Macroeconomic Risk Exposure of Housing Accounting for Spatio-Temporal Correlations

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Abstract

Using data on apartment sales in Paris area, we disentangle the effects of macroeconomic environment on the real estate prices and the extent of temporal and spatial correlation in housing prices. In particular, we estimate a hedonic price model that includes macroeconomic variables, as well as spatial and time lags of the dependent variable. Our results suggest that it is important to distinguish among expected and surprise components of macroeconomic variables, especially the price level. We also find that there is a significant amount of spatial autocorrelation while the time lags, although significant, have comparably lower impact on prices.

JEL classification: C43; C51; O18; R20

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1 Introduction

From a macroeconomic point of view, the housing sector is an important aspect of a nation's economy. Residential real estate represents in general the most important part of a nation's fixed capital stock. The performance of the housing market has a major impact on the overall performance of the economy. Therefore, many models have been developed to analyze the housing sector and their interaction with the rest of the economy. However, the main part of the empirical literature analyzes macroeconomic risks without taking into account either, that the housing prices are autocorrelated in space and time, or that the underlying real estate is heterogeneous in its characteristics.

The aim of the following analysis is twofold: first, we examine to what extend the prices of housing are affected by the macroeconomic environment. Second, we analyze the extent of spatial and temporal correlation in housing prices. For both issues we present approaches which have not been used in previous research on real estate. Furthermore, we control for heterogenous characteristics of the housing objects in our sample.

The fundamental risk factors of real estate, spatial economics as well as hedonic models have been extensively examined in the real estate literature. But we assume that there is – beside didactical reasons – no need in treating them separately. On the contrary, joint analysis provides more accurate results. Traditionally, the influence of the macroeconomic environment, the spatial effects and the calculation of a hedonic index are analyzed in separate models. A single step procedure is proposed here, i.e. to include the macroeconomic as well as the spatio-temporal variables directly in the hedonic model. Thus the cross-sectional dimension of the data will not be reduced, which should lead to a more efficient estimation of the parameters.

We estimate the model using data on apartment sales in the Paris metropolitan area over the period of ten years. Our results suggest that it is important to distinguish among expected and surprise components of the macroeconomic variables. We also find that there is a significant amount of spatial autocorrelation while the time lags, although significant, have comparably lower impact on prices.

The article is organized as follows: Section 2 gives a description of the data. Section 3 outlines the empirical model. The estimation procedure is described in section 4, and estimation returns are provided in section 5. Section 6 provides conclusions.

2 Data description

2.1 Real Estate Data

Real estate purchases in France must by law be attested by a notary. Since 1990, the certified data are supposed to be passed on to the National Chamber of Notaries (Chambre Interdepartementale des Notaire de Paris). For every transaction, about 100 different characteristics can be ascertained. As the passing on of the additional characteristics is voluntary, the data are incomplete. As a result, all data without information on characteristics are dropped and not utilized in the estimation. For example, observation are excluded with price reported to be 1 franc or less as well as observations for which the apartment characteristics, such as price, square meters, location, occupancy status and others, are not reported. See Table 7 with estimation results for a complete list. The data used here is taken from the CD-BIEN Database, Version B, edition no. 18 from July 2000, which include the transaction in the period 1990:01-1999:12. *Maurer et al.* (2004) offer a detailed description of the data.

2.2 Macroeconomic Variables

We follow the literature (e.g. *Chen et al.* (1986); *Chan et al.* (1990), *Giliberto* (1990) or *Gyourko and Linneman* (1998), and use a prespecification of the macroeconomic factors. In the asset pricing literature (e.g. *Chen et al.* (1986) the effect of expected and unexpected components of income, prices and other variables is, in general, different. Note that under the assumption of an efficient market only the unexpected components will have an impact on the price of an asset.

Apartment can be viewed both as an asset investments as well as durable consumer good. Due to its nature of an asset investment, the demand for apartments is expected to be a function of return on alternative asset (e.g. long term yields) and inflation. On the other hand, as a durable consumption good, the demand for apartment purchases will depend on income in addition to interest rates.

We do not expect the changes in the stock of existing apartments to play a considerable role since most of the sales in this sample (92 percent) are units that have been built before 1980, i.e. at least more than 10 years before their sale. Hence one might view the stock of apartments in use to be constant and assume that the arrivals on the market do not react to macroeconomic conditions. By doing so the changes in the existing stock through renovations would be ignored. Since alternations to the stock of apartments usually have to be financed before the units are sold, the difference between the short and long term yields is expected to play an additional role.

