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Dr. Ingrid Nappi-Choulet* and Dr. Tristan-Pierre Maury**

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* Professor, BNP Paribas Real Estate Chair Holder, ESSEC Business School, nappi@essec.fr
** Research Engineer, BNP Paribas Real Estate Chair, ESSEC Business School, maury@essec
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Abstract:
This paper applies the spatiotemporal hedonic approach to analysis of office transaction prices in the Paris property market (i.e. central Paris and its inner suburbs). The analysis focuses primarily on the market’s two main business districts (the CBD and the La Defense District). We find that spatial and temporal dependence effects are strongly present in these submarkets. Additionally, we propose a hybrid method for incorporating a temporal regime into the spatiotemporal autoregressive model proposed by Pace, Barry, Clapp and Rodriguez (1998). Regime switching around 1997 (i.e. in the presence of temporal heterogeneity) substantially affects the significance of spatial and temporal dependences. Finally, we build a new price index that incorporates both spatiotemporal dependences and temporal heterogeneity. This index differs strongly from the usual hedonic price index

Key Words:
Hedonic Prices
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Temporal Heterogeneity

Résumé :

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Introduction

The purpose of this study is to test for the presence of temporal heterogeneity in a hedonic model of office transaction prices for central Paris and its immediate suburbs. We propose an original methodology to estimate whether the hedonic parameters are temporally varying, and choose to address this question through a Spatiotemporal Autoregressive (STAR) hedonic model to additionally control for the presence of spatial and temporal correlation effects.

More precisely, on the question of time heterogeneity, we seek to determine whether it is valid to use a single STAR model for the whole Paris office market transaction price cycle from 1991 to 2005, and whether marginal price attributes, notably spatial and temporal autoregressive coefficients, have in fact altered along the price cycle. To do so, we intend to build a model that incorporates time-varying parameters into a STAR model and compare it to a standard hedonic model or a simple STAR setup.

The standard hedonic method is now widely used in real estate literature, especially for housing. Application of the hedonic method to the office property market is recent, and as a result there is only a small number of past studies. This is primarily explained by the difficulty of collecting the necessary data, as description of properties by their characteristics is generally less reliable for offices than for housing (Downs and Slade, 1999). However, the improvement in information quality since the 1990s has encouraged development of this type of analysis, which for the time being still covers only a limited number of markets.

The oldest and largest body of publications concerns rents. Although this paper’s aim is to analyze transaction prices, not rents, this first series of articles gives an interesting insight into the variables used (Brennan et al. 1984, and Mills 1992, for Chicago; Dunse and Jones 1998 on the market in Glasgow; Nagai et al., 2000, for the central Tokyo market; Sivitanidou 1995, for Los Angeles). Some studies focus on a specific aspect of rent determinants: architectural features of the buildings (Doiron et al., 1992; Hough and Kratz, 1983; Vandell and Lane, 1989); or the vacancy rate (Frew and Jud, 1988; Weathon and Torto, 1988; Sivitanides, 1997).

Research into office transactions and their prices remains extremely rare and primarily concerns US or Asian markets. The first application of the standard hedonic price method to the office property market appears to be the study by Colwell et al (1998) on Chicago and some of its surrounding area over the period 1986-1993, using a notary’s base of transaction prices. Downs and Slade (1999) also use a notarial database, covering the Phoenix market over the period 1987-1996: the objective is principally to compare the properties of indexes based on expert valuations and observed transactions. The study by Gatzlaff and Geltner (1998) proposes an office price index based on the repeat sales method as applied to Florida. Finally, Nappi-Choulet et al. (2007) is the sole study to propose a hedonic transaction-based estimation for the Paris region office market.
The standard hedonic procedure suffers from various shortcomings. In particular, the spatial and temporal dependence effects are neglected: two observations that are close in space or time might be correlated, and the omission of these correlation effects can lead to bias in coefficient estimates and/or heteroskedasticity issues.

There is a large body of literature in real estate on the introduction of spatial dependence effects into hedonic models (see for example Can, 1990, 1992), but the number of papers dealing with both spatial and temporal dependence effects remains very low. One notable exception is the paper by Pace et al. (1998), which proposes an original method to build a STAR model and finds it powerful in a residential real estate context. To our knowledge, the study by Tu et al. (2004) is the only spatiotemporal hedonic model applied to the office market, in this case the Singapore office market over the period 1992-2001. Those authors also propose a Bayesian STAR (B-STAR), to control additionally for heteroskedasticity.

However, the STAR method only provides a way to model spatial and temporal dependence, without controlling for heterogeneity. A general definition of heterogeneity could be that relationships between groups of variables might vary over space (spatial heterogeneity) or over time (temporal heterogeneity). In a hedonic regression, this would mean that parameter estimates might exhibit significant spatial and/or temporal variation and that ‘global’ coefficient estimates cannot be applied identically to a whole region or a whole time sample.

The existence of spatial heterogeneity has been well recognized in the literature since the seminal contribution of Tiebout (1956). Many papers propose testing procedures for spatial drifts: Clapp and Wang (2006) attempt to define neighborhood boundaries; Bourassa et al. (1999), Bourassa et al. (2003) and Ugarte et al. (2004) try to identify an appropriate procedure to endogenously define housing submarkets and check their statistical impact. Notice that we do not apply specific treatment for spatial heterogeneity, since extension of these methods does not appear straightforward in the case of a STAR model. Spatial discrepancies will be more simply taken into account by the usual submarket dummy variables.

The major aim of this paper is to try to detect temporal heterogeneity on the Paris office market. This question is particularly relevant given the large movements in transaction-based office price levels on this market for the period 1991-2005. We could reasonably expect to see that the hedonic parameters have in fact altered along the price cycle.

The importance of temporal heterogeneity has been much less widely discussed than spatial heterogeneity. Knight et al. (1995) relax the usual assumption of stability of attribute prices between time periods for housing hedonic price indexes. For the commercial real estate market, Munneke and Slade (2001) estimate a different model according to the year of transaction and then obtain time-varying parameters. We intend to extend these procedures in two ways: first, we control for temporal heterogeneity within the STAR model, since spatial and temporal effects appear to be significant; second, and more importantly, we propose a method to estimate temporal heterogeneity endogenously.

Following the endogenous determination method of temporal structural breaks which has been extensively studied in the time series literature (Andrews, 1993, Bai and Perron, 1998), we propose a way to obtain endogenous determination of a change point within a Bayesian STAR model. We then construct an original model that appears to outperform the standard hedonic and STAR models.
The paper is organized as follows. In the next section, we present the methodology for the three models and a description of the data set. Results are detailed in the following section, and the final section concludes.

Methodology

We first present the standard hedonic (Model I) and B-STAR (Model II) models before presenting our benchmark setup (Model III): a B-STAR model extended to control for temporal heterogeneity.

Standard OLS Estimation

We first use the traditional hedonic regression time-dummy approach for construction of the sale price index. This regression pools a sample of cross-sectional data concerning prices on one side and quality characteristics, spatial and time dummies on the other side. We have the following hedonic regression model (subsequently referred to as Model I):

\[
\ln(P_i) = \alpha + \sum_{k=1}^{K} \beta_k z_{i,k} + \sum_{j=2}^{L} \gamma_j l_{i,j} + \sum_{\tau=2}^{T} \delta_\tau d_{i,\tau} + \epsilon_i
\]  

The set of observations on properties is indexed \(i=1, 2, \ldots, N\) where \(N\) is the whole sample size. \(T\) is the number of time periods (i.e. number of years in our case). Data are temporally ordered. The first period (reference period) is 1991. \(L\) is the number of spatial submarkets. The first is the reference submarket. \(\ln(P_i)\) is the logarithm of sale price. \(z_{i,k}\) corresponds to the \(k^{th}\) characteristic of property \(i\). \(d_{i,\tau}\) equals one if property \(i\) is sold during time period \(\tau\) and \(l_{i,j}\) is equal to one if property \(i\) has been sold in submarket \(j\). \(\epsilon_i\) is the residual term.

This equation is estimated using the standard OLS technique, where the potential heteroskedasticity of residuals has been taken into account with a robust covariance matrix estimated using White’s (1980) method. Notice that in our case, we started by endogenously estimating the functional form of the sale price and the continuous explanatory variables (i.e. transaction area in square meters) using the Box-Cox methodology. This estimation delivers parameter estimates for the functional form of the sale price that are not significantly different from the logarithm form chosen earlier.

After estimating this regression, the hedonic price index can be calculated very easily and directly by taking the exponential of the time-dummy coefficients and adjusting for the variance of these estimated coefficients (see for example Kennedy, 1981, for cases where errors are assumed to follow a log-normal process). If the parameter estimates are
very accurate, the hedonic price index may be correctly approximated by the following equation:

\[ I_{t,\tau}^{\text{OLS}} \approx \exp(\delta_{\tau} - \delta_{t}) \]  

Then the estimated price index for period \( \tau \) relative to period \( t \) is simply, up to an approximation, the exponential of the time-dummy coefficients. It does not depend on the value of the chosen structural characteristics, nor does it depend on the chosen submarket. Hence, the temporal evolution is the same, whatever the property considered. This method has two main shortcomings:

- First, the well-known problem of spatial (and henceforth spatiotemporal) autocorrelation is neglected. As explained by Anselin (1988) or Can (1990), the presence of spatial dependence deeply affects the estimation of structural characteristics coefficients, and consequently the pattern of the price index. More precisely, two kinds of spatial dependence could potentially affect the analysis. The first occurs when, for example, prices move together due to spatially correlated unobservable variables, leading to a lack of stochastic independence among observations. The error term will be spatially correlated and this problem will lead to inefficient estimates. The second occurs when a spatial correlation in the dependent variable is present. Such dependence leads to both biased and inefficient estimates (see Anselin, 1988, for a further discussion on this question). This second form of dependence has been considerably emphasized in housing literature (see for example, Pace et al. 1998), but much less in the office transaction literature (Tu et al., 2004, being an exception for the Office Singapore Market). We will develop a B-STAR model (Model II) to check for the statistical impact of spatial and temporal correlative effects in our database.

