be a critical issue. In fact, the presence of spatial autocorrelation may violate the underlying assumptions of hedonic models such as uncorrelated residuals with constant variance. If model residuals are spatially correlated the OLS and quantile regressions may generate biased or inconsistent regression coefficients; incorrect inferences and exaggerated R^2 statistics (Abreu et al. 2005).

As an alternative to spatial estimation, some hedonic models introduce space by the inclusion of additional regressors to control for the locational attributes (e.g. distance to various centres, neighbourhood indicators or spatially interactive variables or sub-location dummies). Yet, empirical evidence shows that spatial autocorrelation in residuals could remain even after the inclusion of additional locational control variables (Baumont and Legros 2009, Wang and Ready 2005, Pace et al. 1998). In addition, many neighbourhood and accessibility attributes of a property are not always directly observable. The inclusion of more than desired variables (on the basis of parsimony) may limit the performance of estimations due to a limited degree of freedom. Thus the explicit consideration of spatial relationship is necessary for robust empirical analysis of the real estate markets.

4.2 Diagnosis of spatial autocorrelation

In spatial analysis, the correct specification of the neighbourhood structure through the spatial weights matrix 'W' is a crucial step. Since there is no clear-cut definition for the underlying neighbourhood structure, the spatial weights matrix may be based on various criteria. Distance-based matrices are very widely used in the literature because of their exogenous nature to economic models (otherwise endogenous distance matrices would induce high non-linearity into the model). There are several types of distance-based spatial weights matrices based on contiguity (border sharing), inverse distance or nearest neighbours.

In this study we define the spatial structure (W) as binary distance-based matrix using the k-nearest neighbour criterion. W is built based on the exact location of each property, using the longitudinal and latitudinal coordinates. W consists of individual spatial weights w_{ij} that typically reflect the "spatial influence" of unit j on unit i. The binary k-nearest neighbours matrix is built in the following way: Say d_{ij} is the Euclidian distance between observation i and j. Let distances from each spatial unit i to all units j $\neq$i be ranked as follows:

$d_{ij(1)} \leq d_{ij(2)} \leq \ldots \leq d_{ij(n-1)}$ for each k=1,…,n-1. The set $N_k(i)=\{j(1), j(2),..., j(k)\}$ contains the k closest units to i. For each given k, spatial weights w_{ij} of the W is expressed as:

$$w_{ij} \begin{cases} 1, & j \in N_k(i) \\ 0, & \text{otherwise} \end{cases}$$

Since most houses are excluded from the neighbourhood structure above, the NxN dimensioned distance-based spatial weights matrix contains a large proportion of zeros. This provides a computationally efficiency that enables the testing and specification of models involving a large number of observations. By construction, W is row-standardised so each row sums up to one. Consequently, the associated regression parameter to the spatially lagged variable can be intuitively interpreted as a measure of spatial dependence. This also renders the magnitude of the spatial parameter comparable between models. By convention diagonal elements of W are zero ($w_{ii}=0$ for all i=1,…,n) disallowing an observation to predict itself. The spatial weights are asymmetric in the sense that property i may be a neighbour to property j, but not necessarily vice-versa.

In order to test the robustness of our results to alternative specifications of W, we simultaneously compute three different matrices on the basis of the 5^{th}, 8^{th} and 10^{th} closest neighbour criteria. The descriptive analysis of data shows that the level of valuations per square metre varies substantially among sectors. For instance, the mean of unit valuations in the retail sector are up to 5 times higher than those in the industrial sector. As a result, we opted for a W structure that reflects sectoral differences in unit prices, so that we constructed three separate spatial weights matrices for each market segment and each quarter.

Moran (1950)'s I statistic is the most widely used measure to detect spatial autocorrelation. The statistic reveals to what extent high (low) values of a random variables are surrounded by other high (low) values of it. This makes it possible to evaluate whether the distribution pattern of a variable is clustered, dispersed, or random.

$$I = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \left(y_i - \hat{y} \right) \left(y_j - \hat{y} \right)}{\sum_{i=1}^{N} \left(y_i - \hat{y} \right)} \quad (3)$$

The Moran's I statistics is expressed above, where w_{ij} is the spatial weight between observation i and j and S_0 is the sum of all w_{ij}'s. $\hat{y}$ is the mean value of the variable of interest and N is the number of locations. The Moran's I test is based on the null hypothesis of absence of the clustering in some geographical areas. An index value close to 1 indicates clustering while an index value close to -1 indicates dispersion. Here we use the Moran's I statistic to investigate the spatial distribution pattern of the valuations per square metre in a given commercial property segment. Table 3 reports the Moran's I index values and p-values, evaluating the significance of that index based on z-scores. To ensure that the results are robust for various spatial structures, three separate spatial weights matrices for each sector and each quarter are computed. Reflecting the changing composition of the database from one quarter to another, each cell of Table 3 is based on a distinct spatial weights matrix structure.

The results reject the null hypothesis of no spatial effects for all quarters. Accordingly, commercial properties with high (low) values of unit valuations tend to cluster in the same geographic areas. These results appear qualitatively insensitive to the neighbourhood structure (i.e. 5^{th}.8^{th} and 10^{th} closest neighbours)[21]. As expected, spatial autocorrelation coefficients become smaller with the increasing number of nearest neighbours taken into account. Put differently, the magnitude of spatial interactions between observations decays with distance. The average Moran's I coefficients by sector are summarised in the end of Table 3. Accordingly, the highest spatial autocorrelation is observed in the office sector whereas the residential sector is characterised by the lowest Moran's I values. In other words, the prices (proxied by unit valuations) in the office sector seem to be highly affected by the prices of the neighbouring office buildings. On the other hand, low spatial autocorrelation in the residential sector appears intuitive given the heterogeneity of the residential buildings serving as commercial property.