The expected and surprise components of the market conditions are disentangled, but as there is doubt about the information efficiency of real estate markets, both components are included in the model. To estimate the expected components of the parameters, a simple dynamic model of the French economy is constructed. Monthly data on industrial production (IP), long term yields (LTY), price level (CPI), short term yields (PIBOR), and real effective exchange rates (REER) are used. The sources of the data are described in Table 1 below. We use a sample that starts before our observations on real estate transactions and ends later than the date of our last observed transaction. However, we only use the full sample of the macroeconomic variables to determine the lag and cointegration structure of the macroeconomy. The expected and surprise components for each time period are constructed only using data up to that time period.

First, a full-sample error-correction VAR for the period 1/1970-5/2005 is run and the structure of the model is determined, i.e. the number of co-integrating relationships and the lag structure of the model. The model includes IP, CPI, LTY, Spread, PIBOR and REER series, where the Spread series are defined as the difference between LTY and PIBOR. The Johansen maximum likelihood procedure is employed and, using maximal eigenvalue tests, we find that there seem to be three co-integrating relationships when we allows for quadratic time trend in the data.[1] The Schwarz information criteria for the model in first differences suggest that one should use two lags in error-correction model. The results of the full sample error correction

[1]The interpretation of the co-integrating relationships is always difficult and is not attempted here as it is not the main focus of the paper.

Table 1: Data Sources

Variable Name	Description
IP	Industrial production, seasonally adjusted index, base year 2000
CPI	CPI, 108 cities based index, base year 2000
LTY	10 year government bond yield, benchmark
PIBOR	3-month PIBOR, extended with the 3-month EURIBOR series
REER	Real effective exchange rate based on unit labour costs, index, base year 2000

Table 1, cont.

Variable Name	Source	Range
IP	IMF, series 132 66..C	1/1963-4/2005
CPI	IMF, series 132 64...	1/1963-5/2005
LTY	OECD, series 146265D	1/1963-5/2005
PIBOR	OECD, series 146225D	1/1970-12/1998
EURIBOR	OECD, series EA6225D	1/1999-6/2005
REER	IMF, series 132...REU	1/1978-5/2005

VAR model are reported in the appendix.

The same model (i.e. error-correction VAR with three co-integrating relationships with two lags in the differenced equation) is then estimated using rolling monthly samples where the start date is always 1/1970 and the end point varies between 11/1989 and 11/1999. For each sample we construct and save one-period-ahead forecast errors for the variables of interest. The quarterly surprise series are then constructed as the 3-month averages of the one-month-ahead forecast errors. The expected component is then the difference between the actual level of the variable and the surprise component. Table 2 summarizes the sample moments of the constructed series. The notation ..._res denotes the surprise (or residual) component of a series.

Table 2: Characteristics of Expected and Surprise Components

Variable	Mean	Maximum	Minimum	St. Deviation	Observations
IP	82.67	102.20	38.5	16.21	508
IP_res	-0.01	3.00	-11.17	1.19	192
CPI	59.98	109.90	13.60	33.90	509
CPI_res	0.02	0.60	-0.72	0.20	192
LTY	8.51	17.32	3.38	3.16	509
LTY_res	0.03	0.73	-0.75	0.21	192
Spread	1.05	3.75	-4.29	1.42	425
Spread_res	0.07	1.15	-1.50	0.39	192

3 Empirical Model

We consider the following model:

$$p_{it} = \mathbf{x}_i'\beta + \mathbf{z}_t'\gamma + \sum_{k=0}^{q} \lambda_k \sum_{j=1}^{N} w_{ij} p_{j,t-k} + u_{it}, \tag{1}$$

where $1 \leq i \leq n$, $1 \leq t \leq T$, p_{it} is the log of the price of an apartment i sold at time t, $\mathbf{x}_i$ is the vector of (time invariant[2]) characteristics of the apartment, [3], $\mathbf{z}_t$ is the vector of market conditions at time t (invariant across sales at time t), [4] u_{it} is the time and unit specific disturbance term (specified below) and, finally, β, γ and λ_k are parameters of the model.

Notice that a weighted average of prices of other apartments is introduced as an explanatory variable. Both the contemporaneous effects as well as q time lags of the average neighborhood price are included in order to capture autocorrelation of real estate prices over space and time. The weighted

[2]The data does not allow identifying the apartments and hence each observation is defined to be an individual transaction. Repeated sales of the same apartment are treated as separate units.

[3]These include a measure of size of the apartment (log of square meters) and a set of integer and dummy variables describing the properties of the apartment, such as indicators for age, floor, number of bathrooms, etc. See the data section for a full description.

[4]These are the expected and surprise components of long-term interest rates, GDP, price level and interest rate spread. See below.

averages of 'nearby' observations are called spatial lags of the dependent variable.