- Second, spatial and temporal heterogeneity are poorly modeled in equation (1) since the coefficients of structural characteristics variables, i.e. \( \beta_j \), might be spatially or temporally dependent. The problem of spatial heterogeneity is now deeply documented (see Anselin, 1990 for a survey) and the problem of temporal heterogeneity, i.e. time-varying parameters, has been extensively discussed in the time series literature. The omission of these effects could lead to serious bias in coefficient estimates, and consequently misinterpretation in evaluating the statistical impact of certain explanatory variables on transaction prices.

These two shortcomings have already been considered by Can’s (1992) distinction between adjacency and neighborhood effects. Adjacency effects are externalities associated with the absolute location of the structure. They refer to the external effects of nearby properties on the considered property (i.e. spatial dependence). Neighborhood effects are the array of locational characteristics that will lead to differential office demand for certain locations (i.e. spatial heterogeneity). Neighborhood effects can lead to varying marginal attribute prices. Can (1990) uses Casetti’s (1972) spatial expansion method where the structural parameters of the model are no longer invariant and drift across space. In this setup, the price determination equation depends on neighborhood quality and hedonic prices are spatially varying.
Moreover, Can (1990) explains that if nearby property prices are similar only because they share common locational factors (neighborhood effects), then the spatial expansion method will help reduce spatial autocorrelation. But if the prices of nearby properties have an absolute effect on each other (adjacency effects), then there will be a need to incorporate an autoregressive term in the model to correct for spatial autocorrelation. Then adjacency and neighborhood effects are distinct phenomena and each one should be specifically modeled.

Although there is now widespread awareness of these two shortcomings of Model I, they are rarely considered and corrected in conjunction with each other. Numerous tests on parameter instability in the presence of spatial autocorrelation or heteroskedasticity are available (see Kelejian and Robison, 1992), but spatial-temporal autocorrelation and spatial-temporal heterogeneity have rarely been considered together in a housing or non-residential real estate context. In a housing context, Gelfand et al. (2004) propose a way to incorporate spatial information when explaining the temporal evolution of house prices within a Bayesian setup. They build a very general class of spatiotemporal models containing all kinds of spatial and temporal autocorrelation with time-varying parameters. In Model III, we will propose an original procedure to endogenously estimate the date of the change point within a Bayesian STAR setup for the case of the Paris office market.

**Spatial-Temporal Estimation Procedure**

We now present the STAR model by Pace et al. (1998) and its extension to a Bayesian setup. We first adjust equation (1) by adding spatial and temporal autoregressive terms to correct for the well-known spatiotemporal dependence problem. Adding these terms will also allow for different index patterns at each point in time and space and then provide a correction for one of the two above concerns.

We start by a short presentation of Pace, Barry, Clapp and Rodriguez (1998)’s spatiotemporal estimation procedure. Pace et al.’s (1998) method is not the only one to deal with spatiotemporal dependence effects. Can and Megbolugbe (1997), for example, also propose a method that specifies the extent of influence which a prior sale within a predetermined neighborhood might have on a current transaction price. Their method is thus quite close to the method proposed by Pace et al. (1998) but, as we will see later, Pace et al. (1998) use the time ordered structure of the data set to deeply reduce the computation time of the estimation process. As we will rely on Bayesian estimation procedures which can be very time-consuming, Pace et al.’s (1998) method is useful in our context.

We proceed to a short presentation of Pace et al. (1998)’s spatiotemporal estimation procedure (Model II). They assume the following autoregressive process:

\[(I-W)P = (I-W)X\beta + \epsilon\]  

(3)
where \( P \) is the \( N \) by 1 vector of observations of the time-ordered dependent variable, which is the log of sale price in our case. \( X \) denotes the \( N \) by \( K \) matrix of observations on the independent variables of interest. \( X \) is quite similar to the matrix of independent variables from equation (1), but temporal and spatial dummies are usually excluded from this matrix. In this paper, we will consider two cases:

- First case (Model IIa): \( X \) contains only the structural characteristics of each property.
- Second case (Model IIb): \( X \) contains all the structural characteristics of each property plus all the spatial and temporal dummy variables included in Model I. Model IIb is used to account for both spatiotemporal autocorrelation and spatiotemporal heterogeneity in the intercept. Among others, Pace and Lesage (2004) demonstrate the importance of simultaneously accounting for dependence and heterogeneity effects (not only in the intercept). But as explained by Bourassa et al. (2007), the concepts of spatial dependence and spatial submarkets are closely related. The inclusion of spatial submarket dummy variables might correct a large portion of residual spatial autocorrelation. Accounting for both spatial dummies (i.e. the impact of the specific location of a property within prespecified spatial boundaries) and spatial autocorrelation (i.e. the relationship between spatially close transactions), even though these are two theoretically distinct concepts, may lead to multicollinearity problems. However, due to the large size of our database, this problem is of very small consequence in our case.

\( \beta \) is the \( K \) by 1 vector of parameter. \( \varepsilon \) is an \( N \) by 1 vector of errors. For the moment, the errors are not assumed to follow any specified law of motion.

Let us focus on the \( N \) by \( N \) spatial-temporal matrix \( W \). In a purely spatial CAR or SAR context (see for example Lesage, 1999 for a full discussion), \( W \) contains non-negative elements of neighboring properties. It is generally denoted as the spatial weight matrix. The diagonal entries of \( W \) contain zeros to prevent each observation from predicting itself.

Pace et al. (1998) argue that in a temporal context, multiplying independent and dependent variables by the spatial weight matrix does not remove all autocorrelation effects. It comes down to taking the values of sale prices at each location and subtracting a scaled average of the spatially surrounding values for geocoding coordinates. But these surrounding values may correspond to old office transactions that do not contribute much relevant information for the transaction of interest.

As a result, we also need to take into account previous sale transactions, and subtract their values from the current transaction. As noted by Gelfand et al. (1998), the choice of a weighting matrix \( W \) that incorporates both spatial and temporal autocorrelation effects is not an easy task: they finally choose to include ordinary temporal dummies to cover the temporal effect. Pace et al. (1998) propose another estimation method. They implement a spatiotemporal filtering matrix \( W \) that can be broken down into \( S \), a matrix that specifies spatial relationships between previous observations (observations have been time ordered) and \( T \), that specifies temporal relationships between previous observations. Each line of these matrices is scaled by constants that sum to one. The autoregressive parameters are supposed to be less than one in absolute value. This point may be crucial, since as already noted by Fingleton (1999), spatial unit roots lead to spurious spatial regression, exactly as in the time series literature. Fingleton’s (1999) theoretical benchmark can easily be extended to a spatiotemporal context.
A general specification of matrix $W$ could be:

$$W = \phi_S S + \phi_T T + \phi_{ST} ST + \phi_{TS} TS$$  \hspace{1cm} (4)$$

This specification incorporates a linear combination of spatial and temporal filtering. Additionally, the interaction matrices $ST$ and $TS$ allow for the modeling of potentially compound spatiotemporal effects. $\phi_S$ and $\phi_T$ are spatial and temporal dependence parameters. $\phi_{ST}$ and $\phi_{TS}$ are spatiotemporal compound dependence parameters.

The spatial weight matrix is specified as done by Tu et al. (2004) using a distance-decay scheme. Let $i, j$ indicate the $i^{th}$ row and the $j^{th}$ column in the spatial matrix. $S$ is constructed as follows:

$$S_{i,j} = \left(1 - \frac{(d_{ij} / D_{i,q+1})^3}{\omega_j}\right)$$  \hspace{1cm} if \hspace{0.5cm} (d_{ij} < D_{i,q+1}) \hspace{0.5cm} and \hspace{0.5cm} (j < i)$$

$$S_{i,j} = 0 \hspace{1cm} otherwise$$

$d_{ij}$ is the distance between transaction $i$ and earlier transaction $j$, since our dataset is temporally ordered. $D_{i,q+1}$ is the $q+1^{st}$ shortest distance between transaction $i$ and the buildings where prior transactions are located, within the same spatial submarket as transaction $i$. $\omega$ is the speed of distance decaying.

The temporal weight matrix $T$ is expressed as follows:

$$T_{i,j} = \frac{1}{p} \hspace{1cm} if \hspace{0.5cm} i-p \leq j < i$$

$$T_{i,j} = 0 \hspace{1cm} otherwise$$

where $p$ is the time lag. Since the data set is temporally ordered, the temporal weight term is just the mean of the $p$ earlier transactions.
The forms of $S$ and $T$ are restricted in order to obtain strictly lower triangular matrices (with zero entries for diagonal elements). This property will be very useful for maximization of the log-likelihood function (if errors are assumed to follow a Gaussian process), since it avoids the time-consuming computation of the determinant term (see Pace, 1997, and Pace and Barry, 1997, for computational considerations on this point).