4.3 Spatial model specification

The spatial lag operator is the main distinguishing element of the spatial econometric models. Using the distance weights matrix, the lag operator $Wx_i = \sum_{j \neq i} w_{ij} x_j,$ captures the spatially weighted average of the variable of interest x in a given location i. The spatially lagged variable we introduce in this study is the valuation per square metre of the neighbouring commercial properties of the same segment. The spatial variable captures the impact of the neighbouring unit valuations on the sale price of a property. One of the innovative features of our spatial model is the multidimensional structure the spatial matrix. Indeed, we use a more complex matrix structure than usual in order to take the sectoral dimension of the data into account. For a given property i, the spatially lagged unit valuation includes only the nearest neighbours of the same market segment.

There is an extensive theoretical literature dedicated to spatial econometric model specifications, nevertheless we do not attempt to cover it in full[22]. Briefly speaking, the spatial lag operator (that incorporates spatial information) can be introduced into the model specifications in three main ways: as a spatially lagged independent variable (spatial cross-regressive model), as a spatially lagged dependent variable (spatial lag model) or as a spatially lagged error term (spatial error model). Spatial lag and spatial cross-regressive models consider the spatial process as 'substantive' by showing an explicit interest in the spatial interaction of the dependent or explanatory variables. On the other hand,

[21] As a sensitivity check we also tried alternative matrix specification based on inverse distance criterion with different cut-off points. We obtained very similar test results to those presented in this section.

[22] For a review of spatial econometric models and estimation techniques please refer to Anselin and Bera (1998).

spatial error models interpret the spatial process as a 'nuisance' that needs to be corrected (Anselin 2002).

A large number of recent empirical real estate studies show that the incorporation of the observed spatial relationship improves the accuracy of the predicted market values and time indicators significantly. Only to name a few, in an hedonic price framework Pace et al. (1998) compare the spatiotemporal model with the indicator-based one and show that the former has a larger explanatory power. It also shows that the sale prices of properties are influenced by the sale price of neighbouring properties that previously sold. Osland (2010) demonstrates the significant improvement of hedonic model performance by using spatial regression techniques. Bourassa et al. (2010) find that controlling for spatial dependence in hedonic frameworks enables to generate more accurate house price predictions. Baumont et al. (2009) analyse the spatial effects in the Paris Metropolitan Area and conclude that spatial econometric techniques provide a more accurate modelling of house prices.

Taking the data limitations into account, a spatial cross-regressive model appears to be the most suitable spatial model specification. In fact, the limited number of sales makes it difficult to consider the spatial effects in the neighbourhood in the form of a spatially-lagged dependent variable (i.e. sale prices). For a given property, there is a very low probability of sale in the immediate neighbourhood in each quarter. Hence, a spatial structure based on sale information would be highly sparse, rendering the estimation of the model technically impossible. As a result, in this study we construct the spatial variables using valuations information (rather than sale prices) that are available for a larger number of properties[23].

This leads us to the cross-regressive model specification which is illustrated below in its simplest form:

$$Y = \beta X + \rho WX + \varepsilon \quad (4)$$

Y is an (Nx1) vector of the dependent variable and X is the (Nx1) vector of the exogenous variable. W is the nxn spatial weights matrix and ε is the stochastic error term. ρ is the spatial cross-regressive coefficient that captures the magnitude of the spatial relationship. Florax and Folmar (1992) provide the main motivation for such a model specification by showing that the omission of spatially lagged explanatory variables can cause spatial correlation in regression residuals. As a consequence, in the presence of spatially correlated explanatory variables, the spatial lags of the same explanatory variables should be simultaneously introduced into the model. In the cross-regressive model specification, the spatially-lagged variables are assumed to share the same properties with other explanatory variables. Therefore, the model can be estimated, using standard regression techniques such as the OLS or quantile regressions.

[23] As floor space is not available for a considerable number of properties listed in the IPD database, in the spatial model specification the sample size drops considerably. For the residential sector data on unit valuations were available at all until March 2005. Therefore this sector is not represented or very slightly represented in the all property indicator.

Equation 5 shows the spatial extension of the baseline model where in addition to the composite hedonic variable (*Val*), valuation per square metre (*UVal*) as well as their spatial lags (*WUVal)* are introduced into the model.

$$\ln SaleP_t = \beta_0 + \beta_1 \ln Val_{t-2} + \beta_2 \ln UVal_{t-2} + \beta_3 \ln WUVal_{t-2} + \beta_4 retail + \beta_5 indus + \beta_6 resid + \varepsilon \quad (5)$$

As before, the β_1 coefficient, associated with the valuations captures a systematic bias in valuations between high and low value assets. The β_2 coefficient associated with the unit valuations is expected to capture a systematic bias in valuations relative to quality. In other words, it refers to a systematic discount or premium given by appraisers to low or high quality buildings.

W is a multi-dimensional spatial weights matrix and the coefficient β_3 captures a systemic valuation bias due to location. The inclusion of the spatially lagged variable assumes the existence of significant interdependencies in valuations within the same neighbourhood. If such interdependencies (or bias) do(es) not exist, the estimated value of β_3 will be low or insignificant.

Before estimating Equation 5, we investigated a possible multicollinearity issue in the model specification. We suspected that high (low) valued buildings may also have high (low) unit valuations (or quality). The results did not give evidence on multicollinearity. In fact, the absolute value of correlation coefficients between valuations and valuations per square metre was larger than 0.3 only in a few cases.

