Liquidity Risk and Housing Price Dynamics

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Objectives

- Survey of the empirical and theoretical literature on correlation between price and liquidity on real estate markets.

- Introduction of an additional dimension to capture a mechanism affecting the price dynamics : liquidity risk.

- Empirical illustration of the relevance of this mechanism with a GARCH-in mean Panel VAR model with local and global components on Paris Region data.

Empirical Regularities

- For both non-residential real estate and housing : strong positive correlation between prices/trading volumes (Stein, 1995, Genesove & Mayer, 2001) and negative correlation between prices/time to sell (Anglin *et al.*, 2003)

- Dynamic literature : bivariate (price/volumes) VAR models show a temporal diffusion process of volumes on prices (Clayton *et al.*, 2008)

- This pattern appears to be inconsistent with theories on standard financial assets. Housing is not a standard asset (heterogenous, indivisible, generates a service, characterized by incomplete and asymmetric information).

Theoretical Explanations

Buyer's and seller's strategies depend on many factors (rents, user costs of capital, ...) but in particular on market liquidity, i.e. the ability to buy and sell more or less rapidly a dwelling.

- *(i)* sunk costs, *(ii)* delay in setting a match between a buyer and a seller by lack of information, *(iii)* administrative delays.

Positive correlation between prices and volumes may results from:

- *(i)* liquidity constraints (Stein, 1995), *(ii)* search frictions (Wheaton, 1990, Krainer & Leroy, 2001), *(iii)* loss aversion (Genesove & Mayer, 2001).

A New Mechanism: Liquidity Risk

This literature on liquidity and housing prices relies on various frictions with *deterministic* levels of severity (i.e. liquidity changes over time, but is *known* or variance is *constant)* .

Households face uncertainty about liquidity (and price): the volatility of the market conditions affects the probability of a conclusive match between a buyer and a seller and then **the expected sale date**.

This uncertainty in time to sell/sale date may have drastic consequences for risk adverse sellers who try to reduce delays between the new house purchase date and old house sale date (ex: *bridge loans*). **Intuitively, risk adverse sellers facing higher liquidity uncertainty may post lower prices**.

This liquidity risk should be added to the usual **price risk**.

Liquidity Risk: Theoretical considerations

Let $\mathcal{V}_{u,t}$ be the value of being a seller who bought a new house at date t

$$\begin{aligned}\mathcal{V}_{u,t} &= \max_{p} \int q(p,\varepsilon)\left[u(p-p^*)-\kappa+\beta\mathcal{V}_{m,t+1}\right] \\ &\quad + (1-q(p,\varepsilon))\left[u(-p^*)-\kappa+\beta\overline{\mathcal{V}}_{u,t+1}\right] dF(\varepsilon)\end{aligned}$$

p: posted price. p^*: purchase price. κ: search costs. β: discount factor. $\mathcal{V}_{m,t+1}$: value of being matched at date $t+1$. $\overline{\mathcal{V}}_{u,t+1}$: value of staying unmatched. $u(.)$ utility function. $F(.)$: market conditions distribution.

Under some (mild) assumptions : *(i)* $u''(.) \neq 0$ (non-linear preferences), *(ii)* a match probability $q(p,\varepsilon)$ such that $[\partial q(p,\varepsilon)/\partial p]/q(p,\varepsilon)$ depends on ε.

$\rightarrow p$ will depend on $F(.)$, even if we keep $\int q(.,\varepsilon)\,dF(\varepsilon)$ (expected sale date) constant. **More volatility in $q(.,\varepsilon)$ distort p decisions.**