Another specificity of this method is that the spatial neighborhood is estimated only within prior sales, whereas in the traditional spatial literature, the spatial neighborhood consists of all transactions within a short distance of the transaction under consideration. Hence, in Pace et al. (1998) the spatial matrix $S$ can itself be considered as a spatial-temporal matrix. According to a previous analysis of the dataset, we determine the values of $q$ and $p$ within the $S$ and $T$ matrices and impose $q=25$ and $p=55$.

We do not specify the spatial matrix $S$ in the same manner as Pace et al. (1998). We require the spatial neighborhood defined by $S$ for each transaction to be included in the spatial submarket where transaction $i$ is located. Thus, for each transaction $i$, the spatial matrix $S$ defines a neighborhood including the closest transactions that occurred in the same prespecified spatial submarket as transaction $i$. This procedure will enable us to disentangle the impact of this variable on office prices with that of the spatial submarket dummy variables in Model IIb. The spatial dummy variable will control for drift across submarkets and the spatial matrix $S$ will control for the remaining correlation within each submarket. The spatial submarket boundaries will be presented in detail in the Data Collection section.

Finally, Pace et al. (1998) assume a more general specification than equation (4) and estimate:

$$
P = X\beta_1 + TX\beta_2 + SX\beta_3 + STX\beta_4 \\
+ TSX\beta_5 + \phi_1 SP + \phi_2 TP + \phi_3 STP + \phi_4 TSP + \varepsilon
$$

(5)

where $\beta_1, \ldots, \beta_4$ are $K$ by 1 vectors of parameters. Pace et al. (1998) estimate equation (5) using a standard OLS procedure. Following Tu et al. (2004) we use a Bayesian estimation procedure instead (Model II or B-STAR for Bayesian Spatiotemporal Autoregressive Regression). Lesage (1999) has shown that Bayesian spatial autoregressive models are of particular relevance. It is well known that Bayesian regression methods implemented with diffuse, non-informative prior information can replicate maximum likelihood estimation results. Lesage (1999) adopts the approach taken by Geweke (1993) to extend the spatial autoregressive models. Tu et al. (2004) extend this method to a spatiotemporal autoregressive model. Like Geweke (1993), they model residual heteroskedasticity by assuming:

$$
\pi(\varepsilon) = N(0, \sigma^2 V)
$$

Where $V$ is a $N$ by $N$ matrix defined as

$$
V = \text{diag}(v_1, v_2, \ldots, v_N)
$$

The problem of estimating the $N$ parameters $v_1, v_2, \ldots, v_N$ in addition to the rest of the parameters with only $N$ data observations cannot be solved with classical econometric procedures. Bayesian methods do not have the same degree-of-freedom constraints.
since they use prior information for these parameters. The chosen prior for the \(v_1, v_2, ..., v_n\) parameters is the same as Lesage (1999).

\[
\pi(r / v_i) = \chi^2(r)
\]

where \(r\) is a hyperparameter following a prior Gamma distribution. \(\sigma\) follows a diffuse prior. Finally, \(\beta\) follows a multivariate normal prior with diffuse mean and variance.

We will see in the following subsection how heteroskedasticity matters in spatial hedonic models in real estate. The rest of the parameters follow the same prior distribution as in Geweke (1993).

The posterior distribution of all parameters is directly deduced from Lesage (1999). The presence of an additional temporal effect matrix \(T\) and compound effects matrices \(ST\) and \(TS\) in addition to the usual spatial matrix has absolutely no impact on the analytic formula of the conditional distribution of the parameters.

Since the unconditional posterior distribution of the parameters cannot be analytically deduced from the conditional formula, we use the Markov Chain Monte Carlo (MCMC) approach. More precisely, we will rely on Gibbs sampling, following the work of Geman and Geman (1984) in image analysis. This approach partitions the vector of parameters and draws each parameter (or block of parameters, as we will see later) from the conditional distribution using the initialization of the parameter vector. Once a new sample is drawn, it replaces the initialized vector. Geman and Geman (1984) demonstrated that this stochastic process represents a Markov Chain with the correct equilibrium distribution.

We deduce a posterior distribution for each parameter of equation (5) and for the parameters on the distribution of the residuals.

**Heterogeneity**

The previous estimation procedure is general enough to assess for spatial and temporal autocorrelation effects. However, it does not propose a modeling scheme for heterogeneity. Our aim is to propose an endogenous way to assess for temporal heterogeneity within a B-STAR model.

Notice that we do not include an endogenous detection procedure for the presence of spatial heterogeneity, since the most recent techniques (see Clapp and Wang, 2006) cannot be directly applied in our B-STAR setup. The question of the optimal definition of endogenous neighborhood boundaries goes far beyond the scope of this paper. Nevertheless, the inclusion of spatial and temporal dummy variables will enable us to control for spatial and temporal drifts in the intercept.
The main idea of this paper is that we expect an endogenous detection technique for temporal heterogeneity to be highly relevant for the Paris office market, due to the large swings in price levels observed between 1991 and 2005.

The theoretical foundations of temporal heterogeneity rely on the idea that marginal price attributes may change over time in response to exogenous macroeconomic factors (technological changes or movements in interest rates or income), or as a result of transportation or real estate development decisions that will affect the desirability of a specific characteristic. For example, certain service sectors might have a greater demand for recent buildings or large floor plates, and sudden growth in those sectors’ business might affect the overall desirability of recent buildings or the marginal price of floor plates. Gelfand et al. (1998) also show that the desirability of a specific location may itself change over time in response to a variety of micro-market changes. The construction of a road may alter the accessibility of a property location, and in such a case, the contribution of location to the overall property value will be modified.

Knight et al. (1995) provide a time-varying parameter technique in a housing hedonic model to account for temporal heterogeneity. In a non-residential real estate context, Munneke and Slade (2001), propose three different methods (chained, Laspeyres and Paasche indexes) to evaluate temporal heterogeneity effects by proceeding to different estimations for each year of transaction. But Munneke and Slade (2001) work with a traditional hedonic model, not a spatiotemporal autoregressive model.

An alternative procedure for controlling for heterogeneity is the random coefficient approach introduced by Hildreth and Houck (1968), where the coefficient estimates are randomly varying around an intercept. That model itself is not spatial or temporal, but has been extended by Can (1982) and Casetti and Can (1998) to DARP (“Drift Analysis of Regression Parameters”) analysis. The literature on random coefficient models is generally concerned with capturing spatial drifts in parameters. Each hedonic parameter is a stochastic variable evolving around a spatial drift, which depends on structural and locational attributes of the considered property. This method attempts to estimate a spatial surface for parameters rather than identifying explicit boundaries. Goodman and Thibodeau (1998, 2003), however, use this methodology for housing market segmentation. They examine a two-level hierarchical model of house price determination with random coefficients. The hedonic coefficients of the structural characteristics are assumed to vary across submarkets. The authors then test for optimal submarket segmentation.

In the case of temporal heterogeneity, Gelfand et al. (1998, 2004), relying on the random coefficient models within a Bayesian framework, propose a temporally varying estimation of the posterior distribution of hedonic parameters. They build a house price index that appears to be deeply affected by the temporal evolution of marginal price attributes.

Our main objective in this paper is to propose a way to endogenously detect heterogeneity when relying on a STAR model. We want to test whether the parameters of equation (5), and in particular the spatial and temporal autoregressive parameters, are statistically stable over the whole time sample from 1991 to 2005. More precisely, we investigate the question of the relative weight of autoregressive variables and structural characteristics over the time sample. We have a strong expectation that there was a downward phase from 1991 to 1997 followed by an upward phase from 1997 to 2005 (although this point will be confirmed by the estimation) and we want to know if the
relative importance of spatial and temporal neighbors is the same between these two time subsamples.

Our objective is thus to produce a mixed model that covers both temporal heterogeneity, since that appears to be an important factor for commercial real estate, and spatiotemporal autocorrelation effects, since they are widely acknowledged to deeply influence transaction prices in residential and non-residential real estate.

As for Models IIa and IIb, this model will be estimated without (Model IIIa) and with (Model IIIb) spatial and temporal dummy variables.

We proceed as follows:

First step: Data are temporally ordered and the dataset is broken down into 2 subsequent temporal segments. The structural break date $\tau$ will be endogenously determined. This means that we use a change point model procedure to determine significant changes in parameter slopes. Notice that we restrict our estimates to one structural break, since each new change point deeply increases the number of parameters to be estimated: a new set of structural characteristics parameters ($\beta$) and a new set of autoregressive parameters ($\phi$). This increases the computation time for our Bayesian estimation procedure.

Second step: We run a spatiotemporal regression for each time segment following our Bayesian estimation procedure and allowing for residual heteroskedasticity:

$$
\begin{align*}
P &= X\beta_1 + TX\beta_2 + SX\beta_3 + STX\beta_4 + TSP + \phi_{1,\tau}T + \phi_{3,\tau}ST + \phi_{7,\tau}TSP + \epsilon
\end{align*}
$$

(6)

Each parameter differs according to the date of the transaction $t$, i.e. whether $t \leq \tau$ or $t > \tau$.

