Volatility Spillovers between U.S. Home Price Tiers during the Housing Bubble

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October, 2014

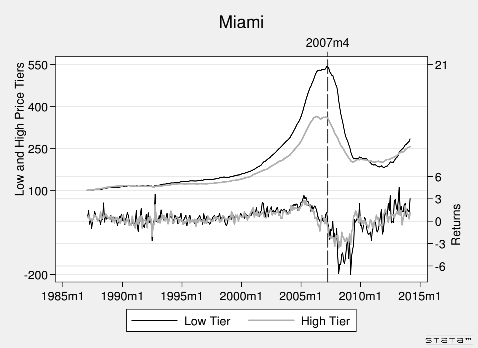
Outline

Contribution and intuition

- Analyze the volatility transmission between three S&P Case Shiller tiered price indices for 12 MA.
- Use DCC-GARCH specification.
- Importance:
  - Volatility of returns in a major factor affecting portfolio performance of mortgage lenders and mortgage insurers.
  - Heterogeneity within MAs.
  - Correlation estimates are major inputs in portfolio allocation.
  - Existence of mortgage backed securities.
  - Implications for Real Estate Investment Trusts (REIT).
  - Home owners.
- Findings:
  - Dynamic correlations across tiers are positive and persistent.
  - The housing bubble burst increases the dynamic correlations.
  - There is a contagion effect after the bubble burst as prices are driven by mortgage defaults and increased supply.
  - The burst limited the effectiveness of portfolio diversification.

Contribution and intuition

Figure: Bubble in Home Prices



- Bubble in housing prices.
- Dynamic correlation between returns.

Data

- Three tiers (Low, Medium, and High).
- Twelve MAs (Cleveland, Denver, Las Vegas, Miami, Minneapolis, New York, Phoenix, Portland, San Francisco, Seattle, Tampa, Washington DC).
- From January 1987 through March 2014.
- S&P Case Shiller methodology constructs the indices as three month moving averages.

Formulation for the Price Tiers

- Multivariate GARCH in Engle (2002) to estimate the DCC between the returns of different price tiers.
- $\text{PRICE}_{it}^{\text{TIER}}$ for $\text{TIER} = (\text{LOW}, \text{MID}, \text{HIGH})$.
- Three advantages:
  - Robust to heteroscedasticity.
  - Mean equation can include additional regressors.
  - Allows including multiple returns without including too many coefficients.
- The mean equation is modeled as:

$$\text{RET}_t = \delta_0 + \delta_1 \cdot \text{RET}_{t-1} + \delta_2 \text{RET}_{t-1}^{\text{S\&P500}} + \varepsilon_t$$

- Where $\text{RET}_t = (\text{RET}_t^{\text{LOW}}, \text{RET}_t^{\text{MID}}, \text{RET}_t^{\text{HIGH}})'$, $\varepsilon_t = (\varepsilon_t^{\text{LOW}}, \varepsilon_t^{\text{MID}}, \varepsilon_t^{\text{HIGH}})$, and $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$.

Conditional Variance

- The conditional variance is modeled as:

$$H_t = D_t R_t D_t,$$

- R_t is the correlation matrix of interest and D_t is a diagonal matrix.
- The elements in D_t are $\sqrt{h_t^{\text{TIER}}}$ with $\text{TIER} = (\text{LOW}, \text{MID}, \text{HIGH})$.
- Two-stage approach to estimate the covariance H_t:
  1. Get estimates of $\sqrt{h_t^{\text{TIER}}}$ by fitting univariate volatility models.
  2. Transforms the residuals from stage (1) $u_t^{\text{TIER}} = \varepsilon_t^{\text{TIER}} / \sqrt{h_t^{\text{TIER}}}$, then estimates the parameters of the conditional correlation using u_t^{TIER}.
- The evolution of the correlation is modeled as:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}$$

- Where α and β and $(\alpha + \beta) < 1$.
- $\bar{Q} = E[u_t u'_t]$: unconditional variance-covariance matrix of u_t.
- Q_t: time-varying conditional variance-covariance matrix of u_t.

