Integration of Funding and Market Liquidity in Real Estate: International Evidence

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Idea and contribution

- Regional private real estate markets move in tandem
- This holds for returns as many studies show
- But to what extent does this apply to liquidity?
- And is the integration stronger or weaker?
- And are there differences across asset classes and countries?

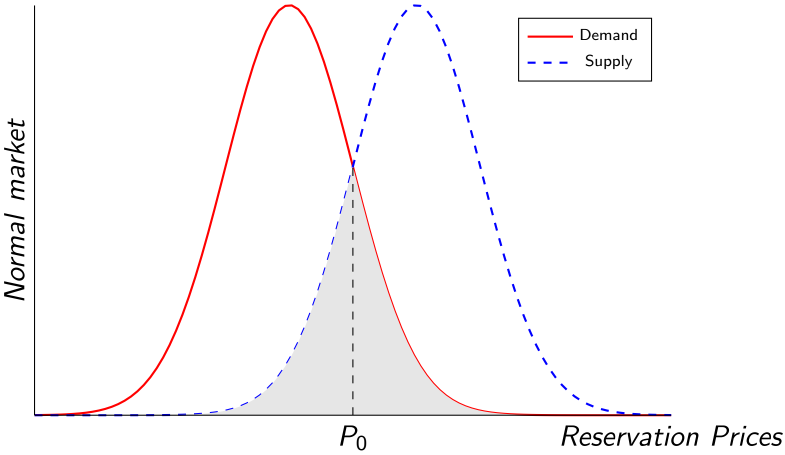
Idea and contribution

- We estimate investor demand en supply indexes for eight different asset-country combinations (Van Dijk, Geltner, and van de Minne, 2018)
- We compare the degree of integration of both returns and market liquidity for different countries and asset classes
- We examine one particular driver behind this commonality: funding liquidity
- Prices are determined by both space and capital markets and liquidity more by capital markets (which are more integrated than space markets)
- Implications for aggregate portfolio liquidity risk and policy regarding capital markets

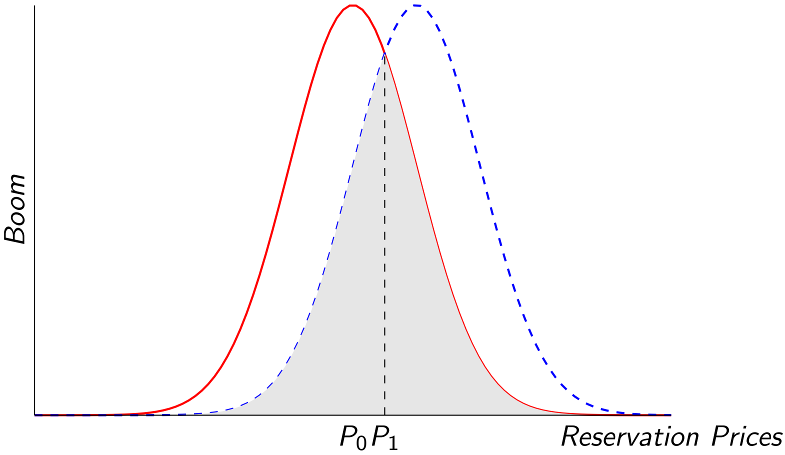
Main findings

- Market liquidity within a country and asset class shows strong co-movements
- Market liquidity shows stronger commonalities than returns in almost all markets
- Reservation prices lie closer together in residential markets than in commercial markets
- Residential markets are more integrated
- Funding liquidity is an important driver of the commonality in market liquidity