If the number of points in each subsample is too small, the estimates could be unreliable. $\tau$ is endogenously determined, as is now usual in the time series literature (see Bai and Perron, 1998) and the timing of the structural break should also be endogenously determined (see for example Andrews, 1993). Andrews (1993) or Bai and Perron (1998) employ testing procedures relying on the supremum Wald statistic. But these tests are not directly extendable to a spatial context with irregular transactions on the time segment. Some papers choose to use standard Wald statistics in a spatially autoregressive setup (Anselin, 1990, see for example Le Gallo and Dall’Arbella, 2006 for an application). However, these procedures do not allow for endogenous determination of the structural break.

We therefore propose a new sequential procedure to endogenously determine $\tau$, the date of the change point. Following Carlin, Gelfand and Smith (1992), we consider $\tau$ as another parameter to be estimated within our Bayesian procedure. We apply the Gibbs sampler procedure already described, and also draw a sample for the change point $\tau$ and derive an unconditional posterior distribution for this parameter. To do so, we draw the change point from the discrete distribution:
\[ p(\tau = t / Y, \beta, \phi) = \frac{L(\tau = t / Y, \beta, \phi)}{\sum L(\tau = t / Y, \beta, \phi)} \]

where \( Y \) is the set of all observable variables, \( \beta \) is the set of structural characteristics parameters and \( \phi \) the set of autoregressive parameters (both depend on \( \tau \) according to equation 6). \( L(.) \) is the likelihood of \( \tau \) and has to be evaluated at each time point for each Gibbs sampler step. This procedure has been applied by Western and Kleykamp (2004) in a historical time series context. The results of the Gibbs sampling can be compared to Chin Choy and Broemeling’s (1980) analytical derivation for the marginal posterior distribution of parameter \( \tau \).

Hence, this procedure considers \( \tau \) as a stochastic parameter and delivers a marginal posterior distribution of that parameter.

Third step: An overall price index is built using the standard techniques developed by Munneke and Slade (for time varying chained price indexes). The index construction procedure is made more complicated by the Bayesian estimation procedure, since we have to use the posterior distribution of the whole set of parameters. We follow Gelfand et al. (2004) and construct an index at each point in time and space for each observed log of selling price.

We summarize all the models to be estimated:

- Model I: Standard OLS hedonic regression with spatial and temporal dummies (no spatiotemporal autocorrelation or heterogeneity).
- Models IIa and IIb: Pace et al.’s (1998) spatiotemporal model. Bayesian estimation procedure with heteroskedasticity. Heterogeneity is neglected, but spatial and temporal dummy variables are included for Model IIb.
- Models IIIa and IIIb: benchmark model. Model II is extended to consider endogenous temporal heterogeneity within our Bayesian setup. Spatial and temporal dummy variables are included for Model IIIb.

Data Collection

The Paris Office Market

Of the 47 million m² of office space in the Paris region listed by the business property observer Observatoire Régional de l’Immobilier d’Entreprise at January 1, 2004 (ORIE 2005), almost three quarters (38.4 million m²) are located in Paris and the
three départements (France’s administrative units) making up the city’s immediate suburbs. Central Paris (with 16 million m²) contains approximately one third of the region’s total office space. The 21 towns directly bordering Paris offer nearly 7 million m², or 36% of the total immediate suburb office space and 14% of the total regional office space, and together with Paris account for almost half of all Paris region office space in 2004. As the ORIE points out, while the amount of office space in the Paris region more than doubled between 1975 and 2004, more than half of this growth concerned the immediate suburbs; in other words, Paris office work is highly polarised in its central zone and the city’s immediate suburbs.

Turning to the office property markets and market sale and rental values for Paris and the immediate suburbs, the Immostat¹ data show that several submarkets exist. Details of the four largest submarkets, with the highest market sale and rental values, are given below (Figures 1 and 2).

**The Paris Central Business District (CBD):**

With total office space of 8.5 million m², this sector covers almost all of the 8th arrondissement and part of the 1st, 2nd, 9th, 16th and 17th arrondissements². The CBD alone contains approximately half of central Paris’ tertiary property, and offers users the capital’s most prestigious office blocks.

**Paris’ “Golden Triangle”:**

This micro-market is internal to the Paris CBD. It lies essentially in the 8th arrondissement, bounded by the Arc de Triomphe, Place de la Concorde and Avenue d’Iéna. The region’s most expensive office buildings are concentrated here, generally six to eight-storey Haussmannian³ buildings. This privileged part of the French capital, which alone contains over 3 million m² of office space, was the setting for most of the massive-scale property renovation operations of the late 1980s turning buildings into business centres of 20,000 to 50,000 m², at prices in excess of 15,000 euros/m² (head offices of NMPP, Philips, Péchiney, etc).

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¹ Immostat is an Economic Interest Grouping which since 2001 has collated data on office transactions and office rental values supplied by its five founding real estate consultancy firms: ATISREAL Auguste Thouard, CB Richard Ellis, Insignia Bourdais, DTZ Jean Thouard and Jones Lang LaSalle

² Just as France is divided into “départements”, geographical and administrative units, Paris is divided into 20 districts or “arrondissements”.

³ Prestigious buildings of a style named after the Baron Haussmann who oversaw the modernisation of Paris in the second half of the 19th century.
The “Golden Crescent” or western business district

This market covers the towns immediately on Paris’ western borders, from Issy-les-Moulineaux to Levallois-Perret, where office developments accounted for up to 70% of planning permission granted in the region in the late 1980s. Today these towns offer office space of between 500,000 m² and 1.4 million m². With variations for individual years, the sector represents approximately 20% of rental demand in the Paris region.

La Défense:

Created in 1958 on land belonging to the three towns of Puteaux, Courbevoie and Nanterre, the most intense development of La Défense business district took place between 1985 and 1992, and since 2000. This major business district, which owes its existence entirely to the public authorities, now offers 3 million m² of office space. La Défense quickly became one of the few areas in the Paris region to concentrate its standardised, generally very high-rise office buildings, offering a wide range of amenities from divisibility of floors to basement parking. With variations for individual years, this market represents approximately 9-10% of rental demand for the Paris region.

(Insert Figures 1 and 2)

The Paris region office market experienced an unprecedented over-supply crisis and real estate recession during the period between 1991 and 1996. This recession was mainly caused by deregulation of the planning approvals procedure, but also by the banking system, which financed speculative development projects in the late 1980s without demanding any collateral. This office market crisis resulted in a significant fall in both rental and capital values, which dropped by two thirds between 1990 and 1995, leading to ruin for both operators and their financial backers.

The first investors to return to the French market after the crisis were North American opportunity and private funds. Skilled in investing against the business cycle, they bought huge portfolios which had been owned by now bankrupt companies and were on the market at bargain prices. These funds benefited from this strategy and made large capital gains from 1995 to 1999, when high levels of demand caused a 40-50% surge in the rental values of "prime" offices.

By 2006, the commercial property market had recovered from the slump of the mid-1990s and international investors had developed a considerable interest in French commercial property markets. The property investment market in the Paris region had seen a spectacular reversal of its downward trend, with several factors contributing simultaneously. First, the reduction of registration duties on property sales (from 20% to
4.80% on transfers of both buildings and real estate companies) increased their attractiveness. Second, low interest rates made it possible to offer attractive internal rates of return, encouraging investors to borrow large sums in addition to using their own capital.

**Data Description**

The working data set on property sales comes from the Paris Chamber of Notaries. In France, all property sales have to be registered by a Notary, who collects the realty transfer fee to be paid to the Inland Revenue. These transaction data have been gathered by the Paris Chamber of Notaries since the mid-1990s and are published by the CINF ("Chambre Interdépartementale des Notaires de Paris"). The database includes information on the transaction price, along with detailed characteristics (size, period of construction, etc.).

From this CINF dataset, we have a large sample of transaction prices for Paris and its inner suburbs between January 1991 and October 2005. This data set has frequently been used for academic research into the Parisian housing market.

This study, however, is the first to focus on an extract from the CINF data set for Paris region office transactions. Additionally, the exact geocoded X–Y coordinates provided for each transaction enable us to conduct the spatiotemporal procedures described earlier.

The data set consists of 6,812 office unit transactions between 1991 and 2005. The CINF also gives information on the coverage rates of their data, which is approximately 70% for the whole office sample, but much higher for the Paris CBD (more than 75% whatever the year considered) than for some geographical areas in the Paris suburbs.

After deleting incomplete records, missing data and significant outliers, 2,516 data are available for analysis. We check for sample selection bias with a standard Chi-square testing procedure. These tests strongly reject the null hypothesis of similar distributions. However, the size difference between the two samples comes principally from missing transaction areas. Since it is not appropriate to reject this variable (it explained almost half of the variance of transaction prices in a standard OLS hedonic regression), we keep the corrected sample. In a technical appendix available upon request, we show that the estimates of the main parameters are not deeply affected by the size of the sample (when the transaction area is entered as a qualitative variable with a special class for a missing area).

Because the coverage rates for the CINF database are much less satisfactory for La Défense business district (below 60% whatever the year considered) than for the Paris CBD, we complete our data sample for La Défense.

To do so, we use specific data from EPAD, ("Etablissement Public d’Aménagement de la Défense"), the public development agency for the site, and complete these with
personal enquiries. This resulted in 71 additional data. Our complete data set thus consists of 2,587 office unit transactions between 1991 and 2005.