Conditional Variance

- Rescale Q_t to obtain the correlation matrix:

$$R_t = \operatorname{diag}\left(\frac{1}{\sqrt{q_t^{\text{Low}}}}, \frac{1}{\sqrt{q_t^{\text{Mid}}}}, \frac{1}{\sqrt{q_t^{\text{High}}}}\right) Q_t \operatorname{diag}\left(\frac{1}{\sqrt{q_t^{\text{Low}}}}, \frac{1}{\sqrt{q_t^{\text{Mid}}}}, \frac{1}{\sqrt{q_t^{\text{High}}}}\right)$$

- Where q_t^{Tier} are the main diagonal elements of Q_t.
- The off-diagonal element of R_t will have the form (dropping High):

$$\rho_t^{\text{Low-Mid}} = \frac{(1-\alpha-\beta)\bar{q}^{\text{Low-Mid}} + \alpha u_{t-1}^{\text{Low}} u_{t-1}^{\text{Mid}} + \beta q_{t-1}^{\text{Low-Mid}}}{\sqrt{(1-\alpha-\beta)\bar{q}^{\text{Low}} + \alpha (u_{t-1}^{\text{Low}})^2 + \beta q_{t-1}^{\text{Low}}}\sqrt{(1-\alpha-\beta)\bar{q}^{\text{Mid}} + \alpha (u_{t-1}^{\text{Mid}})^2 + \beta q_{t-1}^{\text{Mid}}}}$$

- Where $\bar{q}^{\text{Low-Mid}}$ and $q_t^{\text{Low-Mid}}$ are the single off-diagonal elements of $\bar{Q}$ and Q_t.

Log-likelihood Function

- The log-likelihood function to be maximized:

$$
\begin{aligned}
l_t(\gamma,\delta) &= -\sum_{t-1}^{T}\left(3\cdot\log(2\pi)+\log|D_t|^2+\varepsilon_t' D_t^{-2}\varepsilon_t\right) \\
&\quad -\sum_{t=1}^{T}\left(\log|R_t|+u_t' R_t^{-1}u_t-u_t' u_t\right)
\end{aligned}
$$

- γ and δ are the coefficients to be estimated in D_t and R_t.

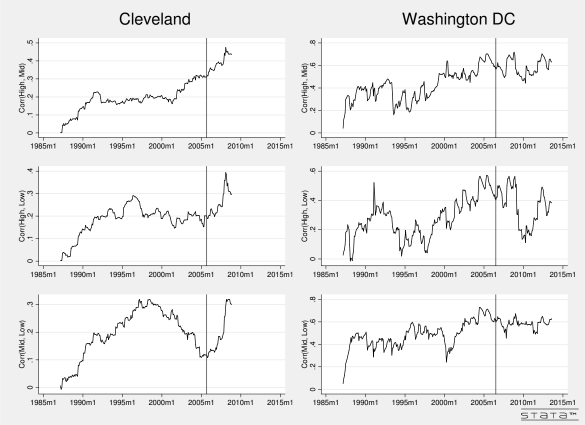
Table: Estimation Results for three DCC-GARCH Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Metro Areas:		Denver				Miami		
Tiers:	Low	Mid	High	S&P500	Low	Mid	High	S&P500
Mean Equations:								
δ_0	0.306***	0.241***	0.211***	0.571**	0.237***	0.165***	0.186***	0.678***
	(0.0483)	(0.0353)	(0.0330)	(0.231)	(0.0549)	(0.0360)	(0.0391)	(0.229)
δ_1	0.499***	0.488***	0.518***	0.00795	0.643***	0.681***	0.619***	0.00589
	(0.0439)	(0.0446)	(0.0421)	(0.0669)	(0.0548)	(0.0457)	(0.0491)	(0.0669)
δ_2	-0.00335	0.000654	0.00355		0.00566	0.00457	0.00363	
	(0.00796)	(0.00651)	(0.00625)		(0.00928)	(0.00717)	(0.00736)	
Variance Equations:								
c	0.0122*	0.00891**	0.00782	1.033	0.0285**	0.0911**	0.0339**	1.226
	(0.00714)	(0.00433)	(0.00535)	(0.764)	(0.0122)	(0.0407)	(0.0151)	(1.093)
a	0.131***	0.125***	0.0963***	0.141**	0.167***	0.289***	0.133***	0.154**
	(0.0397)	(0.0356)	(0.0313)	(0.0620)	(0.0444)	(0.0940)	(0.0410)	(0.0769)
b	0.859***	0.861***	0.882***	0.821***	0.811***	0.504***	0.790***	0.803***
	(0.0394)	(0.0333)	(0.0383)	(0.0674)	(0.0439)	(0.154)	(0.0616)	(0.0943)
Multivariate DCC Equation:								
α		0.0599***				0.0841***		
		(0.0162)				(0.0249)		
β		0.836***				0.639***		
		(0.0436)				(0.103)		
Observations		318				318		
χ^2		221.2				271.4		
χ^2 (p-value)		0				0		