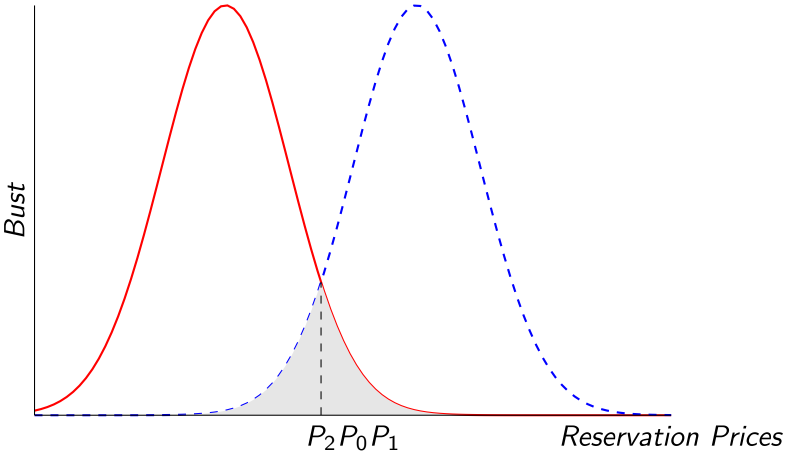
Reservation prices and liquidity: normal market



Reservation prices and liquidity: booming market



Reservation prices and liquidity: crashing market



Econometric strategy

- Estimate supply and demand indexes for regional commerical and residential real estate markets in the US, UK, and The Netherlands (Van Dijk et al., 2018), model here
- Calculate midpoint prices and liquidity metrics:

$$\beta_t = \frac{\beta_t^b + \beta_t^s}{2} \tag{1}$$

$$Liq_t = \frac{\beta_t^b - \beta_t^s}{\beta_t}. \tag{2}$$

App

dvandijk.shinyapps.io/AppLiqInt_HH2019/

Econometric strategy

- Measure integration of prices and liquidity based on two measures: "R^2"-measures and PCA
- PCAs are estimated for each country-asset combination, degree of integration is determined the explanatory power of the first factor
- R^2 measures are calculated as follows: (Roll, 1988; Morck et al., 2000; Karolyi et al., 2012)

$$r_{i,t} = \alpha_i^{Ret} + r_{m,t}\beta_i^{Ret} + \varepsilon_{i,t}^{Ret} \tag{3}$$

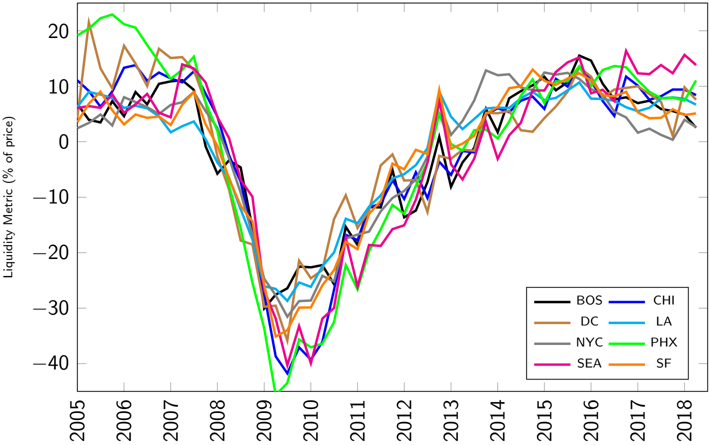
$$Liq_{i,t} = a_i^{Liq} Liq_{i,t-1} + D_\tau + \omega_{i,t}^{Liq} \tag{4}$$

$$\hat{\omega}_{i,t}^{Liq} = \alpha_i^{Liq} + \sum_{j=-1}^{1} \hat{\omega}_{m,t+j}^{Liq}\beta_{i,j}^{Liq} + \varepsilon_{i,t}^{Liq} \tag{5}$$