Space-time autoregressive (STAR) models were introduced in the 80's (e.g. *Pfeiffer and Deutch*, 1980, *Stoffer*, 1986) and have been extensively applied beside economics in geostatistics (see, for example, *Kyriadis and Journel*, 1999 for a review), geography, epidemiology, medicine, environmental studies and elsewhere. Short overviews can be found in *Cressie* (1993, p. 449-452) or *Robinson* (1998, p. 319-328). In real estate economics similar specification was considered by *Pace et al.* (1998). Thus, the STAR literature does not include contemporaneous spatial lags and, as a result, straightforward estimation is feasible. However, the empirical results indicate that the explanatory power of the contemporaneous spatial lag dominates the additional space-time lags of the dependent variable.

Stacking the model in vectors one obtains

$$\mathbf{p}_t = \mathbf{X}\beta + \mathbf{Z}_t\gamma + \sum_{k=0}^{q} \lambda_k \mathbf{W}\mathbf{p}_{t-k} + \mathbf{u}_t, \tag{2}$$

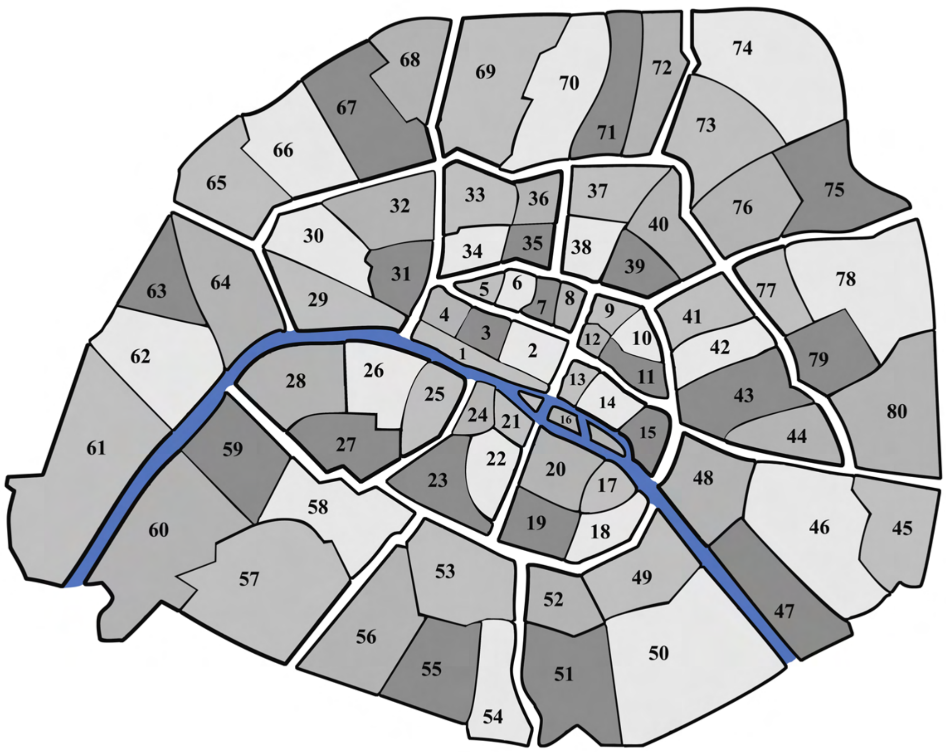
where $\mathbf{p}_t = (p_{1t}, ..., p_{nt})'$, $\mathbf{X} = (\mathbf{x}_1', ..., \mathbf{x}_n')'$, $\mathbf{Z}_t = (\mathbf{e}_n \otimes \mathbf{z}_t')$, $\mathbf{u}_t = (u_{1t}, ..., u_{nt})'$, and the matrix $\mathbf{W}$ collects the spatial weights:

$$\mathbf{W} = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix}. \tag{3}$$

In the case under consideration the structure of the weighting matrix deserves some attention. With over 100,000 observations the dimension is relatively large. However, the dimensions can be reduced by taking advantage of the temporal and spatial structure of the data. The location is characterized by the '*quartier*' and time in which the transaction takes place. Observe that Paris is administratively divided into 20 arrondissements, each of which is further divided into four *quartiers*. In total there are 80 *quartiers* (see Figure 1). Hence, in this case the weighting matrix $\mathbf{W}$ is constructed from a weighting matrix for a model that consists of only one observation in each of the 80 *quartiers*.[5] In particular, the weights are

[5]Therefore, one only needs to keep an 80×80 matrix in the memory which makes the computations feasible.