Notes: The figures in parentheses are standard errors. * significant at 10%; ** significant at 5%; *** significant at 1%. For each metropolitan area the return equations are: $\text{Ret}_t = \delta_0 + \delta_1 \cdot \text{Ret}_{t-1} + \delta_2 \text{Ret}_{t-1}^{\text{S\&P500}} + \varepsilon_t$, with $\text{Ret}_t = (\text{Ret}_t^{\text{Low}}, \text{Ret}_t^{\text{Mid}}, \text{Ret}_t^{\text{High}})'$, $\varepsilon_t = (\varepsilon_t^{\text{Low}}, \varepsilon_t^{\text{Mid}}, \varepsilon_t^{\text{High}})$, and $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$. The variance equations: $h_t^{\text{Tier}} = c^{\text{Tier}} + a^{\text{Tier}} h_{t-1}^{\text{Tier}} + b^{\text{Tier}} (\varepsilon_{t-1}^{\text{Tier}})^2$ for $\text{Tier} = (\text{Low}, \text{Mid}, \text{High})$.

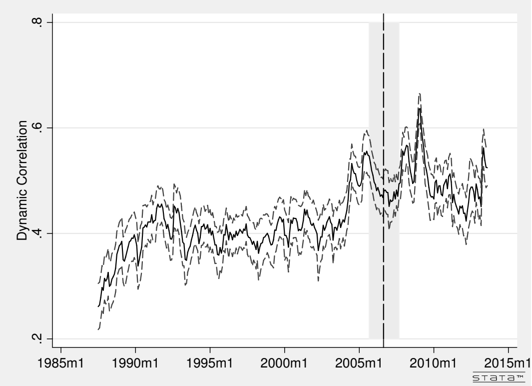
Dynamic Correlations and the Bubble Burst

Figure: Dynamic Correlations for Cleveland and Washington DC



Dynamic Correlations and the Bubble Burst

Figure: Dynamic Correlations Panel Aggregates (with 95% C.I.)



Panel Estimation of the Effect of the Bubble Burst

- Model the effect of the bubble burst on the dynamic correlation:

$$\rho_{it}^{j\text{-}k} = \gamma \rho_{i,t-1}^{j\text{-}k} + \theta \mathrm{Z}_{it} + \eta_i + \nu_{it}^{j\text{-}k}$$

- i denoting the MA.
- j and k denote tiers, $(j, k) = (\textsc{Low}, \textsc{Mid}, \textsc{High})$ for $j \neq k$.
- We model the bubble burst Z_{it} as potentially endogenous:

$$\left.\begin{array}{ll} E(\mathrm{Z}_{is}\nu_{it}^{j\text{-}k}) = 0, & s < t \\ E(\mathrm{Z}_{is}\nu_{it}^{j\text{-}k}) \neq 0, & s \geq t \end{array}\right\}, \qquad \forall i.$$

  - Assume $\nu_{it}^{j\text{-}k}$ is serially uncorrelated.
  - Use moment conditions: $E(\Delta\nu_{it}^{j\text{-}k}\mathrm{W})$ and $E[(\eta_i + \nu_{it}^{j\text{-}k})\mathrm{M}]$.
  - Test the validity of the instument list: W and M.