The main objective of this paper is to focus analysis on the whole Paris Region, but we will also produce specific estimates for the two main business districts of the Paris region office property market: the Paris Central Business District (including the famous “Golden Triangle” presented earlier) and the La Défense business district.

Table 1 presents the descriptive statistics for the sample.

[Insert Table 1]

The main explanatory variables are listed below.

**The transaction area:** The coverage rate for this variable is very low (slightly above 41%) as already mentioned. This variable is responsible for the large drop in our sample size.

**The period of construction of the building:** This is a qualitative variable. It indicates whether the building was erected before 1850, between 1850 and 1913 (the Haussmannian period), between 1914 and 1947, between 1948 and 1969, between 1970 and 1980, between 1981 and 1991, between 1992 and 2000 or since 2001. This variable comes directly from the notary’s office. The exact year of construction is not stated. Notice that this variable does not take into account any renovation of the building: it corresponds to the initial construction period of the building. The coverage rate for this variable is 100%.

**Type of transaction:** This is a qualitative variable indicating whether the transaction concerns the whole building or just part of the building. The coverage rate for this variable is 100%.

**New construction property:** This is a qualitative variable indicating whether or not the building has been renovated/restructured. This variable is important since it contributes information on the quality of the building’s amenities, and complements the period of construction. The coverage rate for this variable is 100%.

**The transaction date:** day, month and year.

**Location of the building:** We have access to the exact X-Y geocoding coordinates of each building in our data sample. These coordinates will be used for Models II (a and b) and Models III (a and b). For Model I, we use the geographical boundaries proposed by Immostat. We distinguish different geographical submarkets for Paris and its inner suburbs, as already shown in Figure 1. The Paris office market can be divided into several geographical areas. We choose to separate the two main historical core business districts of the region, which are the Paris CBD and La Défense. In Model I and within the Paris CBD, we also distinguish a submarket known as the “Golden Triangle” from the rest of the Paris CBD (see Figure 2). The other geographical submarkets are based on Parisian districts and cities in the immediate proximity of Paris. The temporal dummy variable is simply defined as the
year of transaction. The geographical submarket boundaries proposed by Immostat will give the definition of the spatial dummies included in Models I, IIb and IIIb.

Table 1 indicates a strong gap between the average prices per sq.m. in the two business districts and the rest of Paris and its inner suburbs, as well as between the Golden Triangle and the rest of the CBD.

The number of transactions before 1996 in our data sample is low compared to the other time periods, due to the increasing quality of the coverage rate by Paris notaries’ offices. This point will be corrected in the hedonic analysis.

Table 1 also indicates that the transaction area has been decreasing over time while the price per sq.m. is lower for the [1996-2001] period than for the other periods. Finally, the price per sq.m. seems to be higher for whole buildings than for parts of buildings.

Table 1 also shows that price per sq.m. is largely higher for new constructions than for second hand buildings for the whole Paris Region. This gap seems to be more pronounced within the CBD. It is important to include this variable in our estimates even if the total number of transactions on new constructions is small.

Results

This section is divided into three parts, one for each model considered (see the methodology section).

**OLS standard hedonic regression**

Table 2 proposes an estimation of the impact of structural, temporal and geographical characteristics for Model I under equation (1). Results are given for the whole area consisting of Paris and its inner suburbs, using OLS estimations and Weighted Least Squares (WLS). The WLS regression is estimated using the coverage rates made available by the CINP. The extract includes one variable that can be used to measure coverage rates for the value of transactions according to location (“département”), transaction date (month and year) and the nature of the property (whole building or part of building). This variable will indicate the scale of each transaction in value and serve to define the weight of the WLS regression procedure. OLS estimations are also given for the Paris CBD. Lastly, we also estimate the results for both the Paris CBD and La Défense, since the sample is too small for La Défense to be considered alone.

Table 2 only provides estimates of parameters relating to structural characteristics. The results for the parameters for spatial and temporal dummies are not reported here.

[Insert Table 2]
For this model, estimations of $R^2$ are very satisfactory (88.75\% for the OLS estimation on the whole sample and more than 91\% on the Paris CBD - La Défense geographical submarket). Heteroskedasticity is controlled for with the usual White (1980) method. We run a Jarque-Bera test and conclude that the null hypothesis of normally distributed residual is accepted. We also report the median absolute prediction error in each case.

The results may be interpreted as follows. Concerning the period of construction, the period following 2001 is our reference period. The period of construction does not seem to have a significant impact on the transaction price over the whole sample (i.e. Paris and its inner suburbs).

However, the period of construction appears to play a significant role within the Paris Central Business District. All the buildings constructed before 1948 appear to be significantly less expensive than those built after 1980. The price of a building constructed between 1914 and 1947 is about 21\% lower than the price of a building constructed after 1980. Buildings constructed during the Haussmannian period (1850-1913) are significantly less expensive than more recent buildings, all other things being equal (the gap is approximately 35\%). This seems to suggest a spatial drift in the parameter estimates for the period of construction between the Paris CBD and the rest of the Paris Region. This difference disappears once La Défense Business District is included in our estimation sample, since there are absolutely no old buildings in that submarket.

It is important to take note of the sizeable gap between transactions concerning whole buildings and transactions concerning parts of buildings. The former are much more expensive than the latter. The price per sq.m is 25\% higher for whole buildings than for parts of buildings (controlling for the transaction area). This effect is always significant and fairly stable whatever the considered submarket.

As expected, new constructions are more expensive than second-hand buildings. The impact of renovation of a building on the transaction price is 52\% on the whole sample and 41\% in the Paris CBD submarket. Many Haussmannian buildings were renovated and restructured in the 1990s to provide office spaces identical to the spaces on offer in the modern tower blocks at La Défense (15\% of whole building transactions registered by notaries in the sole CBD). The new construction variable is responsible for a large portion of the volatility in the transaction price, even though the total number of new construction transactions only represents about 15\% of the whole sample (see Table 1). The impact of this variable substantially overwhelms that of the period of construction: the gap between a renovated Haussmannian building and a second-hand Haussmannian building is always higher than between a renovated Haussmannian building and a recent newly constructed building. We observe no large impact for the period of construction between buildings with a renovated interior. The period of construction only continues to have an impact for non-restructured/renovated buildings: for such properties, the period of construction gives information on the quality of amenities and can be economically significant.

We control for the robustness of our results. As already explained, we proceed to a extensive correction of the original data sample to correct for missing variables and potential statistical outliers. Our corrected data sample includes 2,587 data compared to the 6,812 in the uncorrected original data set. The transaction area variable accounts for
most of this correction due to its poor coverage rate. We then perform two other estimations:

- One without the transaction area variable,
- One which transforms the transaction area variable into a qualitative variable and creates a specific modality when the transaction area is missing.

The results of these new estimations are not reproduced here. In both cases, the $R^2$ is strongly lower due to an evident misspecification problem. Nevertheless, coefficient estimates do not deeply differ from those presented in Table 2. We may therefore conclude that the selection bias issue remains small.

In Table 2, we also propose a Weighted Least Square (WLS) estimation of our hedonic equation. We attribute a weight to each transaction according to its representativeness (which is estimated by the Paris Chamber of Notaries). We see that the coefficients’ estimates are quite close to those in the standard OLS procedure, confirming the robustness of our estimates. Notice that we do not take the WLS estimation as our baseline procedure for Model I since it is well-known that WLS is a problematic methodology in the event of a misspecified model (see for example Carrington et al., 2000). We face a potential omitted variable problem which could lead to a misspecification in Model I. For this reason, we choose the OLS procedure as our reference estimation.

The same robustness checks are estimated for the relevant submarkets (both Paris CBD and Paris CBD-La Défense). They again confirm the stability of our results.

**B-STAR hedonic regression**

We now turn to our spatiotemporal estimation procedure (B-STAR for Bayesian Spatiotemporal Autoregressive). Results are compiled in Table 3a and 3b for Model IIa and IIb respectively. These tables do not report the coefficient estimates for coefficients SX, TX, STX and TSX, since most of them are quite difficult to interpret and are poorly informative.

[ Insert Tables 3a and 3b ]

Our first comments concern the results of models IIa and IIb for the whole sample (Paris and its Inner suburbs). $R^2$ is slightly higher for model IIa than for model I, but the former does not significantly outperform the results of a standard OLS hedonic estimation. On the contrary, Model IIb significantly outperforms Model I and IIa in terms of $R^2$ and median absolute prediction error. This seems to suggest that even when controlling for spatial discrepancies across submarkets, within-submarket spatial dependence effects are present and play a significant role in explaining the log of selling prices. The relative performances of each model will be evaluated further through an out-of-sample validation procedure.
Comparing Model I and Model IIb, we see that the period of construction is still unable to explain a significant portion of the volatility of transaction prices, although the gap between Haussmannian buildings and more recent buildings is significant for Model IIb. New constructions are still significantly more expensive than others. The gap between new and old buildings is more pronounced than for Model I (63% against only 52%).

More interestingly, the difference between transactions involving whole buildings and transactions involving parts of buildings is no longer significant. This seems to suggest that the significant gap between whole buildings and parts of buildings found in Model I might result from an omitted spatial or temporal autoregressive effect.