Figure 1: Administrative *Quartiers* of Paris (France)



specified as follows:

$$w_{ij} = \sum_{t=1}^{T} d_i^t d_i^t \sum_{k=1}^{Q} \sum_{l=1}^{Q} q_i^k q_j^l w_{kl}^q, \tag{4}$$

where d_i^t is a dummy variable with an entry of one when the i-th observation was concluded at time period t, q_i^k is a dummy variable with an entry of one when the i-the observation was located in quartier k, T is the number of time periods, Q is the number of *quartiers* and, finally, w_{kl}^q is weight related to the distance between *quartiers* k and l. The $Q \times Q$ weighting matrix for the *quartiers* is specified as a simple contiguity matrix; w_{kl}^q is set equal to one over the number of neighbors of *quartier* l when the *quartier* k is a neighbor of l, and to zero otherwise.

The specification adopted here implies that the average price of an apartment in a *quartier* is influenced by current and past averages of prices of apartments in neighboring *quartiers*. Observe furthermore that in this model transaction concluded at time t will influence transactions taking place at all locations in the current and all subsequent periods.

4 Estimation Procedure

The model contains spatial lags of dependent variable and, as a result, direct estimation by OLS will be inconsistent. Observe that the specification

$$\mathbf{p}_t = \mathbf{X}\beta + \mathbf{Z}_t\gamma + \sum_{k=0}^{q} \lambda_k \mathbf{W}\mathbf{p}_{t-k} + \mathbf{u}_t, \tag{5}$$

can be solved for the endogenous variable[6] and obtain

$$\mathbf{p}_t = (\mathbf{I}_n - \lambda_0 \mathbf{W})^{-1} \left(\mathbf{X}\beta + \mathbf{Z}_t\gamma + \sum_{k=1}^{q} \lambda_k \mathbf{W}\mathbf{p}_{t-k} + \mathbf{u}_t \right). \tag{6}$$

As a result, the explanatory variable $\mathbf{W}\mathbf{p}_t$ will be correlated with the error term, i.e.

$$E\left(\mathbf{W}\mathbf{p}_t'\mathbf{u}_t\right) \neq 0, \tag{7}$$

[6]Provided that the matrix $(\mathbf{I}_n - \lambda_0 \mathbf{W})$ is invertible. Since the weighting matrix is row normalized, one needs to assume that $|\lambda_0 < 1|$.

and the OLS procedure is biased (endogenous variable bias). On the other hand, since each observation is included in the sample only once, the time lags of average prices ($\mathbf{Wp}_{t-k}$ for $k > 0$) are exogenous and are not correlated with current period disturbances.

Therefore, the model is first estimated using instruments for the contemporaneous spatial lag of the dependent variable. The instrument set is motivated by an approximation of the matrix $(\mathbf{I}_n - \lambda_0\mathbf{W})^{-1}$ as a finite sum

$$(\mathbf{I}_n - \lambda_0\mathbf{W})^{-1} = \mathbf{I}_n + \lambda_0\mathbf{W} + \lambda_0\mathbf{W}^2 + ..., \tag{8}$$

and consists of two spatial lags of other explanatory variables. Spatial lags of the macroeconomic variables $\mathbf{Z}_t$ as well as the remaining time lags of the average prices are excluded from the instruments set, as these would be collinear ($\mathbf{Wp}_{t-k}$). The instrument set is based on suggestions in *Kelejian and Prucha* (1999).

Our estimate ignore the possibility of spatial autocorrelation in the disturbances. If there is indeed additional spatial autocorrelation in the disturbances, our estimates will remain consistent but will not be efficient. Given the large sample size of over 100,000 observations and the fact that the parameter estimates are significant at 1% level and robust across different subsamples, we conclude that the potential efficiency gains are minimal and do not justify the additional computational costs.[7]

Suppose for concretness that the disturbances of the model are generated from

$$\mathbf{u}_t = \mathbf{R}\epsilon_t, \tag{9}$$

where $\mathbf{R}$ is a sequence of $N \times N$ nonstochastic matrices and ϵ_t is an $N \times 1$ vector of identically and independently distributed innovations. This specification includes several popular models considered in the literature. For example, if the disturbances follow a first order spatial autocorellated process (SAR(1) in the terminology of *Anselin*, 1988), i.e.

$$\mathbf{u}_t = \rho\mathbf{M}\mathbf{u}_t + \epsilon_t, \tag{10}$$

[7]Although the spatial generalized moments estimation is feasible even in such a large sample, it nevertheless requires repeated multiplication of matrices of size $n \times n$. For $n = 129,455$ these represent nontrivial computational costs.

where $\mathbf{M}$ is a sequence of $N \times N$ spatial weight matrices (possibly equal to $\mathbf{W}$), then we can specify $\mathbf{R} = (\mathbf{I}_N - \rho\mathbf{M})^{-1}$. Note that the instruments we use are still valid, that is, it still holds that

$$E(\mathbf{W}^s\mathbf{X}\mathbf{u}_t) = E(\mathbf{W}^s\mathbf{X}\mathbf{R}\epsilon_t) = \mathbf{W}^s\mathbf{X}\mathbf{R}E(\epsilon_t) = 0. \tag{11}$$

As a result our instrumental variable procedure is still asymptotically valid.