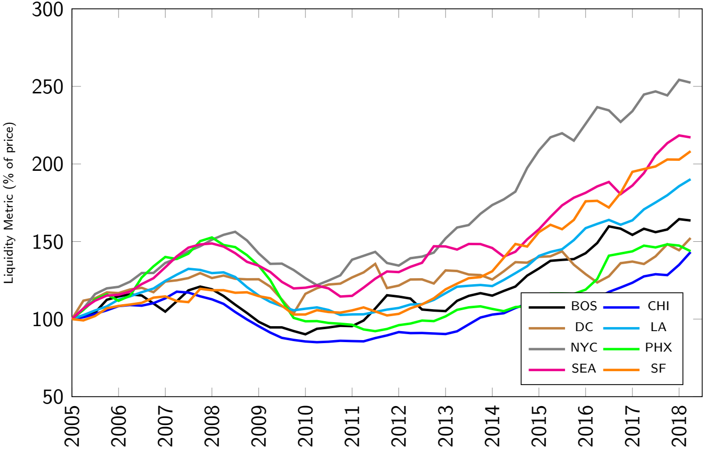
Data

- Indexes are estimated for 8 CRE markets in the US (RCA), 7 CRE and RES markets in the UK (RCA/HMLR), and 4 CRE and RES markets in NL (RCA/Kadaster)
- In total more than 110K and 22MLN RES transactions
- Assumption of model is that whole property universe is observed (capture rate RCA 2000–2018 $>$ 90%, capture rates RES $\approx$ 100%)
- Data on (national) credit conditions from Fed SLOOS, BoE CCS, ECB BLS
- CRE: 2005Q1 – 2018Q4, RES: 2000Q1 – 2017Q4

US CRE liquidity commonality

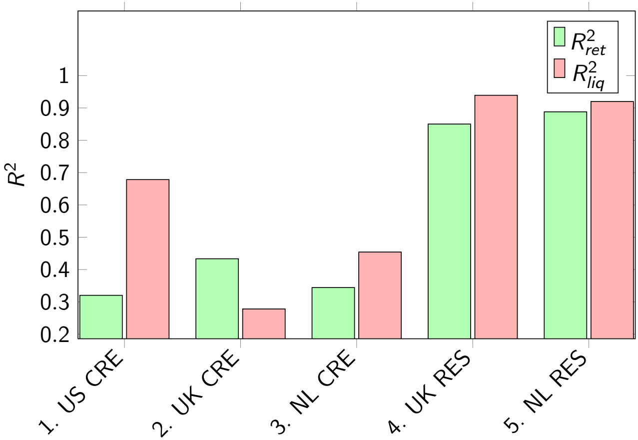


US CRE price commonality



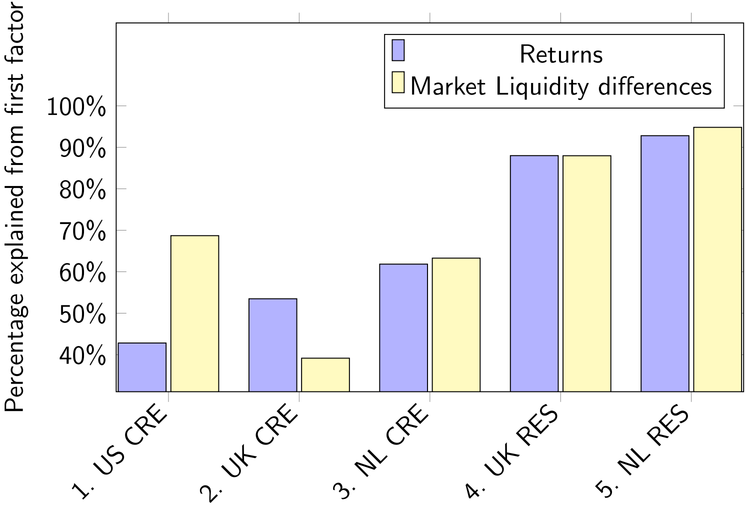
- Prices seem less correlated accross MSAs

Degree of integration (R^2)



