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Public Finance Review
2016, Vol. 44(1) 132-159
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DOI: 10.1177/1091142114537674
pfr.sagepub.com

US House Price Bubbles and Busts: Implications for Property Taxation

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Abstract

We use data for a large panel of US Metropolitan Statistical Areas (US MSAs) in order to assess the *ex ante* likelihood of house price bubbles. We employ a vector error correction–based model in order to project house prices under different scenarios. Projected house price (and employment) distributions are generated for each MSA. The model's predictions are compared to actual outcomes—focusing primarily on the house price bubble and bust of the Great Recession. In applying these results to local governments, we document a substantial rise in property tax rates during the recent crisis. Results from this exercise suggest that interactions between the property tax and house price fluctuations may have exacerbated the bubble and bust. More generally, our analysis underscores the complexity of forecasting bubbles and cautions against attempting to do so using the notion of a national housing market. Even in recent years, housing markets are heavily influenced by local supply and demand conditions.

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Keywords
house price bubbles, property taxation, forecasting, financial crisis

The bursting of the recent housing bubble has caused substantial damage to many segments of the economy tied to housing as well as a persistent negative impact on the overall economy. The impact has been devastating for many metropolitan areas and regions in which the bubble and bust was most stark. Indeed, the long-run ramifications are still unknown, though it seems likely that a full recovery for some of the hardest hit areas may be years or even decades away (Follain 2011).

The severity of the bubble and bust has generated great interest among policy makers who are now searching for ways to detect and combat house price bubbles. In his September 2010 speech at Princeton University titled "Implications of the Financial Crisis for Economics," Federal Reserve Board Chairman Ben Bernanke acknowledged that bubble detection is an area that "clearly needs more attention." He further stated that we do not have convincing models that explain when and why bubbles start or how to stop them once they begin. The president of the Federal Reserve Bank of New York William Dudley elaborated on these two themes in an April 2010 speech. Dudley (2010) emphasized both the inherent difficulty of predicting bubbles and a second but critical issue—what to do about them once they are identified with some confidence.

Sentiments, like those expressed by Bernanke and Dudley, are a motivating factor in our research into house price bubbles and how this research can be used to improve public policy. In this article, we investigate the relationship between house prices and several explanatory variables using a large panel of US Metropolitan Statistical Areas (US MSAs) in order to assess the *ex ante* presence of price bubbles. We estimate a vector error correction (VEC) model for a number of different periods (using data from 1980 to 2007) and subsets of MSAs. Estimated coefficients from these models are inputted into a Monte Carlo simulation model in order to project future house prices as well as the distribution of potential house price paths. These paths include the median or "expected" price path as well as paths associated with extreme events such as the path associated with a three-year price decline whose severity is projected to occur with a less than 1 percent probability. These projected house price income (and employment) distributions are generated for each MSA (based on pooled regression estimates), which allows us to test the role of local market conditions in the

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formation of price bubbles. The model's predictions are then compared to actual outcomes—focusing primarily on the house price bubble and bust surrounding the Great Recession.[1]

The results from this exercise are then applied to local government finance. We argue that local governments respond to house price shocks in ways that moderate swings in property tax revenues. Such responses help to stabilize the provision of local government services. However, it is not widely recognized that these polices may also have procyclical effects, possibly amplifying bubbles and busts. That is, such policies lower effective tax rates on housing during upswings and raise them during downswings. We find evidence that changes in effective property tax rates are in fact negatively correlated with house prices. We present several ways in which our bubble indicators could be used in policies designed to counteract this phenomenon, without destabilizing local government finances. These policies are centered on a "buffer" tax (or a component of the property tax) that would increase as evidence of price bubbles emerges and decrease during busts. We also raise several caveats that should be taken into account before considering such policies.[2]

The efficacy of the policies we consider relies heavily on the ability to anticipate house price bubbles. Bubbles are generally not consistent with the (narrowly defined) rationality assumption that underlies most economic models. Furthermore, as bubbles inflate, a variety of plausible explanations can be offered to justify the divergence of prices from traditional benchmarks. The validity of these explanations is extremely difficult to assess in real time. During the house price bubble in the early to mid-2000s, some called attention to the unusually high appreciation rates in housing prices in some parts of the country relative to the appreciation rates suggested by traditional measures such as the rent to value ratio and income growth. These observations were often countered by those who emphasized the low interest rate environment, the benefits of expanded access to mortgage credit, and expectations of steady flows of immigrants pushing housing demand higher, while also noting that, in the post–World War II era, the United States had never experienced a sustained decline in the nominal national house price index (Shiller 2005).[3]

One difficulty in detecting bubbles stems, in part, because such experiences typically fall outside the predictions of standard econometric models, which often focus on central tendencies. Indeed, the severity of the current drop in house prices exceeds what many (including government regulators) considered to be an extreme stress event at the start of the Great Recessions of 2007 to 2009 (Follain and Giertz 2011a). It is the most severe events that,

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while very rare, often have the greatest impact and are the most difficult to predict. Such events are generally triggered by a sudden regime change or shock followed by complex interactions that magnify the situation. Their rare nature implies that empirical analysis based on a relatively narrow slice of historical experiences will not be fruitful (and may even yield a false sense of security). Nicolas Taleb (2007) champions this idea in his book *The Black Swan: The Impact of the Highly Improbable*. Follain (2013) applies some of the concepts in Taleb's book to the issue of generating capital rules for extreme scenarios, concluding that Taleb's arguments have substantial merit.