Regression Estimates

Table: Panel Data Results. Within Tiers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable:	$\rho_{it}^{\text{High-Low}}$		$\rho_{it}^{\text{High-Mid}}$		$\rho_{it}^{\text{Mid-Low}}$		All	
VARIABLES	Pooled	FE	Pooled	FE	Pooled	FE	Pooled	FE
Bubble Burst	0.0779***	0.0726***	0.0873***	0.0750***	0.0909***	0.0776***	0.0854***	0.0751***
	(0.00428)	(0.00328)	(0.00416)	(0.00301)	(0.00471)	(0.00303)	(0.00261)	(0.00200)
Cleveland		0.182***		0.207***		0.183***		0.191***
		(0.00538)		(0.00493)		(0.00497)		(0.00328)
Denver		0.411***		0.466***		0.516***		0.464***
		(0.00495)		(0.00454)		(0.00457)		(0.00302)
Las Vegas		0.185***		0.395***		0.282***		0.287***
		(0.00563)		(0.00516)		(0.00520)		(0.00344)
Miami		0.417***		0.469***		0.470***		0.452***
		(0.00492)		(0.00451)		(0.00454)		(0.00300)
Minneapolis		0.583***		0.715***		0.701***		0.666***
		(0.00514)		(0.00471)		(0.00474)		(0.00314)
New York		0.360***		0.407***		0.256***		0.341***
		(0.00493)		(0.00451)		(0.00455)		(0.00301)
Phoenix		0.402***		0.488***		0.549***		0.480***
		(0.00514)		(0.00471)		(0.00474)		(0.00314)
Portland		0.382***		0.457***		0.364***		0.401***
		(0.00491)		(0.00450)		(0.00453)		(0.00300)
San Francisco		0.422***		0.524***		0.490***		0.479***
		(0.00493)		(0.00452)		(0.00455)		(0.00301)
Seattle		0.368***		0.511***		0.350***		0.410***
		(0.00523)		(0.00479)		(0.00483)		(0.00319)
Tampa		0.271***		0.373***		0.358***		0.334***
		(0.00493)		(0.00452)		(0.00456)		(0.00301)
Washington DC		0.275***		0.443***		0.489***		0.402***
		(0.00493)		(0.00452)		(0.00456)		(0.00301)
Constant	0.358***		0.454***		0.418***		0.410***	
	(0.00221)		(0.00214)		(0.00242)		(0.00135)	
Observations	7,206	7,206	7,206	7,206	7,206	7,206	21,618	21,618
R-squared	0.044	0.912	0.058	0.950	0.049	0.944	0.047	0.923

Notes: The figures in parentheses are standard errors. * significant at 10%; ** significant at 5%; *** significant at 1%.

Dynamic Panel Data Results. Within Tiers.

Table: Panel Data Results. Within Tiers.

	(1)	(2)	(3)	(4)
Dep. Variable:	$\rho_{it}^{\text{HIGH-LOW}}$	$\rho_{it}^{\text{HIGH-MID}}$	$\rho_{it}^{\text{MID-LOW}}$	All
Lagged Dep. Variable	0.792***	0.784***	0.787***	0.775***
	(0.0130)	(0.0126)	(0.0149)	(0.00327)
Bubble Burst	0.0192***	0.0116***	0.0183***	0.0153***
	(0.00153)	(0.00147)	(0.00116)	(0.000496)
Observations	9760	9760	9760	29280
Instruments	32	32	32	96
Serial Correlation[a]	-1.466	0.361	1.163	0.676
Serial Correlation (p-value)	0.143	0.718	0.245	0.499
Hansen[b]	29.32	29.85	23.34	94.49
Hansen (p-value)	0.448	1	0.761	0.437

Notes: Figures in parentheses are the Windmeijer finite-sample corrected standard errors of the GMM two-step estimates. * significant at 10%; ** significant at 5%; *** significant at 1%. [a] The null hypothesis is that the errors in the first-difference regression exhibit no second-order serial correlation (valid specification). [b] The null hypothesis is that the instruments are not correlated with the residuals (valid specification).

- Passes the serial correlation test.
- Hansen validates the instrument list W and M.

Conclusions

- Methods account for autocorrelations, momentum, is parsimonious, allows including other factors.
- Account for potential endogeneity in the burst.
- Higher dynamic correlation after the bubble burst.
- Lower opportunities for diversification.
- Our findings are consistent with other markets (e.g., international equity markets) when we observe higher dynamic correlations in (1) periods of high volatility, (2) during bear markets, and (3) during financial crises.
- Suggest some directions for future research.
    - Asymmetric correlations in bull and bear markets.
    - VaR application and examine correlations in the tail of the distribution.

