Regional Price Bubbles and Implications for Credit Risk Management

Presentation to the May 2014 Meetings of the Weimer School
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Based upon 3 working papers for the Lincoln Institute of Land Policy that estimate models of house price growth during three different time frames and using various methods.

These are available at the LILP web site:

Two were coauthored with Prof. Seth Giertz of the U of Nebraska
http://cba.unl.edu/people/sgiertz/


Used in a Webinar for FI Consulting in December
http://www.ficonsulting.com/Regional-Price-Bubbles

References New Credit Risk Model from Collateral Analytics
Key Conclusion #1: Wide variations among markets even within large MSAs.

Key Conclusion #2: Local housing market conditions play a substantial role in house price patterns.

Key Conclusion #3: Hard to predict but we do know something. And we can debunk the notion of a national housing market.
Perspectives on Bubble Detection

Bubble definition: Persistent and *unsustainable* departure of market prices from prices dictated by fundamentals

Detection is inherently difficult because bubbles are extreme events
- Black Swan Blindness also plays a role

Local market conditions affect house price bubbles
- Housing markets contain a substantial local component, which may be hard to measure/capture
- These affect responses to national shocks
- Financial market analogy: S&P versus individual stocks

The role of momentum
Model and Estimation Approach

1st stage VEC to estimate deviations of the level of house prices from the amount suggested by the “fundamentals”
- \( P = f(\text{employment}, \text{income per capita}, 10 \text{ yr Treasury}, 1 \text{ yr Treasury}, \text{MSA fixed effects}) \)

3 equation VAR
- Dependent variables are the growth rates in Real house prices; Total employment; Real income per capita
- Right hand side variables: VEC residuals; 3 lags of each dependent variable; FE

Multiple Time Periods and MSA Groups
Simulation generates 500 paths per MSA per model
- Challenge is specifying key drivers
- Conduct our own “quasi” impulse response analysis
Model

$$\log(HP_{it}) = \alpha_i + \sum_{j=1}^{3} \beta_j \log(\text{Income}_{it}) + \sum_{j=1}^{3} \gamma_i \log(\text{Emp}_{it}) +$$
$$\delta_1 (TB10_{t-1} - TB1_{t-1}) + \delta_2 TB10_t + \varepsilon_{it}^{EC}.$$ 

$$\log(Y_{it}) = \alpha_t + \alpha_{\text{group}} + \alpha_{\text{EC}} \hat{\varepsilon}_{it}^{EC} + \sum_{j=1}^{3} \beta_j \log\left(\frac{HP_{it-j}}{HP_{it-1-j}}\right) + \sum_{j=1}^{3} \gamma_j \log\left(\frac{\text{Emp}_{it-j}}{\text{Emp}_{it-1-j}}\right) +$$
$$+ \sum_{j=1}^{3} \theta_j \log\left(\frac{\text{Income}_{it-j}}{\text{Income}_{it-1-j}}\right) + \varepsilon_{it}.$$
Share of Residences with Negative Equity

Red is low (<8%) and Green in high share (>27%)

Source: Collateral Analytics
Model Projections vs. Actual Outcomes 2008-10
Projections vs. Outcomes for the Largest MSAs
Model Projections vs. Actual Outcomes 2006-09

Actual HP Percent Change from 2006:q3 to 2009:q2

5 eqn Prediction thru 2009:2

Cities listed include:
- Las Vegas-Paradise, NV
- Bakersfield-Delano, CA
- Fresno, CA
- Sacramento-Fremont-Hayward, CA (MSAD)
- Oakland-Miami Beach-Kendall, FL (MSAD)
- San Diego-Carlsbad-San Marcos, CA (MSAD)
- Detroit-Livonia-Dearborn, MI (MSAD)
- Orlando-Kissimmee-Sanford, FL (MSAD)
- San Jose-Sunnyvale-Santa Clara, CA (MSAD)
- Phoenix-Mesa, AZ (MSAD)
- Tucson, AZ (MSAD)
- Worcester, MA (MSAD)
- Bridgeport-Stamford-Norwalk, CT (MSAD)
- New Haven-Milford, CT (MSAD)
- Washington, DC (MSAD)
- Portland-Vancouver-Hillsboro, OR-WA (MSAD)
- Seattle-Bellevue-Everett, WA (MSAD)
- Milwaukee-Waukesha-West Allis, WI (MSAD)
- Atlanta-Sandy Springs-Marietta, GA (MSAD)
- Cincinnati-Middletown, OH-KY-IN (MSAD)
- Memphis-Nashville, TN-MS-AR (MSAD)
- Philadelphia-Camden, PA (MSAD)
- St. Louis, MO-IL (MSAD)
- Indianapolis-Carmel, IN (MSAD)
- Albany-Schenectady-Troy, NY (MSAD)
- Fort Worth-Arlington, TX (MSAD)
- Austin-Round Rock San Marcos, TX
Predictive Power of the Bubble Indicator:
Difference Between Actual Prices and Predicted Levels
Key Conclusions on Bubble Detection

- **Key Conclusion #1:** The models provided some indication that a bubble was emerging.