Some researchers have examined house price bubbles building on the notion of a national housing market—Greenspan (2010) and Dokko et al. (2011) are recent examples. Others have taken another approach, focusing not on the national housing market but rather on local housing markets in recognition or belief that no single national housing market truly exists. These latter articles are based on the premise that housing and mortgage markets within the United States are heterogeneous. That is, economic factors vary across local markets and the impact of national economic factors, which may not vary across markets, may have very different impacts depending on the characteristics of the local market. Two good examples that focus on local markets are Leamer (2002) and Goodman and Thibodeau (2008).

Our analysis allows for heterogeneity across markets and imposes relatively few theoretical restrictions. Several important findings are as follows:

- The estimated coefficients of the lagged covariates in the three-equation VEC model—the core coefficients—are surprisingly similar for the various groups and periods examined.
- The estimated MSA fixed effects in the first stage VEC equation vary substantially across MSAs but are relatively stable across time periods. These MSA fixed effects capture the effect of persistent and unobserved local market conditions.
- Despite stable model coefficients, the simulation projects substantial variation in future house price appreciation across MSAs for each period and group of MSAs. This suggests that local market conditions are important drivers of future house price movements. In particular, measures of extreme events vary dramatically among these local housing markets.
- The projections based upon the model with data through 2007 receive special attention. The median predictions of this model for

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2008 to 2010 are highly correlated with the actual house price outcomes. However, the magnitudes of the house price declines substantially exceed the predictions. That is, the model missed the severity of the price declines that were to come, especially among the MSAs hardest hit by this most recent bubble bust. Again, this is consistent with the central theme of the current article: a wide variety of local market conditions, some of which are very difficult to capture in our model, affect the nature of house price bubbles and busts.

- Our bubble indicator measures (particularly, a simple measure based on the first stage VEC equation) track countercyclical patterns in effective property tax rates. This suggests that such a measure may be helpful in designing local government policies to combat house price bubbles.

Data and Estimation Methods

Several sources are used to create an annual pooled time series data set that includes 384 US MSAs. Data are available as far back as 1976, but relatively few MSAs are included in the early years. Restricting the sample to begin in 1980 results in 129 MSAs in which the core variables for the analysis are observed every year. Generally not included in the 129 are the smaller MSAs. The sample reaches 380 MSAs in 1996. Data are collected from the Federal Housing Finance Agency (FHFA), Bureau of Labor Statistics (BLS), Bureau of Economic Analysis (BEA), and Standard & Poor's. Our analysis relies on versions of these data from Woods and Poole that are constructed holding MSA definitions constant over time.

Key variables used in the analysis include median house prices, employment, and income per capita. Median house prices are constructed based on FHFA's house price index. The index is converted to levels using cross-sectional data on median house prices from both the FHFA and the National Association of Realtors (NAR) as a point of reference. Comparing median home prices for MSAs that appear in both the FHFA and the NAR data suggests that the two measures are very similar. Income per capita is constructed by dividing the total MSA income measure by MSA population (both from BEA). Dollar values are in real 2009 terms (as adjusted by the Consumer Price Index for urban consumers).[4] See table 1.

The overall average median house price (weighted by MSA employment) was US$146,014 in 1980 and US$225,357 in 2008. For 1980, average per capita income was US$26,364. By 2008, this number was US$42,782. Average population was more than 1 million in 1980 and

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Table 1. Summary Statistics.

Population Levels	Population growth	House price	Population	Employment	Income per capita	*N*
All in 1980 (147 MSAs)		146,014	1,002.18	527.24	26,364	147
All 1980 MSAs in 2008		245,824	1,400.96	857.35	44,699	147
All in 2008 (384 MSAs)		225,357	665.50	403.22	42,782	184
Low	Low	77,362	194.34	106.05	29,610	73 (7)
	Medium	129,172	198.20	116.00	31,324	133 (22)
	High	154,487	190.87	102.25	30,927	58 (14)
Medium	Low	137,693	715.29	396.32	35,839	11 (9)
	Medium	160,604	606.82	355.56	33,292	28 (21)
	High	138,732	514.75	256.49	28,385	14 (9)
High	Low	210,642	2,478.11	1,398.53	39,070	16 (16)
	Medium	203,807	2,357.87	1,414.24	38,255	23 (23)
	High	153,031	1,816.10	1,066.52	35,814	28 (26)
Year-over-year growth rates						
All	All	0.0035	0.0225	0.0312	0.0304	
Low	Low	0.0005	0.0011	0.0120	0.0276	
	Medium	0.0073	0.0202	0.0293	0.0286	
	High	−0.0090	0.0460	0.0516	0.0264	
Medium	Low	0.0010	0.0019	0.0130	0.0312	
	Medium	0.0054	0.0210	0.0312	0.0330	
	High	−0.0235	0.0456	0.0490	0.0217	
High	Low	0.0175	0.0013	0.0119	0.0339	
	Medium	0.0074	0.0200	0.0286	0.0318	
	High	−0.0088	0.0475	0.0548	0.0282	