Finally, the elasticity of transaction prices with regard to the transaction area is still slightly below one (0.94 for Models I and IIb).

We turn now to the impact of the autoregressive parameters: both spatial and temporal parameters estimates are statistically significant. The magnitude is more pronounced for the spatial autoregressive parameters than the temporal parameters, suggesting that temporal neighbors are less influential than spatial neighbors. For Model IIb, the magnitude of the spatial dependence parameter is significantly less pronounced than for Model I, due to the presence of spatial dummies. It suggests two important results:

- The presence of spatial heterogeneity (i.e. spatial drift in the intercept in our case) is sizeable in the Paris office market.
- Omitting spatial heterogeneity leads to spurious estimates of the spatial autoregressive parameter.

Moreover, the temporal dependence parameter is almost zero in Model IIb, suggesting that temporal correlation effects are not significant, once we control for a dummy year effect. As explained in the methodology section, such a result was to be expected, since the spatial neighborhood captures some of the temporal effects due to the temporal ordering of our data sample.

The compound effects S*T and T*S are less influential than direct spatial and temporal autoregressive effects. It nevertheless appears that the cross product S*T still has a significant impact on determination of the transaction price for Model I, but this is no longer true for Model IIb once spatiotemporal dummy variables are included. This means that the price of spatial neighbors or temporal neighbors is not a significant piece of information for the current transaction price.

In the geographically restricted samples (the Central Business District area and the CBD + La Défense area), the magnitude of spatial and temporal autoregressive parameters remains relatively unchanged. The impact of the spatial autoregressive parameter is still above the impact of the temporal autoregressive parameter, although the difference has been reduced. Notice that the spatial dependence effects are slightly lower for the Paris CBD area, which seems to suggest a spatial drift in the influence of spatial neighborhood.

The price gap between new buildings and second-hand buildings is still stronger in the CBD geographical area than in the whole sample (Paris and its inner suburb). Moreover, we still have the significant difference between buildings constructed in the Haussmannian period and recent buildings, similar to Model I.

One interesting result is the sizeable gap between transactions concerning whole buildings and transactions concerning parts of buildings, since the price of the former is
B-STAR hedonic regression with structural break

We now present results for models IIIa and IIIb. We run the same B-STAR model as in the preceding section, but adding a new parameter to be estimated. Using the temporally ordered data set property of Pace et al. (1998)’s estimation procedure, we endogenously estimate the presence and dating of a temporal break in the Parisian office transaction market.

Results are compiled in Table 4a and 4b for models IIIa and IIIb respectively. For small sample reasons (the number of parameters to be estimated is now twice that of Model II), we do not reproduce our B-STAR with temporal heterogeneity estimates on the geographically restricted samples.

[ Insert Tables 4a and 4b ]

Once again, Model IIIb (with dummies) largely outperforms Model IIIa. We will therefore focus on the results of Model IIIb. The first important result is that we find a significant temporal break in December 1997 (and November 1997 for Model IIIa). The first sub-period corresponds to a major slowdown in prices, and the subsequent period corresponds to a recovery (this point will be confirmed in the following subsection with the index construction). Notice that the 95% confidence interval for the change point dating remains narrow, running from December 1996 to December 1998. R² is substantially higher in both subsample periods and the general R² (i.e. for the whole time period) is much higher than for model I or IIb. Moreover, the median absolute error has been largely reduced due to the temporal break parameter.

Let us first comment the temporal pattern of the spatial and temporal autoregressive parameters. It appears that the impact of these parameters is much more pronounced in the second time period. The coefficient estimate for the spatial autoregressive term jumps from 0.11 before December 1997 to 0.50 after this date. It suggests that while the direct influence of nearby properties was almost negligible between 1991 and 1997, it became sizeable since 1998. The behavior of buyers and sellers on the Paris office market has strongly changed: the use of neighborhood information has been much greater in the upward phase than the downward phase. It also suggests that results from Model IIb (i.e. without an endogenous change over time) suffer from an estimation bias: it largely underestimates the influence of nearby properties in the upward phase of the Paris office property cycle.

Notice that the spatial coefficient magnitude remains higher than the temporal coefficient magnitude, which is very low in both sub-samples for Model IIIb.

The difference between Haussmannian buildings and recently constructed buildings is more pronounced in the second temporal sample than in the first. Moreover, in the
[1997-2005] period for transaction prices, we also found significant differences between properties dating from the [1914-1947] and the most recent construction periods\(^4\).

The impact of new buildings does not greatly vary in the time sample considered. On the contrary, the gap between transactions for whole buildings and parts of buildings seems to concern the first temporal subsample: the former are considerably cheaper than the latter, all other things being equal. The gap between these two transaction types vanishes in the [1997-2005] time period.

Generally, the parameter estimates are more precise in the second time period than in the first (and consequently \(R^2\) is higher for this subperiod). This fact may also result from higher quality in the notary office data.

**Out-of-sample cross validation test**

An out-of-sample cross validation test is applied to the three models. Results are contained in Table 5.

\[\text{[ Insert Table 5 ]}\]

We proceed as follows: we first select a random sample of 90% of the whole data sample, making sure that this sample is temporally uniformly drawn (i.e. 90% of the original data sample for each transaction year). Each one of the five models is estimated on this reduced sample, and the ex-sample prediction properties are evaluated on the remaining 10%. This procedure is repeated 100 times. The results show that the predictability of the B-STAR with a change point is higher with regard to all testing statistics. In particular, Model IIIb significantly increases the out-of-sample \(R^2\) as well as the absolute error (median and mean). Notice that Model IIa does not seem to offer any sizeable improvement over Model I, suggesting that the inclusion of an endogenous change point might be more effective than the use of spatial and temporal autoregressive terms. Hence, Model IIIb outperforms all the other models, including Model IIIa. This confirms the need to include both spatiotemporal dummies and spatiotemporal dependence parameters.

The percentile statistics of the ex-sample error term confirm this result: the interval of 10% and 90% of the error distribution show that the hedonic error in Model IIIb is smaller than for the other specifications. Moreover, the inclusion of spatial dummy variables helps to improve the fit of the model in the tails of the error distribution: ex-sample error terms at the 10 percentile or 90 percentile are much lower in absolute value for Model IIb than for Model IIa and for Model IIIb and Model IIIa. It suggests that the spatial dummies are crucial given the large differences in price across market shown in Table 1.

\(^4\) Notice that since the number of buildings constructed after 1981 is very small in the first subsample, we do not report coefficient estimates for the corresponding parameters.
Another procedure for measuring the impact of the different estimation methods on the price determination is to build a temporal index in each of the three cases. Figure 3 below reports the hedonic price indexes for the different models (for Models II and III, only the out-of-sample preferred version, i.e. Model IIb and Model IIIb, are reported). Model I, Model IIb and Model IIIb include spatial and temporal dummies. Hence, comparison of Models I and IIb will enable us to directly measure the impact of spatiotemporal dependence terms, and comparison of Models IIb and IIIb will enable us to assess the scale of the estimated temporal break.

We report this figure for the whole sample. Figures for geographically restricted samples are available upon request. Notice that for Model IIb and IIIb, the Bayesian estimation procedure drastically complicates the calculation of such an index. For a methodological explanation, please refer to Gelfand and al. (2004).

For all models, we found a downturn period followed by a recovery period, both corresponding to the change point endogenously determined in Model IIIb. The main difference comes from the divergence in the cycle’s amplitude. From 1992 to 1997, the transaction price is generally lower for Model IIb (53% in 1997 with 100-reference in 1992) and IIIb (45% in 1997) than for Model I (58% in 1997).

Similarly, from 1997-2005 the prices increase is larger for Models IIb and IIIb (mean annual percentage growth of 12.7% and 15.4% respectively) than for Model I (10.7%).

Hence, the impact of spatial and temporal autoregressive parameters and the inclusion of an endogenous change point cause significant reassessment of the office market transaction price cycle from 1991 to 2005. The comparison of Models IIb and IIIb shows discrepancies (lower price level around 1997 for the former) that can be attributed to the temporal break in the latter. There is considerable temporal heterogeneity, generating a major reassessment of the price cycle between 1991 and 2005.

Conclusion

This paper shows that the presence of temporal heterogeneity should not be neglected for the Paris region office market. We propose a method that can endogenously estimate the date of a change point in a Spatiotemporal Autoregressive setup. We obtain three different results:

First, we find that the size of spatial and temporal dependence coefficients differ strongly according to the transaction date. In particular, spatial dependence effects
significantly increased during the recovery period, from 1997 to 2005, compared to the slowdown of 1992 to 1997. Hence, agents behave differently according to the position in the price cycle. This effect is confirmed by a standard out-of-sample cross validation test.

Second, we show that the presence of temporal heterogeneity deeply affects the assessment of price changes from 1991 to 2005 for the Paris Region Office market.

Finally, we also prove that the importance of spatial heterogeneity here modeled as a spatial drift in the intercept should not be neglected even in the presence of spatial autoregressive terms.

This study still needs to be extended in two main aspects. First, spatial heterogeneity is poorly modeled, since we only use predefined spatial boundary dummy variables. It would be useful to extend this analysis to more refined spatial submarkets, following the analysis of Clapp and Wang (2006), who propose an original technique to optimally define endogenous neighborhood boundaries that depart from fixed “hard boundaries”.