- **Key Conclusion #2:** The evidence was stronger for some markets than for others, and the predictions were sensitive to the specific models used and time periods covered.

- **Key Conclusion #3:** While not perfect, the results revealed information that may have been helpful to policy makers as they developed programs in mid-crisis and as they now consider options for preventing new house price bubbles from forming.
Implications for Credit Risk for Regulators - Countercyclical Capital Policies

Glimpse of policy debate

- Shared conclusion with Greenspan – Monetary Policy not the primary culprit. Much more complex set of factors and wide ranging outcomes among markets
- Flip side of this conclusion: Neither is it very effective in combatting bubbles owing to the large variations among markets

Key issues

- How to predict prices
- How to define a bubble
Implications for Credit Risk Management for Financial Institutions

- Incorporate local market conditions in loan pricing and capital allocation, and work harder to price the risk in your local market. Banks must do a better job of pricing in “their own backyard.”
- Note on Concentrations in CA White Paper about Fed Guidance
Option 1: Simple, Transparent and Rules Based

  

- Focuses upon trends at the state level in house prices

- Substantial deviations above trend would trigger an increase in capital

- Substantial deviations below trend would trigger capital reductions
Option 2: Use Predictions of Econometric Models

- This would be more complex, less transparent, and likely less rules-based.
- Judgments of model builders would play a role.
- Econometric models of the type estimated by Follain and Giertz fit this type.
- Examples of the output of our first model regarding the size of stress scenarios are in Table 2.
## 5th Percentile Forecasts for Three Time Periods

<table>
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<tr>
<td>Austin-Round Rock-San Marcos</td>
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<td>3.3%</td>
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<td>Providence-New Bedford-Fall R</td>
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<td>Min</td>
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<tr>
<td>Std. Dev.</td>
<td>8.3%</td>
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<td>14.5%</td>
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Follain and Sklarz 2005 provide example of pricing credit risk among MSAs that differ in terms of their potential for a bubble. We recently announced a new Credit Risk Model at Collateral Analytics that expands upon these ideas and make use of the enormous amount of data and AVM products produced by CA.

- We use nonagency mortgage data assembled from Lewtan to estimate models of default and prepayment at the MSA level.
- The model incorporates CA generated house price scenarios specific to each MSA.
- CLTV is updated at the zip code level in most cases
- It also relies upon REO Discount estimates at the zip level
- Our focus has been on the 20 CBSAs in the Case-Shiller Index.
Exhibit 1: CRS by CBSA

- Exhibit 1 contains estimates of the Credit Risk Spread for 20 CBSA.
- The CRS = EL + (r – risk free rate) * Capital
- CRS 1 uses CBSA specific HP scenarios and default and prepayment equations
- CRS 3 uses the same default/prepayment equations based upon a pooled model and CBSA specific HP scenarios
- They are distinguished by FRM vs ARMs
- These apply to a 80/740 Prime Mortgage but we can generate these for any combination and other mortgage traits
<table>
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<tr>
<th>CBSA Name</th>
<th>FRM CRS 1</th>
<th>FRM CRS 3</th>
<th>ARM CRS 1</th>
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<td>Dallas-Fort Worth-Arlington, TX</td>
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**Grand Total**  
25 29 24 47

CRS 1 uses CBSA def/prep eqns and MSA HP Scenarios  
CRS 3 uses pooled eqns and MSA HP Scenarios
Exhibit 2: Capital Ratios by CBSA

- This plots the capital ratios by CBSA
- Ranked from the largest to the smallest capital ratios for ARMs
- Applies to a 740 credit score 80 LTV
- This is based upon CBSA specific HP Scenarios and Default/Prepayment Equations
- The range is substantial: .5 to 2 percent for ARMs and about the same for FRMs
Exhibit 2: Capital 1 by CBSA and ARM/FRM
Three Short Articles on CA Web Site about the CA Credit Risk Model

- **Measuring Variations in Credit Risk among Markets**

- **Drivers of Variations in the CRS among Markets**

- **Regional Impacts of Credit Scores on CR Spreads**

- **We continue to make improvements and welcome any feedback that you may have**
Similar Approach being Done with Robert Dunsky (FHFA) and Seth Giertz

- Same basic approach
- Use FHFA Default and Prepayment Model
- Use Representative Portfolios of GSE Mortgages
- Use Follain and Giertz HP Scenarios
**Our Greatest Challenged and Opportunity**

- Technically challenging but that’s not all.
- The greatest challenge is whether decision makers would be able to implement tougher stress tests as a bubble is developing.
- Black Swan Blindness by Follain 2012.
- Counteracting these challenges is the extraordinary amounts of data available today to analyze the drivers of local housing markets.
Selected References


- The Lincoln Institute of Land Policy is a leading resource for key issues concerning the use, regulation, and taxation of land, find our more here: [http://www.lincolnninst.edu/aboutlincoln/](http://www.lincolnninst.edu/aboutlincoln/)

- Follain and Sklarz (2005), Mortgage Banking Magazine
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