4.4 Spatial model results

Table 4 reports the coefficient estimations and their significance levels for the spatially-augmented TBI model[24] (Equation 5). As in the baseline model, this hedonic composite variable *Val* is highly significant in all quarters. In addition, unit valuations and/or their spatial lags appear significant at the 10 per cent confidence level in 22 quarters (out of 44), revealing significant bias in valuations due to quality and location. According to these results, the inclusion of unit valuations as well as their spatial lag appears to improve the explanatory power of the model.

Figure 5 compares the alternative transaction-based CPPI indicators, namely the baseline TBI, the baseline model with unit valuations[25] and the spatially-augmented TBIs based on the 5th, 8th and 10th closest neighbours criteria. Here we report the aggregated TBIs for the all property sector, since it was not possible to estimate the spatial models at sectoral level due to insufficient number of transactions or/and missing information on floor space. For the baseline model 1 two distinct series, which are both estimated from Equation 1, are reported. The dashed series are obtained from a larger number of

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[24] To save space, here we only report estimations based on the 5th neighbour criterion. We also estimated the spatial model using the 8th and 10th nearest neighbours criteria, the resulting indicators are presented in Figure 5.

[25] The estimations results for the baseline model with unit valuations are not reported here but are available from the author upon request.

observations (reported in Table 2), whereas the rest of the series are estimated from the same data sample.

Figure 5: Spatially augmented TBI versus the baseline model specification for the 'all property' aggregate

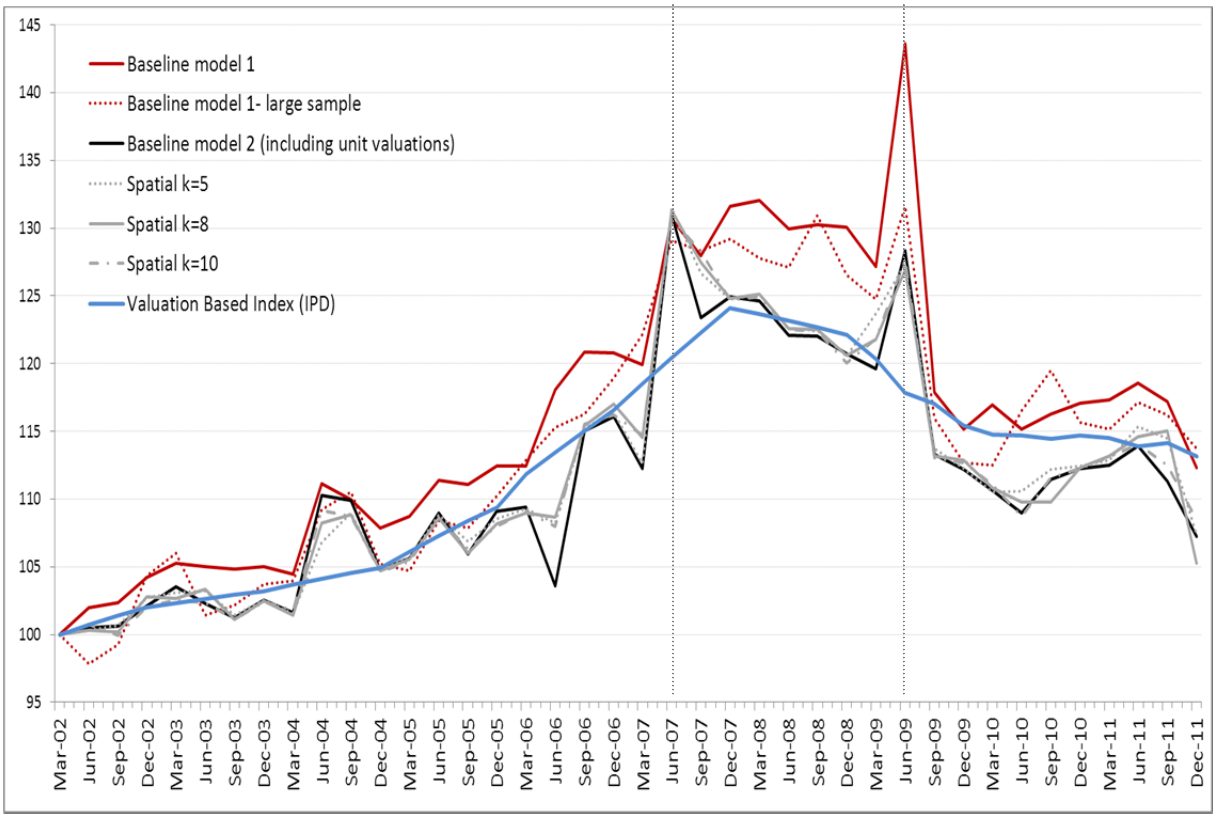

Figure 5 reveals that the baseline model 1, which does not include any information on quality or location of the buildings, shows a clear upward bias for the entire period considered. As regards to the general trends and the turning points in June 2007 and June 2009, all series display a very similar pattern. Another interesting finding is that the baseline model 1 tends to overshoot in June 2009 compared to the other models that rely on information from unit valuations. Put differently, in times of market turning points, the baseline model (that does not include any information on quality or location) tends to show an erratic behaviour. We also observe that the baseline model 1 is likely to overshoot to a smaller extent when the number of observations is larger. In sum, compared to the baseline model 1, the TBIs including unit valuations appear to be more robust for small sample sizes and fluctuate less. The results also show that the spatial TBI is not highly sensitive to alternative neighbourhood structures.