Note: MSA = Metropolitan Statistical Area. Authors' calculations based on Federal Housing Finance Agency (FHFA), Bureau of Labor Statistics (BLS), and Bureau of Economic Analysis (BEA) data. House price and income per capita averages are weighted by population. Population and employment are in thousands. Numbers not in parenthesis are based on 2008 data. Numbers in parenthesis are based on a balanced sample.

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665,500 in 2008. Because the panel is unbalanced, changes in the average from 1980 to 2008 reflect a combination of actual changes for the 147 MSAs observed in 1980 and from the addition of 237 MSAs over this period. MSAs added over this period tend to be smaller than the original 129 and also tend to have lower house prices and incomes. In fact, just four MSAs not observed every year are in our high population group (defined subsequently).

The data are divided into groups based on 2008 population and on population growth rates since 1980. MSAs with fewer than 500,000 residents in 2008 are in the low population group. Those with more than 500,000 but fewer than 1 million residents in 2008 are in the medium group. MSAs with more than 1 million residents in 2008 are in the high group. With respect to population growth, MSAs that have grown by less than 15 percent from 1980 to 2008 are in the low-growth group. MSAs that have grown in population by more than 15 percent but less than 69 percent are in the medium-growth groups. MSAs that have grown by more than 69 percent are in the high-growth group. Interacting the three groups defined by population size with the three groups defined by population growth since 1980 yields 9 distinct groups. Table 1 shows great variation across these groups both in the levels for the core variables and for their growth rates. House prices increase monotonically with population and income generally increases with population. Within each population group, there is no general pattern.

Overall growth rates show average annual increases of between 2.3 and 3.1 percent for population, employment, and income per capita from 1980 to 2008.[5] Average employment growth varies greatly, ranging from 1.2 to 5.5 percent. By contrast, real house price increases average just 0.4 percent, ranging from −2.4 to 1.8 percent. Interestingly, for all three population groups, high population growth is associated with declining real house prices. The low population growth portion of the high population group has the most rapid growth in (average median) house prices. There are a number of potential explanations for these patterns. One is that population and house prices are determined simultaneously. Population increases housing demand, pushing prices higher. However, high house prices discourage in-migration, pushing population growth lower. Additionally, housing supply elasticities vary across these groups as suggested by Glaeser and Gyourko (2005) and Follain (2011). Some MSAs likely have restrained population growth due to geographic or political constraints that make the supply of housing more inelastic. Thus, increased housing demand in these areas may result in increased housing prices but only modest population growth. While our model does not explicitly include information on housing supply elasticities, separately analyzing different groups of MSAs allows us to partially account

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for this factor. This again assumes that the elasticities differ greatly across MSA groups but are fairly similar within a group.

Estimation Approach

A three-equation vector error correction model (VECM) is run for different groups of MSAs. The model is used to test whether the relationship between housing prices and the covariates changes over time and across MSAs. Additionally, results from the VECM are a key component in a simulation exercise used to project alternative paths for house prices.

A first-stage equation is estimated in log form and is used to estimate residuals (i.e., the error correction term), which are then included as a regressor in the three-equation model. The equation can be expressed such that

$$\log(\mathrm{HP}_{it}) = \alpha_i + \gamma \log(\mathrm{Emp}_{it}) + \theta \log(\mathrm{Inc}_{it}) + \delta_1(\mathrm{TB10}_{t-1} - \mathrm{TB1}_{t-1}) + \delta_2 \mathrm{TB10}_t + \varepsilon_{it}^{\mathrm{EC}}. \quad (1)$$

In log form, real (annual) median house prices (HP) for MSA i in year t are regressed against employment (Emp) and mean personal income (Inc). Also included among the regressors is the ten-year treasury rate (TB10) because it is correlated with mortgage interest rates and is also exogenous (i.e., not influenced by changing lending practices, etc.). Additionally, a one-year lag of the yield spread ($\mathrm{TB10}_{t-1} - \mathrm{TB1}_{t-1}$) is included because it has been shown to be a good predictor of real economic activity (e.g., see Estrella and Hardouvelis 1991; Estrella and Mishkin 1998). Finally individual MSA fixed effects (α_i) are included to control for time-invariant unobservable factors that vary across MSAs.