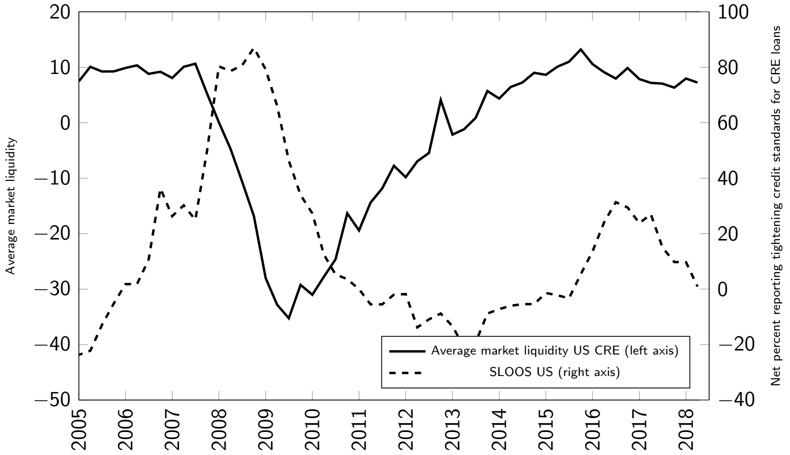
- Returns show less commonality than changes in liquidity
- RES markets more integrated than CRE markets

Degree of integration (PCA)

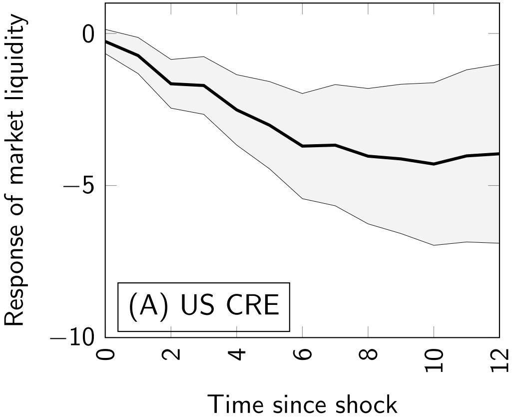


- Similar results

US CRE market liquidity and credit conditions of US CRE loans

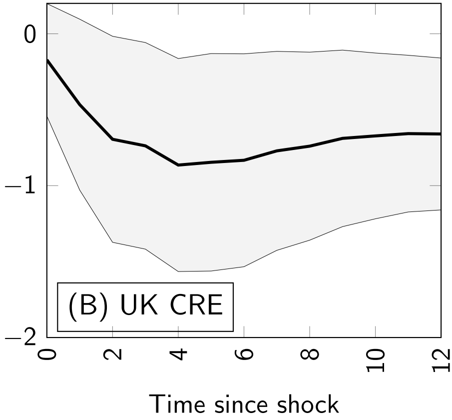


Funding liquidity and market liquidity in VARs (1/4)



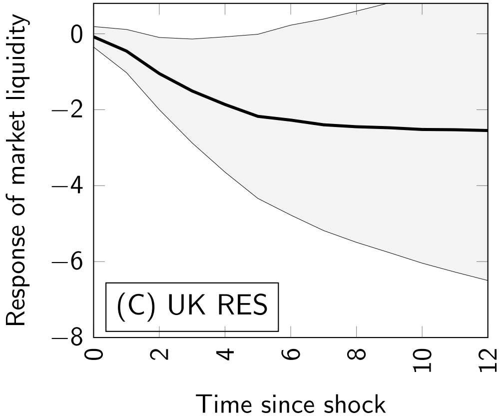
- Market liquidity responds negatively to a shock in funding liquidity
- Based on VAR with ΔCC and $CF_{\Delta Liq}$

Funding liquidity and market liquidity in VARs (2/4)



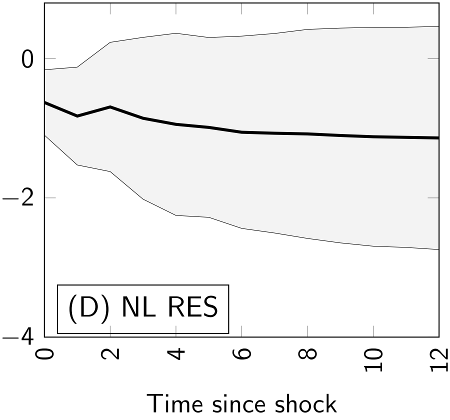
- Also in UK commerical

Funding liquidity and market liquidity in VARs (3/4)