Figure 5 also reports the official IPD valuation-based CPPI for the Netherlands over the period of study. It is striking that compared to the various transaction-linked indicators above; the valuation-based CPPI captures market developments in an extremely smoothed manner. Moreover, the valuation-based indicator completely overlooks the market turmoil in the second half of 2009.

CONCLUSION

This paper assesses the performance of the various transaction-based commercial property price indices for the Netherlands. The study contributes to the real estate economics literature by introducing spatial econometric techniques into a hedonic framework in the form of spatially lagged explanatory variables.

In fact, even though location is one of the most important price determinants of a real estate asset, the applied real estate analyses have shown so far very limited awareness of the availability of spatial analytical methods and tools.

Our empirical outcomes encourage the systematic use of the spatial econometric tools in real estate analysis. The results provide significant evidence of the presence of spatial dependence in unit valuations in all commercial property sub-sectors, namely retail, office, industrial and residential. Accordingly, high (low) priced commercial properties tend to be geographically clustered rather than randomly distributed over space. The comparison of the alternative transaction-based indices shows a systematic upward bias in the baseline transaction-based indicator that relies solely on prior appraisals. In addition, compared to the baseline indicator, the spatially augmented transaction linked price indicator appears to fluctuate less and is more robust to small sample sizes. As regards to the turning points and general trends, the spatially-augmented transaction-based indicator shows a very similar pattern to the baseline transaction-based indicator. To summarise, our empirical findings support the explicit inclusion of spatial interactions in hedonic models in order to obtain more accurate price and performance indices.

The spatial model specification we employ in this study is relatively basic and essentially guided by data availability. In the future, better data availability will make it possible to use the state of the art spatial econometric techniques to determine the most adequate spatial model specification to the underlying price dynamics. For instance, a country-wide systematic reporting of the transaction and locational information will allow for the estimation of the spatial autoregressive and error models.

Real estate markets interact significantly with macroeconomic activity and the financial systems. This requires the close monitoring of price developments in the commercial property markets for financial regulation, risk management and monetary policy design. Therefore, filling the data gaps in the area of commercial property is crucial. In this study, the commercial property market of the Netherlands is analysed as a pilot case. In the future, the availability of the quarterly-valuation information will make it possible to extend this methodology to other countries. To obtain reliable hedonic price indices, statistical efforts should be directed to make the qualitative real estate data (such as floor space, age, size, material quality) available. In addition, the availability of sectoral weights is crucial for the constructions of accurate national real estate price aggregates. It is also worth investigating whether the properties that traded are representative of the market in terms of their characteristics and price trends. Therefore, the sample selection bias is another research area that needs to be explored in the future.

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Table 1: Sectoral composition of traded and non-traded assets per quarter

	Number of held assets					Number of sold assets					Ratio
	Total (1)	Retail	Office	Indus.	Res.	**Total (2)**	Retail	Office	Indus.	Res.	**(1)/(2)**
Dec-01	**5354**	1548	1064	410	2332	**295**	121	81	40	53	**0.06**
Mar-02	**5138**	1513	1033	410	2182	**264**	112	64	44	44	**0.05**
Jun-02	**4948**	1440	990	374	2144	**196**	66	42	16	72	**0.04**
Sep-02	**5068**	1427	1012	374	2255	**226**	83	40	18	85	**0.04**
Dec-02	**5121**	1450	1034	374	2263	**231**	85	31	32	83	**0.05**
Mar-03	**4892**	1376	1025	366	2125	**173**	55	31	28	59	**0.04**
Jun-03	**4792**	1342	1010	340	2100	**108**	35	30	6	37	**0.02**
Sep-03	**4905**	1349	1006	326	2224	**112**	35	34	4	39	**0.02**
Dec-03	**4984**	1361	1013	338	2272	**166**	52	40	8	66	**0.03**
Mar-04	**4795**	1325	990	332	2148	**158**	38	35	8	77	**0.03**
Jun-04	**4690**	1298	973	330	2089	**41**	7	21	0	13	**0.01**
Sep-04	**4782**	1317	987	346	2132	**51**	15	21	4	11	**0.01**
Dec-04	**4945**	1386	1009	362	2188	**133**	43	38	10	42	**0.03**
Mar-05	**4819**	1356	988	352	2123	**168**	42	37	14	75	**0.03**
Jun-05	**4728**	1338	964	346	2080	**120**	26	19	14	61	**0.03**
Sep-05	**4700**	1326	951	328	2095	**188**	32	46	18	92	**0.04**
Dec-05	**4819**	1368	968	340	2143	**295**	37	83	32	143	**0.06**
Mar-06	**4554**	1330	904	336	1984	**182**	21	58	26	77	**0.04**
Jun-06	**4486**	1328	867	318	1973	**58**	18	22	8	10	**0.01**
Sep-06	**4418**	1343	849	312	1914	**108**	62	37	4	5	**0.02**
Dec-06	**4723**	1394	891	322	2116	**182**	85	57	2	38	**0.04**
Mar-07	**4510**	1325	846	326	2013	**126**	41	39	4	42	**0.03**
Jun-07	**4450**	1315	825	330	1980	**96**	9	11	4	72	**0.02**
Sep-07	**4392**	1328	759	314	1991	**106**	10	19	4	73	**0.02**
Dec-07	**4523**	1390	776	320	2037	**241**	16	111	8	106	**0.05**
Mar-08	**4375**	1354	748	318	1955	**311**	42	112	12	145	**0.07**
Jun-08	**4199**	1374	656	314	1855	**216**	129	31	12	44	**0.05**
Sep-08	**4011**	1355	583	250	1823	**135**	96	25	8	6	**0.03**
Dec-08	**4146**	1284	590	250	2022	**63**	32	7	6	18	**0.02**
Mar-09	**4085**	1284	600	244	1957	**87**	41	11	4	31	**0.02**
Jun-09	**4023**	1254	600	240	1929	**41**	28	10	0	3	**0.01**
Sep-09	**4079**	1333	601	242	1903	**56**	37	7	6	6	**0.01**
Dec-09	**4394**	1360	643	264	2127	**120**	43	15	10	52	**0.03**
Mar-10	**4238**	1335	631	260	2012	**133**	32	9	6	86	**0.03**
Jun-10	**4129**	1310	626	254	1939	**56**	15	9	2	30	**0.01**
Sep-10	**3882**	1370	559	250	1703	**55**	21	6	0	28	**0.01**
Dec-10	**4282**	1416	598	254	2014	**120**	65	7	4	44	**0.03**
Mar-11	**4068**	1382	476	254	1956	**169**	80	11	10	68	**0.04**
Jun-11	**3975**	1362	468	250	1895	**74**	31	9	6	28	**0.02**
Sep-11	**3852**	1403	385	214	1850	**44**	11	9	10	14	**0.01**
Dec-11	**4018**	1403	382	292	1941	**65**	26	6	14	19	**0.02**