After imputing residuals from equation (1), attention turns to estimating the system of autoregressive equations. Equation (2) relates the dependent variable to factors that are believed to influence it. It is estimated in first differences and can be expressed such that

$$\log(Y_{it}) = \alpha_t + \alpha_{\mathrm{group}} + \alpha_{\mathrm{EC}} \hat{\varepsilon}_{it}^{\mathrm{EC}} + \sum_{j=1}^{3} \beta_j \log\left(\frac{\mathrm{HP}_{it-j}}{\mathrm{HP}_{it-1-j}}\right) + \sum_{j=1}^{3} \gamma_j \log\left(\frac{\mathrm{Emp}_{it-j}}{\mathrm{Emp}_{it-1-j}}\right) + \sum_{j=1}^{3} \theta_j \log\left(\frac{\mathrm{Income}_{it-j}}{\mathrm{Income}_{it-1-j}}\right) + \varepsilon_{it}. \quad (2)$$

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Y_{it} is a vector of dependent variables for the three-equation model. Regressors include three years of lags for each of the endogenous variables. Year (α_t) and MSA group dummies (α_{group}) are included in order to absorb unobserved factors. $\hat{\varepsilon}_{it}^{EC}$, the estimated error correction term from equation (1), is also included among the regressors in equation (2). Equation (1) is intended to represent a market in equilibrium. Thus, $\hat{\varepsilon}_{it}^{EC}$ is an estimate of how current HP deviates from a longer-run equilibrium. High values for $\hat{\varepsilon}_{it}^{EC}$ suggest that house prices are above equilibrium levels, with the intuition being that prospective growth rates will be low (or negative). Low values, on the other hand, should predict faster house price appreciation.

Results

The model is estimated for twelve different samples. Included are the three distinct MSA groups based on population size and defined in the previous section as well as three different periods (1980–1995, 1980–2000, and 1980–2007). The combination of population groups and periods results in the estimation of nine different specifications. The model is also estimated separately for each of the three periods when including all groups, which brings the number of estimated specifications to twelve.

The key results from the regressions are summarized in table 2. The table contains six summary statistics from the twelve different specifications. Three statistics are the sums of the coefficients for the three lagged (endogenous) variables. These are included for each of the three equations. The next three statistics are the number of observations, the unadjusted R^2, and the root mean square error (RMSE). The fixed effect estimates are not presented. The table highlights similarities and some dramatic differences in the estimates of the core coefficients across the different groups and periods.[6]

Consider, first, the sum of the coefficients on the lagged house price variables in the house price growth equation. We interpret these coefficients as indicators of the degree of "momentum" in the model. The sum of these lagged coefficients, when including all groups and data through 2007, is .63, which is the same number obtained when using data through 1995 and just slightly higher than when using data through 2000 (.60). In fact, the sums of these coefficients are quite similar—between .6 and .65—with one modest exception. The results for group 1—the smallest MSAs in terms of population and often the group with fewer time series observations—are systematically smaller, ranging from .51 to .58. As such, the results suggest substantial momentum in house prices, though momentum may be a little

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Table 2. Dashboard of Selected Output for Various Models and Equations.

	1995 Group 1	2000 Group 1	2007 Group 1	1995 Group 2	2000 Group 2	2007 Group 2	1995 Group 3	2000 Group 3	2007 Group 3
Sum of the lagged terms				dep var: median HP growth					
d.log HP	0.54	0.51	0.58	0.62	0.60	0.64	0.65	0.62	0.63
d.log EMP	0.34	0.28	0.30	0.49	0.32	0.38	0.34	0.31	0.33
d.log income/capita	0.27	0.28	0.10	0.17	0.32	0.18	0.11	0.35	0.26
R^2	45%	46%	50%	63%	63%	64%	73%	72%	72%
RMSE	3.67	3.19	3.34	3.80	3.36	3.41	3.37	3.08	3.29
Sum of the lagged terms				dep var: MSA employment growth					
d.log HP	0.02	0.01	−0.02	−0.02	−0.01	−0.02	−0.04	−0.03	−0.04
d.log EMP	0.20	0.25	0.30	0.38	0.38	0.44	0.55	0.57	0.58
d.log income/capita	0.19	0.15	0.13	0.12	0.12	0.09	0.03	0.02	−0.02
R^2	42%	38%	44%	60%	58%	60%	76%	75%	75%
Sum of the lagged terms				dep var: per capita Income growth					
d.log HP	0.04	0.03	0.00	0.06	0.07	0.05	0.06	0.06	0.04
d.log EMP	−0.11	−0.06	0.04	−0.02	−0.07	−0.01	−0.13	−0.18	−0.04
d.log income/capita	0.14	0.09	0.03	0.17	0.23	0.18	0.39	0.49	0.26
R^2	42%	38%	44%	60%	58%	60%	76%	75%	75%
Fixed effect estimates for three groups of MSAs in terms of population growth between 1980 and 2008									
Declining population	0.0000	0.0045	0.0000	0.0000	0.0085	0.0000	0.0000	0.0000	0.0000
Modest population growth	−0.0020	0.0031	0.0000	−0.0069	0.0046	−0.0036	−0.0072	−0.0047	−0.0033
Fast growing	−0.0061	0.0000	−0.0004	−0.0139	0.0000	−0.0056	−0.0161	−0.0136	−0.0112

Note: dep var = dependent variable; Emp = employment; HP = house price; RMSE = root mean square error.