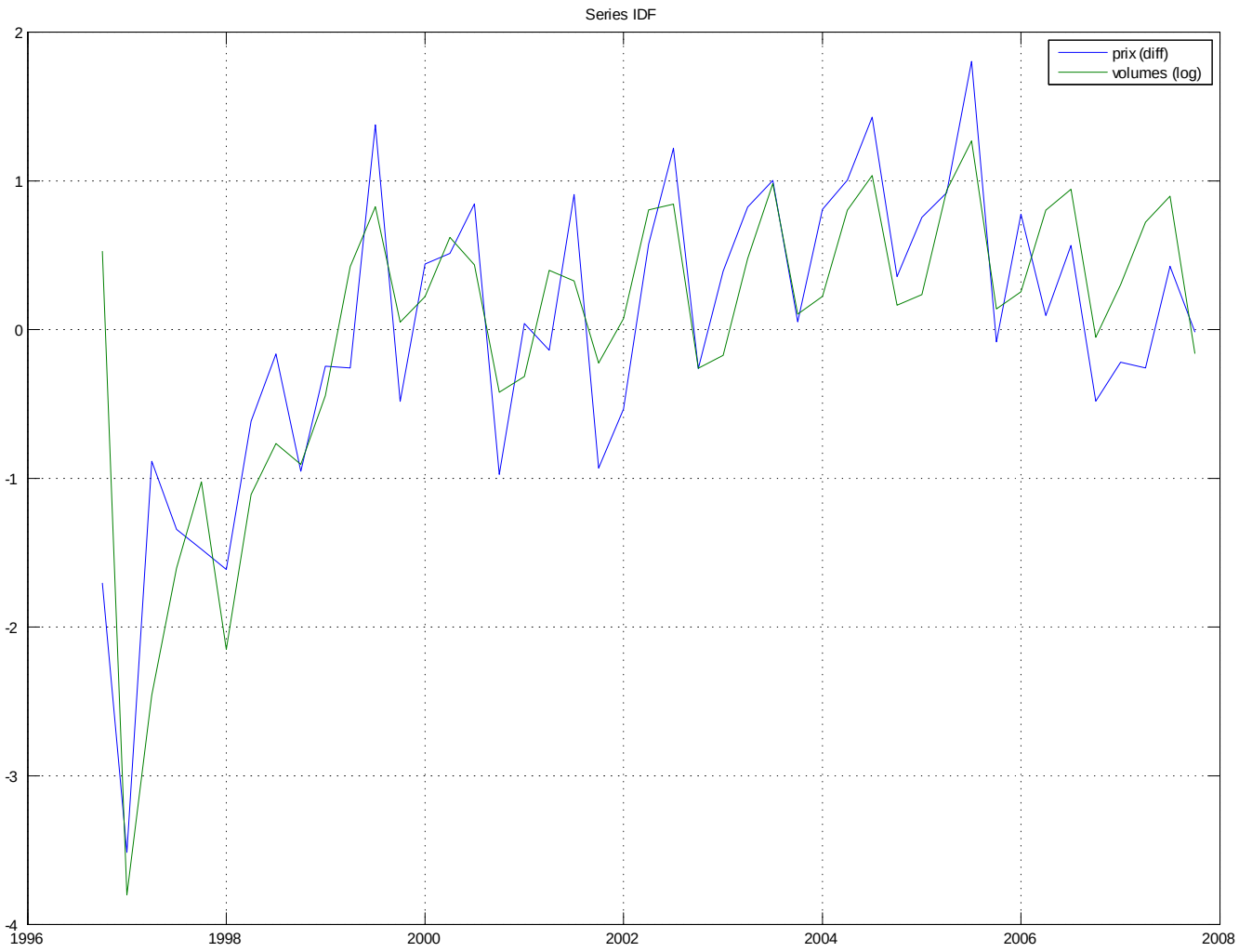
Data

Data for Paris region : second-hand flat prices and transactions for the 8 adm. units (départements) from 1996 to 2008 (quarterly basis).