Table 2: Pooled baseline estimations: Selected coefficients and statistical inferences

	B_1(ln Val)			Sector dummies		Model	
	Coeff.	std. errors	P>|t|	F-stat	P-val.	Pseudo R^2	No of obs.
Jan-02	0.998	0.00	0.00	182.2	0.00	0.96	295
Mar-02	1.001	0.00	0.00	38.4	0.00	0.96	264
Jun-02	0.972	0.01	0.00	0.7	0.57	0.93	196
Sep-02	0.988	0.00	0.00	0.4	0.78	0.94	226
Dec-02	1.008	0.00	0.00	4.7	0.00	0.96	231
Mar-03	1.009	0.00	0.00	11.5	0.00	0.95	173
Jun-03	0.990	0.01	0.00	0.4	0.78	0.91	108
Sep-03	0.999	0.01	0.00	7.8	0.00	0.92	112
Dec-03	1.000	0.00	0.00	2.4	0.07	0.96	166
Mar-04	1.000	0.00	0.00	3.7	0.01	0.96	158
Jun-04	1.001	0.01	0.00	6.4	0.00	0.95	41
Sep-04	1.008	0.01	0.00	3.1	0.03	0.95	51
Dec-04	0.997	0.00	0.00	4.0	0.01	0.95	133
Mar-05	0.993	0.00	0.00	4.4	0.01	0.95	168
Jun-05	0.987	0.01	0.00	0.2	0.88	0.90	120
Sep-05	0.974	0.00	0.00	1.7	0.17	0.92	188
Dec-05	0.993	0.00	0.00	13.2	0.00	0.94	295
Mar-06	0.998	0.00	0.00	275.7	0.00	0.94	182
Jun-06	1.009	0.01	0.00	1.3	0.29	0.88	58
Sep-06	0.986	0.01	0.00	2.8	0.04	0.88	108
Dec-06	0.986	0.01	0.00	85.2	0.00	0.94	182
Mar-07	0.998	0.00	0.00	7.0	0.02	0.96	126
Jun-07	1.004	0.01	0.00	3.4	0.00	0.91	96
Sep-07	1.010	0.01	0.00	7.5	0.00	0.91	106
Dec-07	1.011	0.01	0.00	2.3	0.08	0.95	241
Mar-08	0.998	0.00	0.00	1.3	0.27	0.94	311
Jun-08	1.000	0.00	0.00	2000	0.00	0.96	216
Sep-08	1.000	0.00	0.00	3700	0.00	0.97	135
Dec-08	0.998	0.01	0.00	2.2	0.09	0.95	63
Mar-09	0.996	0.00	0.00	57.4	0.00	0.93	87
Jun-09	1.009	0.01	0.00	28.5	0.00	0.92	41
Sep-09	0.997	0.00	0.00	19.2	0.00	0.95	56
Dec-09	0.994	0.00	0.00	11.3	0.00	0.96	120
Mar-10	0.988	0.00	0.00	8.1	0.00	0.96	133
Jun-10	1.004	0.01	0.00	1.9	0.15	0.95	56
Sep-10	1.011	0.01	0.00	0.2	0.83	0.95	55
Dec-10	0.993	0.00	0.00	7.5	0.00	0.96	120
Mar-11	0.992	0.00	0.00	7.9	0.00	0.96	169
Jun-11	0.998	0.00	0.00	4.3	0.01	0.95	74
Sep-11	0.995	0.01	0.00	0.6	0.64	0.92	44
Dec-11	0.979	0.01	0.00	1.1	0.36	0.93	65

Note: All models above are estimated including an intercept.