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less important in smaller markets and when using the data through 2000, which, of course, excludes the growth of the house price bubble in the early 2000s.

A similar presentation for the employment and income per capita equations is presented in the bottom portion of table 2. Here, momentum effects are consistently smaller for both employment and income per capita than for house prices. The sums of the lagged coefficients of employment growth in the employment growth equation are .48, .49, and .51 for the 1995, 2000, and 2007 models. The sums of these coefficients in the income per capita equation are even smaller (.31, .38, and .19) and are substantially smaller when including data through 2007.

Forecasts

Simply examining the VEC coefficient estimates does not reveal the long-run implications of interactions among the three dependent variables. This is in contrast to a traditional structural economic model. Here, the dynamic properties of the model are quite general and complicate the simple calculation of the long-run elasticities. Two additional features of our approach add to this complexity: MSA fixed effects in the VEC equation and year fixed effects in the three VAR equations. We employ a Monte Carlo simulation that is based on a similar approach that we developed in a previous article (Follain and Giertz 2011a).[7] This approach captures the interactions among the dependent variables and the fixed effects. It also generates three-year projections for each of the dependent variables which offer insights into the model's performance.[8] One of these insights is the importance of local market conditions.

Each set of simulated projections uses the estimated regression coefficients for the respective period and group of MSAs. As noted previously, this represents twelve different sets of simulations. The simulated paths are used to compute the cumulative three-year projected change for each of the three dependent variables.[9] This approach incorporates interactions among the three variables into the projections.

Table 3 present results from house price projections for the specification using MSAs with price indexes available from 1980 for three different periods: 1980 through 2007, 1980 through 2000, and 1980 through 1995. The table presents cumulative projected (median) house price growth for the three years following the last year of data used in the estimation. For example, column 1 shows the median three-year cumulative forecast for 1996 through 1998, and the others pertain to median forecasts for 2001 through 2003 and for 2008 through 2010. The results are sorted by the predictions

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Table 3. Median Three-Year Projections of Cumulative Real House Price Growth (selected MSAs).

MSA	1996–1998	2001–2003	2008–2010	Rank
Stockton, CA	−3%	16%	−29%	127
Modesto, CA	−8%	13%	−28%	126
Salinas, CA	5%	13%	−28%	125
Merced, CA	−14%	8%	−26%	124
Riverside–San Bernardino–Ontario, CA	−11%	14%	−24%	123
Sacramento–Arden–Arcade–Roseville, CA	−1%	17%	−23%	122
Santa Barbara–Santa Maria–Goleta, CA	2%	13%	−21%	121
Vallejo–Fairfield, CA	−7%	23%	−21%	120
Fresno, CA	−2%	11%	−20%	119
San Diego–Carlsbad–San Marcos, CA	−2%	19%	−20%	118
Allentown–Bethlehem–Easton, PA-NJ	6%	17%	7%	66
Canton–Massillon, OH	12%	−1%	7%	65
Denver–Aurora–Broomfield, CO	17%	11%	8%	64
Colorado Springs, CO	14%	6%	8%	63
Bremerton–Silverdale, WA	−7%	8%	8%	62
Wichita, KS	17%	9%	26%	10
Fort Worth–Arlington, TX (MSAD)	20%	22%	27%	9
Little Rock–North Little Rock–Conway, AR	23%	11%	28%	8
Baton Rouge, LA	26%	9%	28%	7
San Antonio–New Braunfels, TX	24%	24%	29%	6
Corpus Christi, TX	23%	19%	29%	5
Beaumont–Port Arthur, TX	15%	13%	30%	4
Oklahoma city, OK	24%	24%	31%	3
Tulsa, OK	26%	17%	32%	2
Houston–Sugar Land–Baytown, TX	21%	25%	33%	1
Simple average	11%	12%	5%	
Standard deviation	10%	9%	16%	
Max	30%	32%	33%	
Min	−19%	−11%	−29%	

Note: MSAD = Metropolitan Statistical Area Division. Each column of median projections was generated using data through the year just prior to the beginning of the forecast. Rankings are based on 2008–2010 projections for the full sample of 127 MSAs with house price data since 1980.

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for 2008 through 2010 (column 3). Summary statistics for 15 of the 127 MSAs and overall summary statistics based on the results for the 127 MSA are at the bottom on the table.

The simple average of the (median) three-year projections of cumulative house price appreciation from 2008 through 2010 is 5 percent (see last column and bottom of table 3). The range of projections for this period is particularly striking: −29 percent to 33 percent. Twenty-seven MSAs had predicted price declines of more than 10 percent, and 9 percent had predicted declines in excess of 20 percent. At the other end of the spectrum, twenty-three MSAs had predicted increases of more than 20 percent. Much higher average growth in median house prices was projected when using only pre-2001 data—11 and 12 percent, respectively. The projections for the earlier period also had lower standard deviations and a narrower range of outcomes. These results highlight the substantial variation in projections across MSAs. This suggests that using national averages to analyze housing market trends may mask important underlying dynamics and may be misleading, since no local market may fit the profile of the national average.