An alternative to pre-specifying the macroeconomic factors (as we do in Section 3.2) is to integrate these directly into the hedonic equation for the individual apartment sales price. That is, if we view each apartment as an investment and hence derive its pricing equation, as a discounted value of expected future stream of payoffs. Then, following Campbell and Schiller (1987, 1988a, 1988b), we would specify a VAR system that includes both the excess return on investing into (each) apartment as well as all the other macroeconomic variables.

If such VAR system is the true data generating process (DGP), it might seem that our approach of ignoring the real estate variables when constructing the expected and surprise components of the macroeconomic variables will be inconsistent. However, this is not necessarily correct. Note that we can think of the Campbell-Schiller DGP as a VAR of the following form

$$\begin{pmatrix} \mathbf{p}_t \\ \mathbf{y}_t \end{pmatrix} = \sum_{k=1}^{q} \begin{bmatrix} \lambda_k \mathbf{W} & (\iota_n \otimes \delta_k') \\ (\gamma_k \otimes \mathbf{a}') & \mathbf{\Phi}_k \end{bmatrix} \begin{pmatrix} \mathbf{p}_{t-k} \\ \mathbf{y}_{t-k} \end{pmatrix} + \begin{pmatrix} \rho_0 \mathbf{W}\mathbf{p}_t + \mathbf{X}_t\beta \\ \mathbf{0}_{m\times 1} \end{pmatrix} + \begin{pmatrix} \mathbf{u}_{1t} \\ \mathbf{u}_{2t} \end{pmatrix}, \tag{12}$$

where p_{it} is (log of) the price of apartment i at time t; n is the total number of existing apartments; $p_t = (p_{1t}, .., p_{nt})'$; $y_{1t}, .., y_{mt}$ are the relevant macroeconomic variables; $y_t = (y_{1t}, .., y_{mt})'$; q is the number of lags; $\lambda_k \mathbf{W}\mathbf{p}_{t-k}$ $(k = 0, .., q)$ are the spatial lags of the real estate prices; ι_n is an $n \times 1$ vector of ones; δ_k is a $m \times 1$ vector of parameters relating to the impact of the macroeconomic variables on the real estate prices; $\mathbf{a}$ is an $n \times 1$ vector of aggregation weights so that $\mathbf{a}'\mathbf{p}_{t-k}$ becomes a weighted average of real estate prices; γ_k are $m \times 1$ vectors of the associated loading factors relating the impact of real estate prices on the macroeconomic variables; $\mathbf{\Phi}_k$ are $k \times k$ parameter matrices of the VAR system involving the macroeconomic variables; $\mathbf{X}_t$ is a matrix of apartment characteristics; β is an associated parameter vector; and finally $\mathbf{u}_{1t}$ and $\mathbf{u}_{2t}$ are vectors of the disturbances.

Estimation of the full system is not feasible because we do not have data on the entire stock of existing apartments (we only have data on sales of apartments). In this paper we first estimate the sub-system involving only the macroeconomic variables $\mathbf{y}_t$ as a function of lags $\mathbf{y}_{t-k}$. However, we determine the number of lags in the estimated system optimally using an information criteria. Therefore, as a result, we have forecasts of the macroeconomic variables that have certain optimality properties. Note that by backward substitution we can eliminate the real estate variables in the equations for the macroeconomic variables and express these as a function of only their own lags at the cost of including a higher number of lags. Advantages and disadvantages of our approach are then related to the question of relative efficiency of forecasts using aggregate and disaggregate data. It has been long recognized in the forecasting literature that omitting certain information might actually improve the performance of the forecasts, see Kunst and Neusser (1986), or the discussion in Hendry and Hubrich (2006).

We thus believe that our macroeconomic VAR model is able to adequately capture the various feedbacks and produce reasonable forecasts of the macroeconomic variables. For similar reasons, we then think that the hedonic equations adequately capture the mutual feedbacks among the real estate prices and the macroeconomic variables and allow us to correctly identify the coefficients in vectors δ_k.