Table 3: Moran's I statistics- and P-values (2nd column): Retail Sector

	5th nearest neighbour		8th nearest neighbour		10th nearest neighbour	
Dec-01	0.302	0.00	0.275	0.00	0.242	0.00
Mar-02	0.321	0.00	0.274	0.00	0.247	0.00
Jun-02	0.301	0.00	0.258	0.00	0.234	0.00
Sep-02	0.309	0.00	0.265	0.00	0.235	0.00
Dec-02	0.316	0.00	0.274	0.00	0.24	0.00
Mar-03	0.322	0.00	0.27	0.00	0.237	0.00
Jun-03	0.32	0.00	0.271	0.00	0.239	0.00
Sep-03	0.319	0.00	0.27	0.00	0.242	0.00
Dec-03	0.312	0.00	0.263	0.00	0.241	0.00
Mar-04	0.31	0.00	0.265	0.00	0.243	0.00
Jun-04	0.301	0.00	0.257	0.00	0.234	0.00
Sep-04	0.303	0.00	0.257	0.00	0.234	0.00
Dec-04	0.295	0.00	0.255	0.00	0.223	0.00
Mar-05	0.287	0.00	0.249	0.00	0.218	0.00
Jun-05	0.286	0.00	0.249	0.00	0.219	0.00
Sep-05	0.281	0.00	0.246	0.00	0.216	0.00
Dec-05	0.291	0.00	0.25	0.00	0.22	0.00
Mar-06	0.295	0.00	0.248	0.00	0.227	0.00
Jun-06	0.312	0.00	0.258	0.00	0.236	0.00
Sep-06	0.311	0.00	0.254	0.00	0.231	0.00
Dec-06	0.319	0.00	0.267	0.00	0.245	0.00
Mar-07	0.322	0.00	0.269	0.00	0.246	0.00
Jun-07	0.324	0.00	0.261	0.00	0.238	0.00
Sep-07	0.324	0.00	0.262	0.00	0.241	0.00
Dec-07	0.303	0.00	0.255	0.00	0.23	0.00
Mar-08	0.292	0.00	0.247	0.00	0.223	0.00
Jun-08	0.294	0.00	0.25	0.00	0.223	0.00
Sep-08	0.302	0.00	0.256	0.00	0.234	0.00
Dec-08	0.316	0.00	0.263	0.00	0.242	0.00
Mar-09	0.329	0.00	0.272	0.00	0.248	0.00
Jun-09	0.332	0.00	0.276	0.00	0.25	0.00
Sep-09	0.342	0.00	0.279	0.00	0.254	0.00
Dec-09	0.336	0.00	0.28	0.00	0.257	0.00
Mar-10	0.335	0.00	0.281	0.00	0.258	0.00
Jun-10	0.335	0.00	0.28	0.00	0.259	0.00
Sep-10	0.333	0.00	0.278	0.00	0.26	0.00
Dec-10	0.338	0.00	0.287	0.00	0.265	0.00
Mar-11	0.341	0.00	0.29	0.00	0.267	0.00
Jun-11	0.349	0.00	0.301	0.00	0.282	0.00
Sep-11	0.337	0.00	0.294	0.00	0.272	0.00
Dec-11	0.334	0.00	0.293	0.00	0.273	0.00

Office Sector

	5th nearest neighbour		8th nearest neighbour		10th nearest neighbour	
Dec-01	0.450	0.00	0.395	0.00	0.372	0.00
Mar-02	0.461	0.00	0.406	0.00	0.386	0.00
Jun-02	0.447	0.00	0.396	0.00	0.372	0.00
Sep-02	0.439	0.00	0.372	0.00	0.349	0.00
Dec-02	0.434	0.00	0.364	0.00	0.347	0.00
Mar-03	0.431	0.00	0.369	0.00	0.349	0.00
Jun-03	0.416	0.00	0.363	0.00	0.349	0.00
Sep-03	0.413	0.00	0.364	0.00	0.346	0.00
Dec-03	0.465	0.00	0.406	0.00	0.384	0.00
Mar-04	0.461	0.00	0.399	0.00	0.373	0.00
Jun-04	0.461	0.00	0.390	0.00	0.369	0.00
Sep-04	0.444	0.00	0.377	0.00	0.355	0.00
Dec-04	0.431	0.00	0.368	0.00	0.346	0.00
Mar-05	0.438	0.00	0.370	0.00	0.342	0.00
Jun-05	0.441	0.00	0.371	0.00	0.344	0.00
Sep-05	0.442	0.00	0.368	0.00	0.347	0.00
Dec-05	0.430	0.00	0.366	0.00	0.342	0.00
Mar-06	0.435	0.00	0.373	0.00	0.354	0.00
Jun-06	0.431	0.00	0.365	0.00	0.348	0.00
Sep-06	0.439	0.00	0.378	0.00	0.356	0.00
Dec-06	0.436	0.00	0.368	0.00	0.343	0.00
Mar-07	0.434	0.00	0.372	0.00	0.349	0.00
Jun-07	0.459	0.00	0.392	0.00	0.384	0.00
Sep-07	0.408	0.00	0.395	0.00	0.484	0.00
Dec-07	0.484	0.00	0.406	0.00	0.396	0.00
Mar-08	0.479	0.00	0.413	0.00	0.400	0.00
Jun-08	0.491	0.00	0.457	0.00	0.449	0.00
Sep-08	0.510	0.00	0.472	0.00	0.462	0.00
Dec-08	0.501	0.00	0.465	0.00	0.464	0.00
Mar-09	0.524	0.00	0.478	0.00	0.480	0.00
Jun-09	0.528	0.00	0.484	0.00	0.489	0.00
Sep-09	0.497	0.00	0.467	0.00	0.463	0.00
Dec-09	0.516	0.00	0.466	0.00	0.462	0.00
Mar-10	0.548	0.00	0.495	0.00	0.494	0.00
Jun-10	0.545	0.00	0.489	0.00	0.488	0.00
Sep-10	0.543	0.00	0.482	0.00	0.480	0.00
Dec-10	0.534	0.00	0.473	0.00	0.472	0.00
Mar-11	0.523	0.00	0.471	0.00	0.466	0.00
Jun-11	0.513	0.00	0.461	0.00	0.458	0.00
Sep-11	0.490	0.00	0.443	0.00	0.452	0.00
Dec-11	0.487	0.00	0.449	0.00	0.461	0.00