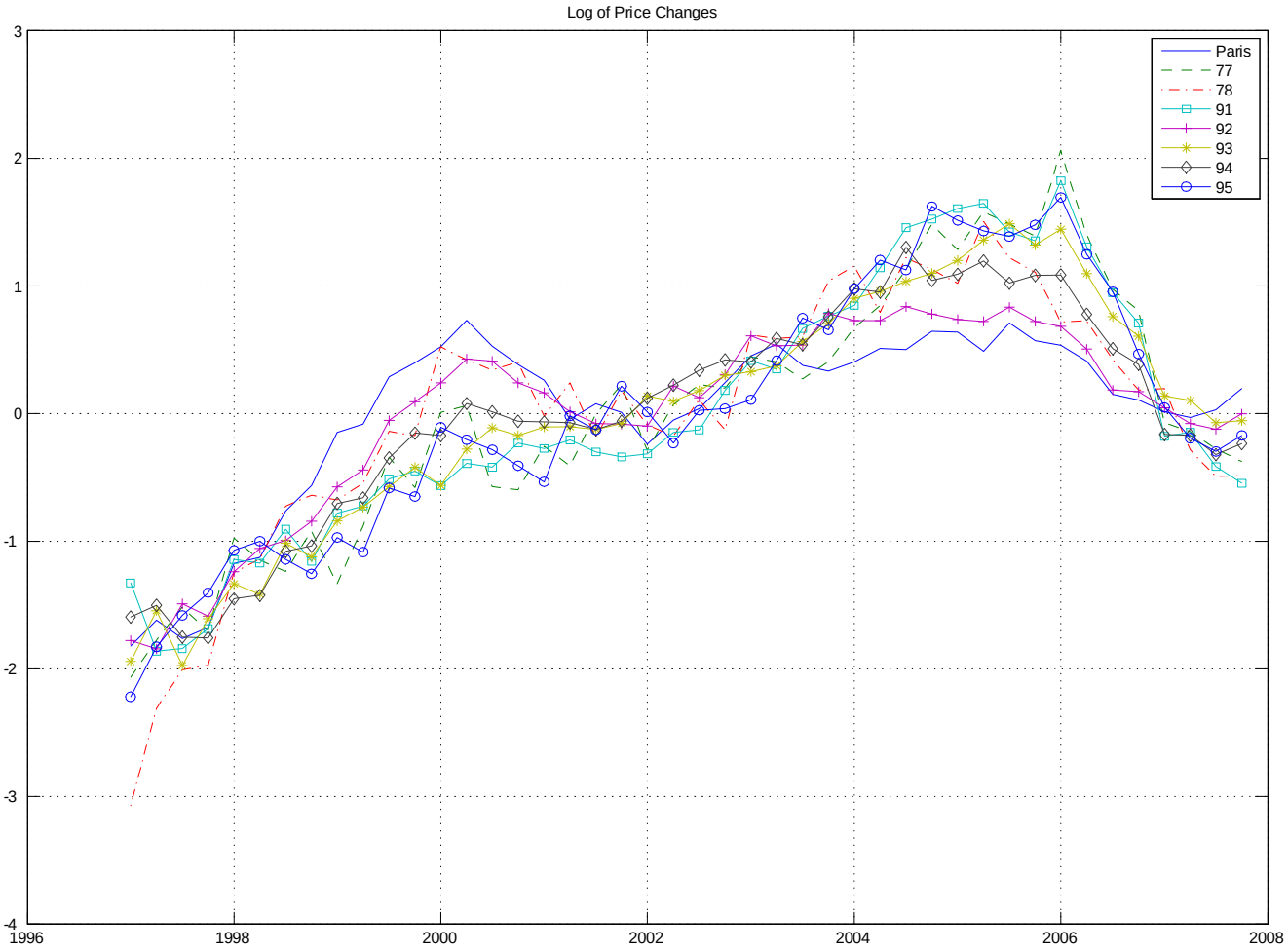
We model the **DGP of endogenous variables** $Y_{i,t} = \left(\Delta p_{i,t}, v_{i,t}\right)$: real growth rate of housing prices and logarithm of sales volumes. i is the spatial unit. t is the time period.

Exogenous variables X_t: constant term, long term real interest rates, number of households, log of real income per household, seasonal dummies.

Sales and Prices are highly correlated (similar to US or UK data). Transaction volumes and growth rates of housing prices display highly spatially correlated patterns : hypothesis of a **common trend in price changes and volume sales across spatial units**.