5 Estimations Results

The tables below present the estimation results from the instrumental variable regression of equation (1). Summary of the regression characteristics is reported in Table 3. The dependent variable is the log of sale price of an apartment. The regression is based on a sample of 129,455 observations. The model fits the data with an R^2 of 0.82 which is comparable to other studies.[8]

Table 4 reports the effect of prices of neighboring units in the current and 4 previous quarters. It is notable that there is a significant spatial component in the prices but, on the other hand, the temporal correlation

[8] *Palmquist* (1980): 0.90; *Milton et al.* (1984): 0.68-0.76; *Rasmussen and Zuehlke* (1990): 0.97; *Maurer et al.* (2004): 0.89.

Table 3: Regression Characteristics

Dependent Variable	logprice		
Observations	129,455	Mean of Dep. Variable	13.44
R-squared	0.82	S.D. of Dep. Variable	0.77
Adjusted R-squared	0.82	Sum of Squared Residuals	14130.40
S.E. of regression	0.33		
F-statistics	16314.11		

is rather small in comparison to the spatial one. In particular, observe that most of the autocorrelations (in space) in sales prices are within the current quarter. However, the time lags of the dependent variable are significant as well. The results imply that the regressions that omit the contemporaneous spatial lag of the dependent variable will be biased (omitted variable bias) and overstate the significance of their findings. Temporal autocorrelation seams to be less relevant.

Table 4: Spatio-Temporal Correlation Coefficients

Variable	Parameter Value	t-statistics
$\mathbf{Wp}_t$	0.47**	127.40
$\mathbf{Wp}_{t-1}$	0.02**	7.42
$\mathbf{Wp}_{t-2}$	0.01**	3.26
$\mathbf{Wp}_{t-3}$	-0.01**	-3.84
$\mathbf{Wp}_{t-4}$	0.01**	5.94

** denotes 1 percent significance level

Table 5 lists the coefficients of macroeconomic variables (or market conditions) that are invariant across units in a particular quarter. The variables include the expected (denoted by ..._E) and surprise (denoted by ..._res) component of GDP (approximated by industrial production), price level (CPI), long term yields (LTY) and spreads (difference between long and short term yields).

With the exception of IP_res, all coefficients are highly significant. In particular, income, approximated by industrial production (IP), has a positive effect on real estate prices. Even if the coefficient for the unexpected level of industrial production IP_res is not significant, the expected as well as the overall level of industrial production (IP_res + IP_E) is positive and significant. A possible explanation might be that a high income leads to a greater demand for apartments which together with the limited supply results in an increase in price.

Surprise increases in the general price level lead to higher housing prices, while expected component of the price level (CPI) slightly depresses the housing prices. However, as the coefficient of CPI_E is with 0.0262 quite small relative to the coefficient of CPI_res with 0.1731, realized price level (CPI_E + CPI_res) has a positive effect on the housing prices. Nevertheless, there is no obvious reason why house prices should decrease as result of the expectation of higher level of consumer prices. One interpretation that we can offer is that given a fixed level of wages, higher general price level means lower real income and hence lower demand for housing purchases.

In contrast to IP and (realized) price levels, interest rates hikes depress the real estate market. As most apartments are financed with dept, i.e. mortgages, the negative parameter of both, the predicted and the surprise component of the long term yield is in line with economic intuition. Both components of the yield spread have a positive impact while the coefficients of the expected and the unexpected yield spread have with 0.745 and 0.743 respectively, about the same order of magnitude.

The results point to the importance of distinguishing between the expected and surprise components of general price level, while the distinction does not seem to be of importance for the other series. The fact that (with the exception to IP_res) both expected and surprise components play a role in real estate prices indicate that real estate markets, or more precisely the market for apartments in Paris, might not be fully information efficient.

Our results for the macroeconomic factors do not reflect all findings of previous work, but, as they are quite heterogenous, are in line with some comparable studies. The most plausible explanation for the deviating results are the different datasets and real estate markets under consideration. For example, *Baffoe-Bonnie* (1998) finds that housing prices in the U.S. are driven by employment growth, inflation, interest rate and money supply. *De Wit and Van Dijk* (2003) examine the determinants of office returns

Table 5: Macroeconomic Variables

Variable	Parameter Value	t-statistics
IP_E	0.0016*	3.80
IP_res	0.0012	1.04
CPI_E	-0.0262*	-27.52
CPI_res	0.1731*	15.15
LTY_E	-0.0563*	-15.02
LTY_res	-0.0684*	-6.53
Spread_E	0.0745*	20.94
Spread_res	0.0743*	8.85

* denotes 1 percent significance level

and conclude that change in GDP and inflation positively affect changes in real estate prices. Furthermore, real estate prices seemed to be negatively influenced by changes in unemployment. *Sing* (2004) shows that term risk structure and unexpected inflation were significantly priced in real estate indices derived from transaction data of commercial and residential real estate markets in Singapore. The results of *Hoskins, Higgin and Cardew* (2004) suggest that gross domestic product, unemployment and inflation are correlated with the (appraisal based) returns of Australian, Canadian, U.K. and U.S. commercial property. *Ling and Naranjo* (1999) used as well appraisal based data for commercial real estate in the U.S. and find evidence for a risk exposure toward consumption expenditures and the real treasury bill. In contrary to *Sing* (2004) or our results they find a significant beta neither for unexpected inflation nor the term structure premium.