Second, we only test for one temporal change point, whereas there could be many. It might be worthwhile to develop a method that endogenously estimates the number of temporal breaks in the model.
## Tables and Figures

**Table 1: Sample statistics on the data set**

<table>
<thead>
<tr>
<th>Transaction Type</th>
<th>Nb of transactions</th>
<th>Price per sq.m. (€)</th>
<th>Transaction Area (sq.m.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (s.d.)</td>
<td>Mean (s.d.)</td>
<td>Mean (s.d.)</td>
</tr>
<tr>
<td>Whole Building</td>
<td>295</td>
<td>2,864 (1,589)</td>
<td>1,882 (2,145)</td>
</tr>
<tr>
<td>Part of Building</td>
<td>2,292</td>
<td>2,039 (2,045)</td>
<td>109 (256)</td>
</tr>
<tr>
<td>Total</td>
<td>2,587</td>
<td>2,133 (1,546)</td>
<td>311 (451)</td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>“Golden Triangle”</td>
<td>125</td>
<td>3,829 (1,710)</td>
<td>555 (741)</td>
</tr>
<tr>
<td>Rest of Paris CBD</td>
<td>413</td>
<td>2,637 (1,840)</td>
<td>690 (802)</td>
</tr>
<tr>
<td>Rest of central Paris</td>
<td>1,179</td>
<td>1,922 (2,556)</td>
<td>310 (456)</td>
</tr>
<tr>
<td>La Défense</td>
<td>80</td>
<td>4,215 (2,870)</td>
<td>15,037 (20,451)</td>
</tr>
<tr>
<td>Rest of Hauts-de-Seine</td>
<td>320</td>
<td>2,422 (3,901)</td>
<td>991 (1,045)</td>
</tr>
<tr>
<td>Seine Saint-Denis</td>
<td>149</td>
<td>1,425 (1,587)</td>
<td>343 (876)</td>
</tr>
<tr>
<td>Val de Marne</td>
<td>320</td>
<td>1,255 (1,456)</td>
<td>1,357 (1,590)</td>
</tr>
<tr>
<td><strong>Year of Transaction</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;1996</td>
<td>392</td>
<td>2,492 (2,488)</td>
<td>255 (401)</td>
</tr>
<tr>
<td>[1996-2001]</td>
<td>1,341</td>
<td>1,827 (1,933)</td>
<td>144 (134)</td>
</tr>
<tr>
<td>&gt;2001</td>
<td>854</td>
<td>2,607 (2,014)</td>
<td>137 (122)</td>
</tr>
<tr>
<td><strong>Transaction</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New construction</td>
<td>280</td>
<td>2,742 (2,568)</td>
<td>521 (451)</td>
</tr>
<tr>
<td>Second Hand</td>
<td>2507</td>
<td>2,047 (1,845)</td>
<td>284 (199)</td>
</tr>
<tr>
<td><strong>Within CBD</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New construction</td>
<td>88</td>
<td>3,510 (2,845)</td>
<td>721 (610)</td>
</tr>
<tr>
<td>Second hand</td>
<td>450</td>
<td>2,708 (2,642)</td>
<td>545 (411)</td>
</tr>
</tbody>
</table>

Table 1: Main descriptive statistics (mean and standard deviation of the price per sq.m. and transaction area) for the sample according to the kind of transaction (whole building or part of building, new construction or second hand), the location and the period of the transaction.
This table reports the estimates of structural characteristics for Model I (standard hedonic model) for the whole geographical area (OLS and WLS), the Paris Central Business district and the Paris CBD and La Défense district. Variable c refers to the period of construction of the building. “Whole building” is a qualitative variable indicating whether the transaction concerns the whole building or just part of the building. “New construction” is a qualitative variable indicating whether or not the building has been renovated/restructured. Area is the logarithm of transaction area. This table also reports $R^2$, SSE, median absolute error and error autocorrelation.

### Table 2: Estimates of structural characteristics (Model I)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Paris &amp; Inner Suburbs (OLS)</th>
<th>Paris &amp; Inner Suburbs (WLS)</th>
<th>Paris CBD (OLS)</th>
<th>Paris CBD and La Défense (OLS)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>s.e.</td>
<td>Coef</td>
<td>s.e.</td>
</tr>
<tr>
<td>$c_{[1850]}$</td>
<td>-0.17</td>
<td>0.15</td>
<td>-0.13</td>
<td>0.16</td>
</tr>
<tr>
<td>$c_{[1850-1913]}$</td>
<td>-0.22</td>
<td>0.14</td>
<td>-0.20</td>
<td>0.16</td>
</tr>
<tr>
<td>$c_{[1914-1947]}$</td>
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<td>-0.20</td>
<td>0.16</td>
</tr>
<tr>
<td>$c_{[1948-1969]}$</td>
<td>-0.17</td>
<td>0.14</td>
<td>-0.15</td>
<td>0.16</td>
</tr>
<tr>
<td>$c_{[1970-1980]}$</td>
<td>-0.11</td>
<td>0.14</td>
<td>-0.09</td>
<td>0.16</td>
</tr>
<tr>
<td>$c_{[1981-1991]}$</td>
<td>-0.08</td>
<td>0.14</td>
<td>0.02</td>
<td>0.15</td>
</tr>
<tr>
<td>$c_{[1992-2000]}$</td>
<td>0.07</td>
<td>0.13</td>
<td>0.11</td>
<td>0.14</td>
</tr>
<tr>
<td>Whole building</td>
<td>0.22***</td>
<td>0.06</td>
<td>0.24***</td>
<td>0.06</td>
</tr>
<tr>
<td>New Const.</td>
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<td>0.06</td>
<td>0.43***</td>
<td>0.07</td>
</tr>
<tr>
<td>Area</td>
<td>0.94***</td>
<td>0.02</td>
<td>0.95***</td>
<td>0.02</td>
</tr>
<tr>
<td>Sample size</td>
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<td>2587</td>
<td>538</td>
<td>618</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.8875</td>
<td>0.8889</td>
<td>0.9122</td>
<td>0.9107</td>
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<tr>
<td>SSE</td>
<td>731.4512</td>
<td>731.4210</td>
<td>456.2345</td>
<td>467.1586</td>
</tr>
<tr>
<td>Med. Abs. Err.</td>
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<td>0.2809</td>
<td>0.2741</td>
<td>0.2690</td>
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<tr>
<td>Autocorrelation</td>
<td>0.4517</td>
<td>0.4580</td>
<td>0.4409</td>
<td>0.4418</td>
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*: p-value 10%, **: p-value 5%, ***: p-value 1%. Dependent variable is the log of price per s.m.
Table 3a: Estimates of structural and spatio-temporal characteristics (Model IIa)

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<thead>
<tr>
<th>Variable</th>
<th>Paris &amp; Inner Suburbs (B-STAR)</th>
<th>Paris CBD (B-STAR)</th>
<th>Paris CBD and La Défense (B-STAR)</th>
</tr>
</thead>
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<td>Coef</td>
<td>s.e.</td>
<td>Coef</td>
</tr>
<tr>
<td>c_{[&lt;1850]}</td>
<td>-0.03</td>
<td>0.09</td>
<td>-0.18*</td>
</tr>
<tr>
<td>c_{[1850-1913]}</td>
<td>-0.20**</td>
<td>0.09</td>
<td>-0.36***</td>
</tr>
<tr>
<td>c_{[1914-1947]}</td>
<td>-0.14*</td>
<td>0.07</td>
<td>-0.12*</td>
</tr>
<tr>
<td>c_{[1948-1969]}</td>
<td>-0.15</td>
<td>0.15</td>
<td>-0.08</td>
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<tr>
<td>c_{[1970-1980]}</td>
<td>-0.09</td>
<td>0.12</td>
<td>-0.05</td>
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<tr>
<td>c_{[1981-1991]}</td>
<td>-0.06</td>
<td>0.28</td>
<td>-</td>
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<tr>
<td>c_{[1992-2000]}</td>
<td>0.05</td>
<td>0.11</td>
<td>-</td>
</tr>
<tr>
<td>Whole-building</td>
<td>0.09</td>
<td>0.11</td>
<td>-0.08***</td>
</tr>
<tr>
<td>New construction</td>
<td>0.48***</td>
<td>0.07</td>
<td>0.55***</td>
</tr>
<tr>
<td>Area</td>
<td>0.97***</td>
<td>0.01</td>
<td>1.01**</td>
</tr>
<tr>
<td>S</td>
<td>0.57***</td>
<td>0.01</td>
<td>0.52***</td>
</tr>
<tr>
<td>T</td>
<td>0.11***</td>
<td>0.01</td>
<td>0.11***</td>
</tr>
<tr>
<td>S*T</td>
<td>0.04**</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>T*S</td>
<td>0.00</td>
<td>0.08</td>
<td>0.00</td>
</tr>
<tr>
<td>Sample size</td>
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<td>538</td>
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<tr>
<td>R²</td>
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<td>0.9289</td>
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<tr>
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<td>Med. Abs. Err.</td>
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<td>0.2608</td>
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<td>Autocorrelation</td>
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<td>0.1005</td>
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*: p-value 10%, **: p-value 5%, ***: p-value 1%. Dependent variable is the log of price per s.m.