- And in UK commercial

Funding liquidity and market liquidity in VARs (4/4)



- And (a bit) in Dutch residential

Conclusions

- We examine co-movements in residential and commercial real estate returns and market liquidity across the world
- Market liquidity co-moves stronger than real returns
- Residential markets are stronger integrated than commercial markets
- Buyers in RES are more similar (and usually simultaneously buyer and seller) and thus reservation prices are closer to each other
- Funding liquidity drives market liquidity in both commercial and residential markets

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Morck, R., B. Yeung, and W. Yu (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics 58*(1-2), 215–260.

Roll, R. (1988). r^2. *Journal of Finance 43*(2), 541–566.

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Reservation price model (short)

- Adapt Heckman selection model for repeat sales developed by (Gatzlaff and Haurin, 1997)
- Estimate probability of sale:

$$S^*_{i,t} = \gamma_t + X_i\omega + \eta_{i,t}, \qquad \eta_{i,t} \sim N(0,1).$$
$$= \Pr(S_{i,t} = 1 | X_i) = \Phi(\gamma_t + X_i\omega)$$

- Estimate the repeat sales model:

$$P_{i,t} - P_{i,s} = \beta_t - \beta_s + \sigma_{\varepsilon,\eta}(\lambda_2 - \lambda_1) + \upsilon_i, \qquad \upsilon_i \sim N(0, \sigma^2_\upsilon)$$
$$\Delta\beta_t = \rho\Delta\beta_{t-1} + \xi_t, \qquad \xi_t \sim N(0, \frac{\sigma^2_\xi}{1-\rho^2}).$$

- λ are the "inverse Mills Ratios" from the probit

Back to main.

Reservation price model (short)

- Combine probit and RS results to obtain investor demand/supply indices (FGGH):

$$\hat{\beta}_t^b = \hat{\beta}_t + \frac{1}{2}\hat{\sigma}\hat{\gamma}_t$$
$$\hat{\beta}_t^s = \hat{\beta}_t - \frac{1}{2}\hat{\sigma}\hat{\gamma}_t$$

- Identification of $\hat{\sigma}$ makes uses of the fact that residuals of repeat sales model are equivalent to residuals of hedonic model with pair fixed effects
- Identification of λ requires no correlation error terms of the first selection (sale) equation and the second sale (selection) and correlation between the first sale and first selection=correlation of the second sale and second selection
- Complete model here.

Back to main.

Reservation price model (long)

Starting point are the reservation prices:

$$RP^b_{i,t} = \beta^b_t + X_i\alpha^b + \varepsilon^b_{i,t},$$
$$RP^s_{i,t} = \beta^s_t + X_i\alpha^s + \varepsilon^s_{i,t}.$$

Normal hedonic model estimates the following:

$$E(P_{i,t}) = \frac{1}{2}(\beta^b_t + \beta^s_t) + \frac{1}{2}X_i(\alpha^b + \alpha^s) + \frac{1}{2}E((\varepsilon^b_{i,t} + \varepsilon^s_{i,t})|RP^b_{i,t} \geq RP^s_{i,t}),$$
$$E(P_{i,t}) = \beta_t + X_i\alpha + E(\varepsilon_{i,t}|RP^b_{i,t} \geq RP^s_{i,t}).$$

We observe $S_{i,t} = 1$ if a transaction is consummated:

$$S^*_{i,t} = RP^b_{i,t} - RP^s_{i,t} = (\beta^b_t - \beta^s_t) + X_i(\alpha^b - \alpha^s) + (\varepsilon^b_{i,t} - \varepsilon^s_{i,t}).$$

Back to main.