Stata GARCH-DCC Example

```
clear

use http://www.stata-press.com/data/r13/stocks

mgarch  dcc (toyota nissan honda = L.toyota L.nissan L.honda, noconstant), arch(1) garch(1)


Calculating starting values....

Optimizing log likelihood

(setting technique to bhhh)
Iteration 0:   log likelihood =  16902.435
Iteration 17:  log likelihood =   17484.95

Refining estimates

Iteration 0:   log likelihood =   17484.95
Iteration 1:   log likelihood =   17484.95
```

Stata GARCH-DCC Example

Dynamic conditional correlation MGARCH model

Sample: 1 - 2015		Number of obs	= 2014
Distribution: Gaussian		Wald chi2(9)	= 19.54
Log likelihood = 17484.95		Prob > chi2	= 0.0210

		Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
toyota							
toyota	L1.	-.051087	.0339825	-1.50	0.133	-.1176914	.0155174
nissan	L1.	.0297836	.0247455	1.20	0.229	-.0187168	.0782839
honda	L1.	-.0162824	.0300324	-0.54	0.588	-.0751448	.0425799
ARCH_toyota							
arch	L1.	.0608224	.0086687	7.02	0.000	.0438321	.0778126
garch	L1.	.9222204	.0111055	83.04	0.000	.9004541	.9439867
_cons		4.47e-06	1.15e-06	3.90	0.000	2.22e-06	6.72e-06
nissan							
toyota	L1.	-.0056722	.0389348	-0.15	0.884	-.081983	.0706386
nissan	L1.	-.0287094	.0309379	-0.93	0.353	-.0893465	.0319278
honda	L1.	.0154975	.0358802	0.43	0.666	-.0548265	.0858214
ARCH_nissan							
arch	L1.	.084424	.0128192	6.59	0.000	.0592988	.1095491
garch	L1.	.8994207	.0151126	59.51	0.000	.8698006	.9290407
_cons		7.21e-06	1.93e-06	3.74	0.000	3.43e-06	.000011
honda							
toyota	L1.	-.0272424	.0361819	-0.75	0.451	-.0981576	.0436728
nissan	L1.	.0617497	.0271378	2.28	0.023	.0085605	.1149389
honda	L1.	-.0635071	.0332919	-1.91	0.056	-.1287579	.0017438
ARCH_honda							
arch	L1.	.0490133	.0073695	6.65	0.000	.0345694	.0634573
garch	L1.	.9331128	.0103685	89.99	0.000	.9127908	.9534347
_cons		5.35e-06	1.35e-06	3.95	0.000	2.69e-06	8.00e-06
corr(toyota,nissan)		.6689557	.0168021	39.81	0.000	.6360242	.7018872
corr(toyota,honda)		.7259631	.0140156	51.80	0.000	.698493	.7534333
corr(nissan,honda)		.633567	.0180412	35.12	0.000	.5982069	.6689271
Adjustment							
lambda1		.0315258	.0088382	3.57	0.000	.0142032	.0488483
lambda2		.8704259	.0613323	14.19	0.000	.7502168	.9906351

Stata GARCH-DCC Example

```
predict r2*, res
predict h2*, variance

gen pnissantoyota = h2_nissan_toyota/(sqrt(h2_nissan_nissan)*sqrt(h2_toyota_toyota))

gen phondatoyota  = h2_honda_toyota/(sqrt(h2_honda_honda)*sqrt(h2_toyota_toyota))

gen phondanissan  = h2_honda_nissan/(sqrt(h2_honda_honda)*sqrt(h2_nissan_nissan))

tsline pnissantoyota, scheme(sj) ytitle("Corr(Nissan,Toyota)")  xtitle("") saving(nissantoyota, replace)
tsline phondatoyota,  scheme(sj) ytitle("Corr(Honda,Toyota)")  xtitle("") saving(hondatoyota,  replace)
tsline phondanissan,  scheme(sj) ytitle("Corr(Honda,Nissan)")   xtitle("") saving(hondanissan,  replace)

tsline pnissantoyota phondatoyota phondanissan, scheme(sj) ytitle("Dynamic Correlations") xtitle("")    \\\
saving(dynamiccorrelations,  replace)

gr combine nissantoyota.gph hondatoyota.gph hondanissan.gph dynamiccorrelations.gph, scheme(sj) col(2)  \\\
iscale (0.5) fysize(100) title( "Dynamic Correlations" )
```

Stata GARCH-DCC Example

Figure: Dynamic Correlations