We control for most of the individual characteristics of the apartment which - in addition to location - potentially have an influence on their value. For completeness, those remaining regressors are listed in Table 6. We perform some robustness checks by estimating the hedonic price equations without the macroeconomic variables but with the space-time lag structure. The estimated coefficients and their significance are essentially the same. This can be expected as the macroeconomic variables do not have (by definition) any cross-sectional variation and hence their omission or inclusion in the model has little effect on the estimates of the remaining parameters. The coefficients on the characteristics of the apartments are

Table 6: Apartment Characteristics

Variable	Parameter Value	t-statistics
constant	5.031142**	35.78277
log (area)	1.036115**	532.2912
number of bathrooms	0.159671**	83.66922
number of service rooms	0.107864**	32.15965
dummy variables:		
construction before 1849	0.143976**	35.80075
construction 1914-1947	-0.019036**	-6.916183
construction 1948-1969	0.029125**	9.473883
construction 1970-1980	0.047723**	14.22260
construction 1981-1991	0.173595**	26.43507
construction 1992-2000	0.445032**	76.72166
garage	0.071475**	24.08012
garden	0.110189**	9.260652
occupied by acquirer	-0.226813**	-42.37100
partly occupied	-0.152832**	-8.908140
occupied by third party	-0.239700**	-50.97046
terrace	0.130251**	21.15486
basement	0.119219**	6.430561
1st floor	0.097556**	22.95342
2nd floor	0.141890**	33.44638
3rd floor	0.150786**	35.37837
4th floor	0.165083**	38.26223
5th floor	0.165300**	37.16662
6th floor	0.142400**	33.23515

** denotes 1 percent significance level

also in line with findings of *Maurer et al.* (2004), who examined the same dataset with a similar model but without space-time lags and replacing the macroeconomic variables with time dummies that capture the effect of any variable that does not vary over the different cross-sections (for a given time period). See as well *Maurer et al.* (2004) for a more detailed description and interpretation of the coefficient parameters.

6 Conclusion

A hedonic model for real estate transaction prices accounting for spatial and temporal correlation has been constructed. Furthermore, a multi-beta asset pricing model has been integrated using a set of four macroeconomic variables: general price level, industrial production, long term yield and the spread between long and short term yield. As real estate markets are not fully information efficient, both, expected and unexpected components of all macroeconomic factors have been included.

It is shown that spatial and temporal correlation as well as changes in the macroeconomic environment should be taken into account while analyzing the fundamental risk of real estate prices. For the sample used in this study, spatial correlation has proved to be more important than temporal correlation. Nevertheless, accounting for the temporal structure of the prices ensures that the macroeconomic variables are not capturing the temporal autocorrelation of the dependent variable and thus leading to biased estimates. Despite the relatively short time dimension (40 quarterly observations), all macroeconomic factors have proved to have a significant impact on the real estate prices. In most cases, the expected as well the unexpected components of the macroeconomic variables have a significant impact, indicating that real estate market are not fully information efficient.

A Appendix - VAR Model

Vector Error Correction Estimates

Sample(adjusted): 1978:04 2005:04

Included observations: 325 after adjusting endpoints

t-statistics in parenthesis

Table A.1: Cointegrating Equations

Variable	Equation 1	Equation 2	Equation 3
IP(-1)	1.00	0.00	0.00
CPI(-1)	0.00	1.00	0.00
REER(-1)	0.00	0.00	1.00
LTY(-1)	1.11	-4.59	1.08
	(2.19)	(-7.29)	(2.35)
Spread(-1)	3.76	1.15	-1.07
	(6.48)	(1.59)	(-2.03)
Trend	-0.04	-0.26	0.14
	(-2.24)	(-11.67)	(8.56)
Constant	-92.45	46.97	-171.49