Estimate the following probit:

$$
\begin{aligned}
S^*_{i,t} &= \gamma_t + X_i\omega + \eta_{i,t}, \qquad \eta_{i,t} \sim N(0,1). \\
&= \Pr(S_{i,t} = 1 | X_i) = \Phi(\gamma_t + X_i\omega),
\end{aligned}
$$

The coefficients are estimated up to scale factor σ:

$$
\begin{aligned}
\hat{\gamma} &= \gamma/\sigma = (\beta^b_t - \beta^s_t)/\sigma, \\
\hat{\omega} &= \omega/\sigma = (\alpha^b - \alpha^s)/\sigma.
\end{aligned}
$$

Calculate IMRs and plug these in the two sales equations:

$$
\begin{aligned}
E(P_{i,s} | S_{i,s} = 1) &= \beta_s + X_i\alpha + E(\varepsilon_{i,s} | S_{i,s} = 1), \\
&= \beta_s + X_i\alpha + \sigma_{1,3}\lambda_1 + \sigma_{2,3}\lambda_2,
\end{aligned}
$$

$$
\begin{aligned}
E(P_{i,t} | S_{i,t} = 1) &= \beta_t + X_i\alpha + E(\varepsilon_{i,t} | S_{i,t} = 1), \\
&= \beta_t + X_i\alpha + \sigma_{1,4}\lambda_1 + \sigma_{2,4}\lambda_2.
\end{aligned}
$$

Back to main.

This results in the following repeat sales equation:

$$P_i^t - P_i^s = \beta_t - \beta_s + (\sigma_{1,4} - \sigma_{1,3})\lambda_s + (\sigma_{2,4} - \sigma_{2,3})\lambda_t + \upsilon_i.$$

We estimate the following restricted version:

$$P_{i,t} - P_{i,s} = \beta_t - \beta_s + \sigma_{\varepsilon,\eta}(\lambda_2 - \lambda_1) + \upsilon_i, \qquad \upsilon_i \sim N(0, \sigma_\upsilon^2).$$

The conditional expected variance of the pricing errors ($\varepsilon_{i,t}^2$) is:

$$E(\varepsilon_{i,t}^2 | S_{i,t} = 1) = \sigma_\varepsilon^2 - \sigma_{\varepsilon,\eta}^2(\gamma_t + X_i\omega)\lambda_{i,t},$$
$$\text{where } \sigma_\varepsilon^2 = \text{Var}((\varepsilon_{i,t}^b + \varepsilon_{i,t}^s)/2) = (\sigma_b^2 + \sigma_s^2)/4 = \sigma^2/4.$$

Rewriting yields:

$$\hat{\sigma}_\varepsilon^2 = (1/N)\sum_{i=1}^{N}\left[\hat{\varepsilon}_{i,t}^2 + \hat{\sigma}_{\varepsilon,\eta}^2(\hat{\gamma}_t + X_i\hat{\omega})\hat{\lambda}_{i,t}\right],$$
$$\hat{\sigma} = 2\hat{\sigma}_\varepsilon.$$

Back to main.

From the probit we have $\hat{\gamma} = (\hat{\beta}_t^b - \hat{\beta}_t^s)/\hat{\sigma}$, we also have $\hat{\beta}_t = \frac{1}{2}(\hat{\beta}_t^b + \hat{\beta}_t^s) \rightarrow \hat{\beta}_t^s = 2\hat{\beta}_t - \hat{\beta}_t^b$:

$$\hat{\gamma} = (\hat{\beta}_t^b - 2\hat{\beta}_t - \hat{\beta}_t^b)\hat{\sigma},$$
$$\hat{\beta}_t^b = \hat{\beta}_t + \frac{1}{2}\hat{\sigma}\hat{\gamma}_t.$$

Similarly:

$$\hat{\beta}_t^s = \hat{\beta}_t - \frac{1}{2}\hat{\sigma}\hat{\gamma}_t.$$

Back to main.

Estimation

- Two-step approach (Heckman, 1979)
- Probit is estimation by Maximum Likelihood
- Repeat sales model is estimated in Bayesian framework (Francke, Van de Minne, and White, 2017)
- MCMC methods, NUTS in RStan (Hoffman and Gelman, 2014)
- Chains=4, Iterations per chain=6000, Warmup=3000

Liquidity in Amsterdam residential real estate