The most severe projected price declines for 2008 to 2010 are for MSAs in California, Nevada, Florida, and Arizona, which are the areas that were, in fact, the hardest hit by the sharp drop in house prices since 2006.[10] At the top of the list is Stockton (CA), where the median predicted price change aggregated over the three years after 2007 is −29 percent. Right behind Stockton are several other MSAs in eastern California: Modesto, Merced, Riverside, Sacramento, and Yuba City, where the median projections suggested that prices would fall by more than 20 percent between 2008 and 2010. MSAs near the median projection of 8 percent cumulative real price growth (after three years) include the Denver, Colorado Springs, Allentown-Bethlehem-Easton (PA-NJ) MSAs. The group with the most upbeat forecasts as of 2007 is, like those hardest hit, concentrated in a few states, that is, Texas and Oklahoma. These include Oklahoma City (OK) and several MSAs in Texas as well as Baton Rouge (LA). The model was conspicuously bullish about these MSAs; each had projected growth from 2008 through 2010 in excess of 28 percent.[11]

Accuracy of the House Price Projections

How effective is the model in the detection of the extreme price declines associated with any bubble bust? This question is of even greater interest for the recent period in which house prices have declined dramatically in many parts of the country and beyond what was considered to be a severe stress

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event prior to the Great Recession of 2007–2009; that is, models relied on prior to the Great Recession did not perform well in this respect. Our data from 1980 through 2007 provide a good opportunity to test how well a model with the best available data prior to the steepest declines can anticipate what actually occurred. Recall that, moving beyond asset price bubbles, even the most sophisticated approaches used for detecting impending financial distress fare poorly (Borio and Drehmann 2009). Our focus also includes a detailed look at the variability of the predictions of the models among MSAs.

We begin by presenting the *actual* three-year cumulative real house price changes for the 127 MSAs observed every year since 1980. Table 4 presents a subset of these MSAs in ascending order based on column 3—that is, house price appreciation from 2008 to 2010. The magnitudes of the real cumulative declines in house prices for this period average 24 percent. The median price decline is 18 percent. The range is striking, that is, from a 92 percent decrease for Merced (CA) to a 1 percent increase for Kennewick (WA). Of the 127 MSAs, 123 experienced a median price decline during this period! The standard deviation of these percentage point changes is 21.

The severity of the recent decline can be seen by comparing these results to the actual price changes for two earlier periods—1996 through 1998 and 2001 through 2003. The maximum declines in these previous periods were relatively modest: 30 and 10 percent, respectively. The standard deviations were also much tighter than the most recent period—11 and 9 percent, respectively. These further highlight the magnitude of the recent (or ongoing) crisis and the wide variation in the MSA experiences, especially during the current crisis.

MSAs with the steepest actual declines are concentrated in California, Nevada, and Florida. The eastern (or noncoastal) portions of California—Merced, Modesto, Stockton, Vallejo, Riverside, and Bakersfield experienced declines of −92 to −62 percent. We highlight the relationship between the model's predictions for 2008 through 2010 with the actual experience for the full sample of MSAs. Figure 1 reveals a strong positive correlation between the predicted and the actual outcomes. Indeed, the simple correlation between the predicted and the actual outcomes for this group of all MSAs is 88 percent.

On the other hand, the predicted values of the model consistently underestimated the declines that actually occurred from 2008 through 2010. Indeed, the actual declines exceeded the predicted declines for each MSA, which seems like a remarkable outcome—although less so when one considers the extraordinary events of 2008 and 2009. Note that the predicted decline is based on the median projection from the simulation. Another comparison

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Table 4. Actual Cumulative Real House Price Changes for Three Periods (selected MSAs).

MSA	1996–1998	2001–2003	2008–2010	Rank
Merced, CA	−15%	9%	−92%	127
Modesto, CA	−19%	7%	−80%	126
Stockton, CA	−18%	13%	−79%	125
Las Vegas–Paradise, NV	−7%	1%	−76%	124
Vallejo–Fairfield, CA	−19%	19%	−69%	123
Port St. Lucie, FL	−11%	0%	−68%	122
Salinas, CA	−11%	24%	−65%	121
Riverside–San Bernardino–Ontario, CA	−29%	13%	−64%	120
Bakersfield–Delano, CA	−17%	−1%	−62%	119
Ft. Lauderdale–Pompano Bch.–Deerfield Bch., FL	−4%	6%	−58%	118
Boston–Quincy, MA (MSAD)	−9%	24%	−18%	66
Allentown–Bethlehem–Easton, PA-NJ	−12%	−1%	−18%	65
Atlanta–Sandy Springs–Marietta, GA	−2%	12%	−18%	64
Salt Lake City, UT	29%	2%	−18%	63
Cleveland–Elyria–Mentor, OH	3%	4%	−17%	62
Baton Rouge, LA	7%	8%	−3%	10
Oklahoma City, OK	2%	5%	−3%	9
Rochester, NY	−10%	−2%	−2%	8
Buffalo–Niagara Falls, NY	−8%	−6%	−2%	7
Tulsa, OK	2%	9%	−1%	6
Wichita, KS	2%	8%	−1%	5
Austin–Round Rock–San Marcos, TX	13%	13%	0%	4
Beaumont–Port Arthur, TX	−1%	7%	0%	3
Houston–Sugar Land–Baytown, TX	−7%	13%	1%	2
Kennewick–Pasco–Richland, WA	8%	1%	1%	1
Mean	−3%	9%	−24%	
Median	−2%	7%	−18%	
Max	29%	36%	1%	
Min	−30%	−10%	−92%	
SD	11%	9%	21%	

Source: Authors' calculations.