Industrial Sector

	5^{th} nearest neighbour		8^{th} nearest neighbour		10^{th} nearest neighbour	
Dec-01	0.091	0.025	0.053	0.059	0.061	0.023
Mar-02	0.113	0.008	0.070	0.022	0.064	0.019
Jun-02	0.125	0.006	0.077	0.021	0.054	0.042
Sep-02	0.105	0.016	0.060	0.046	0.038	0.094
Dec-02	0.104	0.017	0.071	0.026	0.060	0.028
Mar-03	0.100	0.020	0.073	0.024	0.059	0.030
Jun-03	0.190	0.00	0.175	0.00	0.173	0.00
Sep-03	0.177	0.00	0.165	0.00	0.162	0.00
Dec-03	0.234	0.00	0.223	0.00	0.213	0.00
Mar-04	0.328	0.00	0.291	0.00	0.268	0.00
Jun-04	0.242	0.00	0.194	0.00	0.174	0.00
Sep-04	0.238	0.00	0.210	0.00	0.178	0.00
Dec-04	0.252	0.00	0.220	0.00	0.190	0.00
Mar-05	0.238	0.00	0.214	0.00	0.187	0.00
Jun-05	0.250	0.00	0.230	0.00	0.209	0.00
Sep-05	0.184	0.00	0.183	0.00	0.174	0.00
Dec-05	0.170	0.00	0.156	0.00	0.143	0.00
Mar-06	0.151	0.00	0.140	0.00	0.128	0.00
Jun-06	0.304	0.00	0.278	0.00	0.282	0.00
Sep-06	0.330	0.00	0.293	0.00	0.299	0.00
Dec-06	0.386	0.00	0.343	0.00	0.330	0.00
Mar-07	0.397	0.00	0.349	0.00	0.336	0.00
Jun-07	0.401	0.00	0.360	0.00	0.346	0.00
Sep-07	0.421	0.00	0.384	0.00	0.369	0.00
Dec-07	0.422	0.00	0.416	0.00	0.410	0.00
Mar-08	0.541	0.00	0.554	0.00	0.508	0.00
Jun-08	0.512	0.00	0.504	0.00	0.477	0.00
Sep-08	0.542	0.00	0.506	0.00	0.491	0.00
Dec-08	0.604	0.00	0.580	0.00	0.553	0.00
Mar-09	0.602	0.00	0.581	0.00	0.547	0.00
Jun-09	0.603	0.00	0.593	0.00	0.557	0.00
Sep-09	0.608	0.00	0.599	0.00	0.563	0.00
Dec-09	0.480	0.00	0.464	0.00	0.444	0.00
Mar-10	0.488	0.00	0.469	0.00	0.456	0.00
Jun-10	0.489	0.00	0.475	0.00	0.452	0.00
Sep-10	0.481	0.00	0.468	0.00	0.449	0.00
Dec-10	0.156	0.00	0.140	0.00	0.133	0.00
Mar-11	0.156	0.00	0.140	0.00	0.133	0.00
Jun-11	0.159	0.00	0.144	0.00	0.139	0.00
Sep-11	0.171	0.00	0.174	0.00	0.154	0.00
Dec-11	0.208	0.00	0.224	0.00	0.205	0.00

Residential Sector

	5th nearest neighbour		8th nearest neighbour		10th nearest neighbour	
Mar-05	0.094	0.056	0.029	0.116	0.016	0.115
Jun-05	0.096	0.054	0.073	0.026	0.035	0.051
Sep-05	0.151	0.001	0.084	0.006	0.049	0.034
Dec-05	0.173	0.00	0.101	0.001	0.064	0.008
Mar-06	0.180	0.00	0.109	0.00	0.095	0.00
Jun-06	0.182	0.00	0.112	0.00	0.090	0.00
Sep-06	0.183	0.00	0.111	0.00	0.089	0.00
Dec-06	0.183	0.00	0.112	0.00	0.089	0.00
Mar-07	0.183	0.00	0.113	0.00	0.089	0.00
Jun-07	0.182	0.00	0.113	0.00	0.088	0.00
Sep-07	0.186	0.00	0.115	0.00	0.090	0.00
Dec-07	0.377	0.00	0.232	0.00	0.176	0.00
Mar-08	0.375	0.00	0.180	0.00	0.379	0.00
Jun-08	0.379	0.00	0.230	0.00	0.179	0.00
Sep-08	0.377	0.00	0.230	0.00	0.179	0.00
Dec-08	0.375	0.00	0.228	0.00	0.178	0.00
Mar-09	0.090	0.00	0.225	0.00	0.177	0.00
Jun-09	0.088	0.00	0.224	0.00	0.175	0.00
Sep-09	0.177	0.00	0.105	0.00	0.082	0.00
Dec-09	0.071	0.017	0.074	0.003	0.076	0.001
Mar-10	0.054	0.043	0.056	0.012	0.065	0.002
Jun-10	0.044	0.075	0.046	0.032	0.065	0.002
Sep-10	0.104	0.001	0.085	0.001	0.085	0.000
Dec-10	0.098	0.001	0.084	0.001	0.081	0.00
Mar-11	0.135	0.00	0.113	0.00	0.110	0.00

Average Values

	Moran's I statistic-	P-value	Moran's I statistic-	P-value	Moran's I statistic-	P-value
Retail	**0.32**	**0.00**	**0.27**	**0.00**	**0.24**	**0.00**
Office	**0.47**	**0.00**	**0.41**	**0.00**	**0.40**	**0.00**
Industrial	**0.31**	**0.00**	**0.29**	**0.00**	**0.27**	**0.01**
Residential	**0.18**	**0.01**	**0.13**	**0.01**	**0.11**	**0.01**

Note : The Moran's I tests are performed using the 'spatgsa' Stata command.