Prices/Sales Volumes Correlation


Log of Price Changes
Paris
77
78
91
92
93
94
95
3
2
1
0
-1
-2
-3
-4
1996
1998
2000
2002
2004
2006
2008

Our Approach : Panel VAR + GARCH-in-mean effects

$$Y_{i,t} = \underbrace{C_0 + \Phi_1(L)\, Y_{t-1} + \Phi_2(L)\left[Y_{i,t-1} - Y_{t-1}\right] + dX_t}_{\text{part I}}$$

$$+ \underbrace{\Pi_1 \text{vecdiag}\left(\Sigma_{\eta,t-1}\right) + \Pi_2 \text{vecdiag}\left(\Sigma_{\varepsilon,t-1}\right)}_{\text{part II}} + \eta_t + \varepsilon_{i,t}$$

<u>Part I:</u> Autoregressive components (global term Y_t and local term $Y_{i,t} - Y_t$) and exogenous terms dX_t. Spatial diffusion if $\Phi_1(L) \neq \Phi_2(L)$.

<u>Part II:</u> GARCH-in-mean terms. $\Sigma_{\eta,t-1}$ and $\Sigma_{\varepsilon,t-1}$ are the cond. variance-covariance matrices of aggregate (η) and local (ε) error terms. We follow BEKK (1990) approach

$$\begin{aligned} \Sigma_{\eta,t} &= C_1 C_1' + A_1 \eta_{t-1} \eta_{t-1}' A_1' + B_1 \Sigma_{\eta,t-1} B_1' \\ \Sigma_{\varepsilon,t} &= C_2 C_2' + A_2 \varepsilon_{t-1} \varepsilon_{t-1}' A_2' + B_2 \Sigma_{\varepsilon,t-1} B_2' \end{aligned}$$

Diagonal terms of Π_1 (Π_2) are global (local) price and liquidity risk.

Results: Estimation

<u>Estimation Method:</u> Maximum Likelihood Approach.

<u>Spatial Homogeneity</u> (Paris+close suburbs $\approx$ outer suburbs): Accepted (*Likelihood Ratio*).

<u>Spatial Diffusion</u> (relevance of common component): Accepted (LR).

<u>GARCH Estimates</u>:

$$\underbrace{\begin{array}{cc} \widehat{\Pi}_1(\Delta p, 1) & \widehat{\Pi}_1(v, 1) \\ -13.99^{*} & 52.91^{**} \end{array}}_{\text{Global Price Risk}} \quad \underbrace{\begin{array}{cc} \widehat{\Pi}_1(\Delta p, 2) & \widehat{\Pi}_1(v, 2) \\ -0.2265^{**} & -7.1689^{**} \end{array}}_{\text{Global Liquidity Risk}}$$

Higher liquidity uncertainty $\rightarrow$ lower prices and lower volumes.

Results: Variance Decomposition (I)

MA representation : both linear ("usual" VAR terms) and non-linear (GARCH-in-mean terms) components. The variance of each dependent variables may be decomposed into four terms:

(i) η_1: 'usual' (linear VAR structure) part of the variance-covariance related to the *global* shock,

(ii) η_2: part of the vcov. related to the GARCH effects (kurtosis) of the *global* shock,

(iii) ε_1: 'usual' part of the vcov related to the *local* shock,

(ii) ε_2: part of the vcov. related to the GARCH effects of the *local* shock.

Results: Variance Decomposition (II)

Variance decomposition of prices growth (h is the forecast horizon in quarters):

	$h = 1$	$h = 2$	$h = 5$	$h = 20$
$\eta_{1,h}$	30.26%	14.00%	12.37%	11.59%
$\eta_{2,h}$	0%	56.14%	61.86%	64.78%
$\varepsilon_{1,h}$	69.24%	29.82%	25.60%	23.32%
$\varepsilon_{2,h}$	0%	0.04%	0.17%	0.31%

- Long term movements in price come from global shocks ($\eta > \varepsilon$).
- Long term movements in price come from non linear GARCH-in means effects ($\eta_2 > \eta_1$)

Conclusion

- Liquidity Risk proxied by conditional variance has a significant negative impact on price dynamics which is not in contradiction with our intuition.

- In a variance decomposition, common shocks account for about 75% of the variance at a long horizon, it is mainly due to the consequences of uncertainty.

- Caveat 1: Cond. variance is an imperfect approximation of liquidity measure associated to the necessary time to find a match. Caveat 2: Adm. Units (*départements*) are too large spatial units, idiosyncratic risk may be smooothed.