Note: MSAD = Metropolitan Statistical Area Division; SD = standard deviation. Rankings are based on the 2008–2010 period for the full sample of 127 Metropolitan Statistical Areas (MSAs) with house price data since 1980. MSAs are in ascending order, based on actual price growth over the three-year interval. MSAs are in descending order, based on growth in effective property tax rates.

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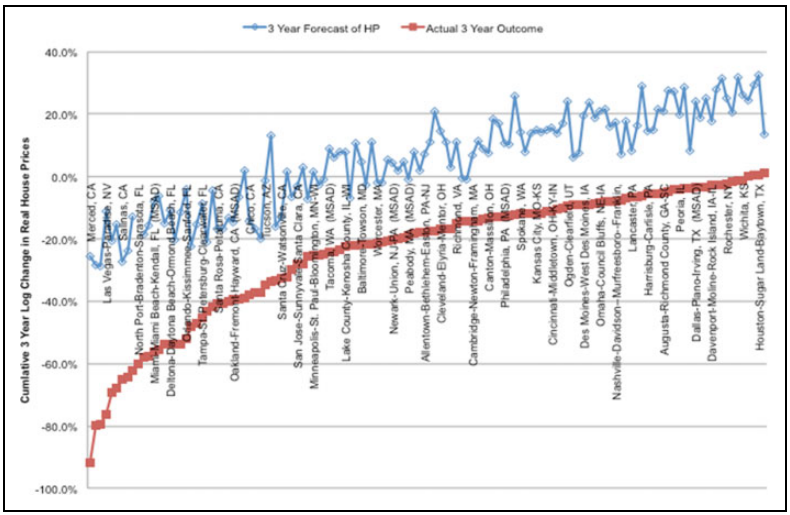

Figure 1. Actual cumulative outcomes versus median forecasts of real house prices for 2008 through 2010.

Source: Authors' calculations.

Note: Metropolitan Statistical Areas (MSAs) are in ascending order, based on actual price growth over the three-year interval.

(that we discuss shortly) would pit actual outcomes against "worst-case scenario" projections, for example, projections at the 1 or 5 percentile. With this comparison, the projections are much closer to the actual outcomes but still generally underestimate the severity of recent price declines.

This same analysis is carried out for all three periods in which the model is estimated. A simple regression of the actual outcomes against the model predictions is computed for each of the three periods. The results for 2008 to 2010 indicate that the predictions were very modestly correlated with the actual outcomes. The R^2 is only .02 and the coefficient of the actual outcome is .18 ($t = 2.93$). The model predictions are much better for the two earlier periods. The R^2 values for the 1996–1998 and 2001–2003 periods are .55 and .63, respectively; the coefficient estimates on the actual outcome variable are .37 and .84 for these earlier periods and highly significant. Thus, the outlier among these three time periods is the most recent period; the model did much better for the earlier periods.

Another way for assessing the predictions is by comparing the actual outcome to extreme values from the simulations. These (extremes) are analogous to stress scenarios and would be more relevant for formulating capital

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requirements for financial institutions—that is, for determining levels of economic capital that would be required for firms to remain solvent through such events. Using a 5 percent scenario (i.e., the model projects price drops of this severity or greater should occur one time in twenty), for example, yields a projected price decline for Stockton of 53 percent, which is still less than the 79 percent decline that actually occurred and implies that (based on this model) the actual outcome was an extreme outlier for the model based upon all MSAs and estimated with data through 2007. More comparisons of this type can be made by comparing the actual outcomes for the 15 selected MSAs presented in table 4 to the 5 percent stress scenarios presented in Follain and Giertz (2011b). Consider the Riverside MSA; house prices declined by −64.3 percent while the median and fifth percentile predictions were only −23.7 and −44.9, respectively. Indeed, the average residual for the ten MSAs with the largest negative residuals was –55 percent. So, although the model captures the ranking of the predictions reasonably well, even its severe stress scenarios consistently underestimate what actually came to pass and, especially, in those areas most hard hit by the housing price bust. More succinctly, the model underestimated the magnitude of the price declines in 2008 through 2010, though the ranking was pretty good.