Table 4 : Spatially-augmented model estimations

	ln val			ln Wval k=5			ln unit val			Model	
	coeff	Std. err.	P>|t|	coeff	std. err	P>|t|	coeff	Std. err.	P>|t|	Psd. R^2	No. obs.
Dec-01	0.998	0.00	0.00	-0.01	0.00	0.05	0.00	0.00	0.58	0.97	230
Mar-02	1.001	0.00	0.00	-0.01	0.00	0.22	0.00	0.00	0.11	0.97	209
Jun-02	0.983	0.00	0.00	-0.01	0.01	0.29	0.02	0.01	0.10	0.94	108
Sep-02	0.994	0.00	0.00	0.01	0.01	0.58	-0.01	0.01	0.09	0.95	126
Dec-02	0.999	0.00	0.00	0.01	0.01	0.22	-0.02	0.00	0.00	0.96	130
Mar-03	1.001	0.01	0.00	-0.02	0.02	0.32	0.00	0.01	0.83	0.96	100
Jun-03	0.999	0.01	0.00	-0.03	0.02	0.10	0.00	0.02	0.85	0.93	64
Sep-03	0.989	0.01	0.00	-0.01	0.03	0.74	0.02	0.02	0.15	0.93	65
Dec-03	0.998	0.01	0.00	0.00	0.02	0.99	0.01	0.01	0.22	0.97	88
Mar-04	1.001	0.00	0.00	0.00	0.01	0.79	0.00	0.01	0.66	0.97	71
Jun-04	0.991	0.03	0.00	0.07	0.08	0.41	-0.05	0.05	0.34	0.95	18
Sep-04	1.007	0.03	0.00	0.01	0.08	0.95	0.04	0.06	0.56	0.95	26
Dec-04	1.006	0.01	0.00	0.00	0.02	0.93	0.02	0.01	0.18	0.96	63
Mar-05	0.994	0.00	0.00	0.00	0.02	0.90	0.07	0.01	0.00	0.94	71
Jun-05	1.000	0.00	0.00	-0.10	0.02	0.00	0.10	0.01	0.00	0.92	45
Sep-05	0.986	0.00	0.00	0.03	0.01	0.05	0.01	0.01	0.49	0.96	78
Dec-05	0.999	0.00	0.00	-0.02	0.01	0.09	0.06	0.01	0.00	0.95	132
Mar-06	1.007	0.00	0.00	-0.01	0.02	0.72	0.05	0.01	0.00	0.93	95
Jun-06	0.995	0.02	0.00	-0.03	0.06	0.69	0.01	0.07	0.85	0.88	49
Sep-06	0.981	0.01	0.00	0.00	0.02	0.80	0.07	0.01	0.00	0.89	103
Dec-06	0.985	0.00	0.00	-0.02	0.01	0.20	0.03	0.01	0.00	0.93	145
Mar-07	0.969	0.01	0.00	-0.05	0.02	0.00	0.01	0.01	0.28	0.95	79
Jun-07	1.021	0.01	0.00	-0.07	0.04	0.12	0.05	0.03	0.10	0.96	17
Sep-07	1.015	0.01	0.00	0.07	0.04	0.07	-0.01	0.02	0.64	0.96	32
Dec-07	1.010	0.01	0.00	0.00	0.01	0.71	0.03	0.01	0.01	0.96	134
Mar-08	1.008	0.00	0.00	0.00	0.01	0.71	0.03	0.01	0.00	0.95	147
Jun-08	1.000	0.00	0.00	0.00	0.00	0.18	0.00	0.00	0.61	0.96	149
Sep-08	1.000	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.94	0.98	123
Dec-08	0.991	0.01	0.00	-0.03	0.02	0.07	0.02	0.01	0.07	0.97	43
Mar-09	0.992	0.01	0.00	-0.03	0.02	0.13	0.04	0.02	0.05	0.94	54
Jun-09	1.005	0.01	0.00	-0.03	0.02	0.16	0.02	0.02	0.23	0.92	37
Sep-09	1.004	0.01	0.00	-0.01	0.02	0.46	0.02	0.01	0.21	0.96	48
Dec-09	1.005	0.01	0.00	-0.01	0.02	0.67	0.01	0.01	0.30	0.97	67
Mar-10	1.001	0.01	0.00	0.01	0.03	0.73	0.00	0.02	0.90	0.97	44
Jun-10	0.969	0.01	0.00	0.07	0.02	0.00	0.06	0.02	0.02	0.97	19
Sep-10	0.975	0.01	0.00	0.09	0.02	0.00	0.08	0.02	0.00	0.95	21
Dec-10	0.998	0.00	0.00	-0.02	0.01	0.13	0.02	0.01	0.02	0.96	73
Mar-11	1.002	0.00	0.00	0.00	0.01	0.98	0.01	0.01	0.24	0.96	81
Jun-11	1.002	0.01	0.00	0.08	0.02	0.00	0.00	0.02	0.94	0.95	28

	ln val			ln Wval k=5			ln unit val			Model	
	coeff	Std. err.	P>|t|	coeff	std. err	P>|t|	coeff	Std. err.	P>|t|	Psd. R^2	No. obs.
Sep-11	0.999	0.04	0.00	0.08	0.11	0.47	0.02	0.09	0.86	0.92	27
Dec-11	0.964	0.01	0.00	-0.01	0.04	0.72	0.03	0.04	0.44	0.92	39

Notes: All models above are estimated including an intercept, Psd. R^2 designates the pseudo R^2 statistics.