This table reports the estimates of structural characteristics and spatiotemporal correlative effects for Model IIa (Bayesian STAR model without dummy variables) for the whole geographical area, the Paris Central Business district and the Paris CBD and La Défense district. S and T respectively refer to the impact of spatial and temporal neighbors. ST and TS are spatiotemporal compound effects.
### Table 3b: Estimates of structural and spatio-temporal characteristics (Model IIb)

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<th>Paris CBD and La Défense (B-STAR)</th>
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<td>Coef</td>
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<td>-0.35***</td>
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<td>-0.13*</td>
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<td>$c_{[1948-1969]}$</td>
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<td>0.17</td>
<td>-0.12</td>
</tr>
<tr>
<td>$c_{[1970-1980]}$</td>
<td>-0.09</td>
<td>0.12</td>
<td>-0.09</td>
</tr>
<tr>
<td>$c_{[1981-1991]}$</td>
<td>-0.07</td>
<td>0.26</td>
<td>-</td>
</tr>
<tr>
<td>$c_{[1992-2000]}$</td>
<td>0.06</td>
<td>0.12</td>
<td>-</td>
</tr>
<tr>
<td>Whole-building</td>
<td>0.17</td>
<td>0.14</td>
<td>-0.06***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.09***</td>
</tr>
<tr>
<td>New construction</td>
<td>0.49***</td>
<td>0.04</td>
<td>0.55***</td>
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<tr>
<td></td>
<td></td>
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<td>0.58***</td>
</tr>
<tr>
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<td>0.94***</td>
<td>0.01</td>
<td>1.00**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.01**</td>
</tr>
<tr>
<td>S</td>
<td>0.32***</td>
<td>0.02</td>
<td>0.26***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.22***</td>
</tr>
<tr>
<td>T</td>
<td>0.06***</td>
<td>0.01</td>
<td>0.02**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.02**</td>
</tr>
<tr>
<td>S*T</td>
<td>0.02</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.00</td>
</tr>
<tr>
<td>T*S</td>
<td>0.00</td>
<td>0.15</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.05</td>
</tr>
</tbody>
</table>

| Sample size       | 2587                           | 538                | 618                              |
| R²                | 0.9177                         | 0.9398             | 0.9358                           |
| SSE               | 679.1288                       | 401.5508           | 411.9187                         |
| Med. Abs. Err.    | 0.2521                         | 0.2533             | 0.2536                           |
| Autocorrelation   | 0.0845                         | 0.0941             | 0.1062                           |

*: p-value 10%, **: p-value 5%, ***: p-value 1%. Dependent variable is the log of price per s.m.

This table reports the estimates of structural characteristics and spatiotemporal correlative effects for Model IIb (Bayesian STAR model with dummy variables) for the whole geographical area, the Paris Central Business district and the Paris CBD and La Défense district. S and T respectively refer to the impact of spatial and temporal neighbors. ST and TS are spatiotemporal compound effects.
### Table 4a: Estimates of structural and spatiotemporal characteristics (Model IIIa)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Paris &amp; Inner Suburbs (B-STAR)</th>
<th>Paris &amp; Inner Suburbs Before change point (November, 1997) (B-STAR)</th>
<th>Paris &amp; Inner Suburbs After change point (November, 1997) (B-STAR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>s.e</td>
<td>Coef</td>
</tr>
<tr>
<td>$c_{[-1850]}$</td>
<td>-0.03</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>$c_{[1850-1913]}$</td>
<td>-0.20***</td>
<td>0.09</td>
<td>-0.08***</td>
</tr>
<tr>
<td>$c_{[1914-1947]}$</td>
<td>-0.14*</td>
<td>0.07</td>
<td>-0.16</td>
</tr>
<tr>
<td>$c_{[1948-1969]}$</td>
<td>-0.15</td>
<td>0.15</td>
<td>-0.11</td>
</tr>
<tr>
<td>$c_{[1970-1980]}$</td>
<td>-0.09</td>
<td>0.12</td>
<td>-0.10</td>
</tr>
<tr>
<td>$c_{[1981-1991]}$</td>
<td>-0.06</td>
<td>0.28</td>
<td>-</td>
</tr>
<tr>
<td>$c_{[1992-2000]}$</td>
<td>0.05</td>
<td>0.11</td>
<td>-</td>
</tr>
<tr>
<td>Whole-building</td>
<td>0.09</td>
<td>0.11</td>
<td>0.38**</td>
</tr>
<tr>
<td>New construction</td>
<td>0.48***</td>
<td>0.07</td>
<td>0.44***</td>
</tr>
<tr>
<td>Area</td>
<td>0.97***</td>
<td>0.01</td>
<td>0.92***</td>
</tr>
<tr>
<td>$S$</td>
<td>0.57***</td>
<td>0.01</td>
<td>0.29***</td>
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<tr>
<td>$T$</td>
<td>0.11***</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>$S*T$</td>
<td>0.04***</td>
<td>0.02</td>
<td>0.06***</td>
</tr>
<tr>
<td>$T*S$</td>
<td>0.00</td>
<td>0.08</td>
<td>0.18**</td>
</tr>
</tbody>
</table>

**Sample size**: 2587 | 762 | 1825

**R²**: 0.9051 | 0.9237

**SSE**: 712.0619 | 695.832

**Med. Abs. Err.**: 0.2716 | 0.2618

**Autocorrelation**: 0.0917 | 0.0283

**Change point**: - | 1997(11) | C1: [1996(09) – 1998(12)]

*: p-value 10%, **: p-value 5%, ***: p-value 1%. Dependent variable is the log of price per s.m.

This table reports the estimates of structural characteristics and spatiotemporal correlative effects for Model IIa (Bayesian STAR model without dummy variables) and Model IIIa (Bayesian STAR without dummy variables before and after the time change point).
Table 4b: Estimates of structural and spatiotemporal characteristics (Model IIIb)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Paris &amp; Inner Suburbs (B-STAR)</th>
<th>Paris &amp; Inner Suburbs Before change point (December, 1997) (B-STAR)</th>
<th>Paris &amp; Inner Suburbs After change point (December, 1997) (B-STAR)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Coef</td>
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<tr>
<td>c[1850]</td>
<td>-0.06</td>
<td>0.10</td>
<td>0.08</td>
</tr>
<tr>
<td>c[1850-1913]</td>
<td>-0.25***</td>
<td>0.10</td>
<td>-0.07*</td>
</tr>
<tr>
<td>c[1914-1947]</td>
<td>-0.11***</td>
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<td>-0.07</td>
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<tr>
<td>c[1948-1969]</td>
<td>-0.16</td>
<td>0.17</td>
<td>-0.08</td>
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<tr>
<td>c[1970-1980]</td>
<td>-0.09</td>
<td>0.12</td>
<td>-0.22</td>
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<tr>
<td>c[1981-1991]</td>
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<td>0.26</td>
<td>-</td>
</tr>
<tr>
<td>c[1992-2000]</td>
<td>0.06</td>
<td>0.12</td>
<td>-</td>
</tr>
<tr>
<td>Whole-building</td>
<td>0.17</td>
<td>0.14</td>
<td>0.52**</td>
</tr>
<tr>
<td>New construction</td>
<td>0.49***</td>
<td>0.04</td>
<td>0.45***</td>
</tr>
<tr>
<td>Area</td>
<td>0.94***</td>
<td>0.01</td>
<td>0.92***</td>
</tr>
<tr>
<td>S</td>
<td>0.32***</td>
<td>0.02</td>
<td>0.11***</td>
</tr>
<tr>
<td>T</td>
<td>0.06***</td>
<td>0.01</td>
<td>-0.06</td>
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<tr>
<td>S*T</td>
<td>0.02</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>T*S</td>
<td>0.00</td>
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<td>0.05</td>
</tr>
<tr>
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<td>1794</td>
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<tr>
<td>Med. Abs. Err.</td>
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<td>Autocorrelation</td>
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<td>0.0270</td>
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<tr>
<td>Change point</td>
<td>1997(12) CI : [1996(12) – 1998(12)]</td>
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<td></td>
</tr>
</tbody>
</table>

*: p-value 10%, **: p-value 5%, ***: p-value 1%. Dependent variable is the log of price per s.m.

This table reports the estimates of structural characteristics and spatiotemporal correlative effects for Model IIb (Bayesian STAR model with dummy variables) and Model IIIb (Bayesian STAR with dummy variables before and after the time change point).
This table reports the out-of-sample cross validation test for the whole Paris Region and for the five models (Model I: Standard hedonic, Models IIa and IIb: Bayesian STAR without and with dummies respectively and Models IIIa and IIb: Bayesian STAR with temporal heterogeneity, without and with dummies respectively). This table provides the percentile (10%, 20%, …) of the ex-sample error terms, the ex-sample R² and ex-sample median and mean absolute error for each model.
This figure shows the geographical delimitation of Paris and its inner suburbs proposed in 2006 by Immostat, an Economic Interest Grouping which since 2001 has collated data on office transactions and office rental values supplied by its five founding real estate consultancy firms.
Figure 2: Paris Central Business District

This figure shows the geographical delimitation of the Paris Central Business District.
This figure reports the transaction price hedonic indexes for the three models (Model I: Standard hedonic, Model IIb: Bayesian STAR with spatiotemporal dummy variables and Model IIIb: Bayesian STAR with temporal heterogeneity and spatiotemporal dummy variables).
Figure 3
References


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