Table A.2: Error Correction

	Δ(IP)	Δ(CPI)	Δ(REER)	Δ(LTY)	Δ(Spread)
CointEq1	-0.04				-0.03
	(-2.07)				(-4.72)
CointEq2		-0.01	-0.01		-0.01
		(-8.08)	(-1.68)		(-2.22)
CointEq3	-0.07		-0.06	-0.01	
	(3.47)		(-3.77)	(-1.20)	
Δ(IP(-1))	-0.23	0.00	-0.02	-0.00	0.04
Δ(IP(-2))	-0.10	-0.00	-0.05	-0.00	0.09
	(-1.76)	(-0.01)	(-1.07)	(-0.21)	(4.71)
Δ(CPI(-1))	0.29	0.12	-0.12	0.32	0.22
	(0.81)	(2.21)	(-0.40)	(3.62)	(1.86)
Δ(CPI(-2))	0.30	-0.19	-0.13	0.03	-0.07
	(0.82)	(-3.39)	(-0.39)	(0.28)	(-0.58)
Δ(REER(-1))	0.07	-0.01	0.33	-0.01	0.06
	(1.07)	(-0.70)	(6.16)	(-0.54)	(2.85)
Δ(REER(-2))	-0.02	0.00	-0.03	0.01	-0.06
	(-0.37)	(0.27)	(-0.60)	(0.80)	(-2.70)
Δ(LTY(-1))	0.25	0.04	0.57	0.21	-0.41
	(1.05)	(0.99)	(2.77)	(3.56)	(-5.14)
Δ(LTY(-2))	0.17	-0.00	-0.05	0.01	0.16
	(0.67)	(-0.02)	(-0.22)	(0.15)	(1.90)
Δ(Spread(-1))	0.17	-0.02	-0.33	0.014	0.29
	(1.06)	(-0.85)	(-2.33)	(0.34)	(5.33)
Δ(Spread(-2))	-0.04	-0.03	0.43	-0.01	0.04
	(-0.22)	(-1.13)	(3.16)	(-0.16)	(0.70)
Constant	-0.05	0.25	0.03	-0.10	-0.05
	(-0.38)	(12.30)	(0.28)	(-3.02)	(-1.13)
R-squared	0.10	0.37	0.18	0.10	0.26
Adj. R-squared	0.06	0.34	0.14	0.06	0.22
Sum sq. resids	433.49	10.38	323.82	26.59	47.99
S.E. equation	1.18	0.18	1.02	0.29	0.39
F-statistic	2.72	14.00	5.17	2.54	8.20
Log likelihood	-507.96	98.50	-460.57	-54.36	-150.32
Mean dependent	0.06	0.23	-0.06	-0.02	0.00
S.D. dependent	1.22	0.23	1.10	0.30	0.45

B Appendix - Regression Results Omitting Q4_99

Table B.1: Regression Characteristics

Dependent Variable	logprice		
Observations	123,746	Mean of Dep. Variable	13.44
R-squared	0.81	S.D. of Dep. Variable	0.77
Adjusted R-squared	0.81	Sum of Squared Residuals	13681.34
S.E. of regression	0.33		
F-statistics	15374.81		

Table B.2: Spatio-Temporal Correlation Coefficients

Variable	Parameter Value	t-statistics
W_logprice_t	0.46**	123.78
W_logprice_t-1	0.02**	6.98
W_logprice_t-2	0.01**	3.57
W_logprice_t-3	-0.01**	-3.51
W_logprice_t-4	0.01**	4.25

Table B.3: Macroeconomic Variables

Variable	Parameter Value	t-statistics
GDP_E	0.0017**	4.10
GDP_res	0.0011	1.00
CPI_E	-0.0259**	-26.56
CPI_res	0.1821**	14.14
LTY_E	-0.0581**	-15.19
LTY_res	-0.0754**	-6.96
Spread_E	0.0780**	20.07
Spread_res	0.0814**	9.40

Table B.4: Apartment Characteristics

Variable	Parameter Value	t-statistics
constant	5.08**	35.20
log_area	1.04**	516.58
bathrooms	0.16**	82.09
service_room	0.11**	31.87
construction_1849	0.14**	34.18
construction_1914_1947	-0.02**	-6.64
construction_1948_1969	0.03**	9.64
construction_1970_1980	0.05**	14.35
construction_1981_1991	0.18**	26.16
construction_1992_2000	0.45**	75.44
garage	0.07**	23.40
garden	0.11**	8.66
occ_acc	-0.23**	-41.53
occ_part	-0.16**	-8.85
occ_tiers	-0.24**	-49.20
terasse	0.13**	20.56
floor_basement	0.12**	6.02
floor_1st	0.10**	22.50
floor_2nd	0.14**	35.52
floor_3rd	0.15**	34.31
floor_4th	0.17**	36.98
floor_5th	0.17**	35.93
floor_6th	0.14**	32.20

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