This point is relevant to an ongoing debate about the nature of a severe house price stress test. Stress tests are used to evaluate the changes in the values of portfolios as a result of a severe and negative economic event. For example, the Office of Federal Housing Enterprise Oversight (OFHEO) Stress test, which was used to set capital standards for the Government Sponsored Enterprises (GSEs), called for a nominal five-year decline of about 15 percent. Follain and Giertz (2011b) adjust that scenario for the inflationary environment in which the stress test was developed—southwest United States in the mid-1980s—and compute the real value of that stress event to be closer to −30 percent, which is still well below what occurred in those areas most hard hit by the house price bust. The actual three-year outcomes for 2008 through 2010 show much more stress than either the existing OFHEO stress test or the one suggested by Follain and Giertz. One hundred forty-eight of the MSAs experienced real price declines in excess of 15 percent, which is about 39 percent of the 380 MSAs in this group. Sixty-four MSAs, or about 17 percent, experienced price declines in excess of 30 percent. In this sense, the last few years are undeniably more stressful than anything previously incorporated into the regulation of the GSEs. The results of our analysis demonstrate that what actually happened exceeded not only the predictions of the model but also the existing notion of a severe stress event in 2007.

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The uniqueness of the 2008 through 2010 period is also captured by comparing the actual house price outcomes for this period relative to two other earlier periods (see the bottom of table 4). The average decline in the recent period was 24 percent versus a 3 percent decline from 1996 to 1998 and a 9 percent gain from 2001 to 2003. The worst outcomes in the previous periods (−30 and −10) paled in comparison to the −92 percent in the most recent period. Furthermore, the standard deviation of the actual outcomes in the recent period was more than double that of the two previous periods.

In sum, several conclusions emerge from comparing projected and actual house price growth. First, the model based upon data through 2007 and the beginning of the house price declines did a good job of capturing the relative *rankings* among MSAs of actual outcomes that were to come in 2008 through 2010. Second, this model systematically underestimated the severity of the declines. Third, the actual outcomes far exceeded previous notions of a stress test in a large share of the MSAs. Fourth, both the predictions of the model and the actual outcomes show dramatic variations among MSAs. This may reflect limitations of the model. For example, it may suffer from the omission of key variables that are not well captured by our time dummies.[12] It is likely that something (or many things) occurred during 2008 through 2010 (and during the preceding bubble) that was unique, substantial, possibly national in scope, and devastating to many local housing markets. It is also suggestive of the powerful role of local market conditions, whose exact nature is not readily captured in our model.

House Price Cycles and Local Government Finances

The housing bust and Great Recession have devastated many local governments. However, despite the tremendous drop in house prices in some areas, the property tax has, thus far, held up better than other revenue sources. A number of researchers have lauded the property tax for its relative stability (e.g., Giertz 2006; Lutz, Molloy, and Shan 2011). Lutz (2008) finds, using state-level data, that property tax revenues are closely tied to house prices, but it takes several years for property tax systems to fully account for changes in in property values. Lutz estimates that 60 percent of potential revenue effects from house price appreciation are offset by policy changes. He further notes that "on the whole there is little evidence that house price declines influence property tax revenues."[13] This finding is bolstered by (aggregated state level) data following the recent housing bust, where Lutz,

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Molloy, and Shan (2011) find that property tax revenues remain resilient even in the face of substantial house price declines.

Lutz, Molloy, and Shan (2011) emphasize that the combination of lags in reassessments and responses by policymakers to raise property tax rates account for the stability of the tax. For example, in Georgia, Buschman, Alm, and Sjoquist (2011) find that localities regularly adjust millage rates to keep budgets in balance.[14] It is also possible that, even over a longer time frame, localities do not fully account for sharp price declines when reassessing house values. Furthermore, Follain (2012) shows that assessing property values during a crisis is very complex and estimated property values are especially sensitive to a number of factors, such as whether values for distressed real estate are incorporated into the assessment process. Whatever the means, stable property tax revenues over house price cycles imply that *effective* property tax rates vary across the cycle—falling during a bubble and rising during a bust. We confirm this by examining MSA-level data. We argue that this phenomenon could in fact exacerbate bubbles and busts. And, these costs should be weighed against the benefits of revenue stability. Next, we provide evidence of the relationship between effective property tax rates and house prices before detailing potential consequences, policy options and important caveats.

Effective Property Tax Rates: 2005 through 2010

Data from the American Community Survey (ACS) are used to compute effective property tax rates, at the MSA level, for years 2005 to 2010. The effective property tax rate is defined as the median property tax liability for owner-occupants divided by the median owner estimate of the house's value. Figure 2 presents averages for all the MSAs in our sample and for a subset of the largest MSAs in our sample that are also include in the ACS data with property tax information. Average effective property tax rates fall from 2005 to 2006, after which the trends for both groups are decidedly upward. The average effective property tax rate for the full sample is 1 percent in 2005 and is 14 percent higher by 2010. For 2005, the average property tax rate for the larger MSAs is higher than for the full sample (1.14 vs. 1.0 percent) and increases by over 18 percent by 2010 to 1.35 percent. The bottom line is that effective property tax rates rose substantially during the crisis. Although they do not calculate effective tax rates, these results are consistent with Lutz, Molloy, and Shan's (2011) finding of stable revenues and falling house prices at the state level. Data are not available for

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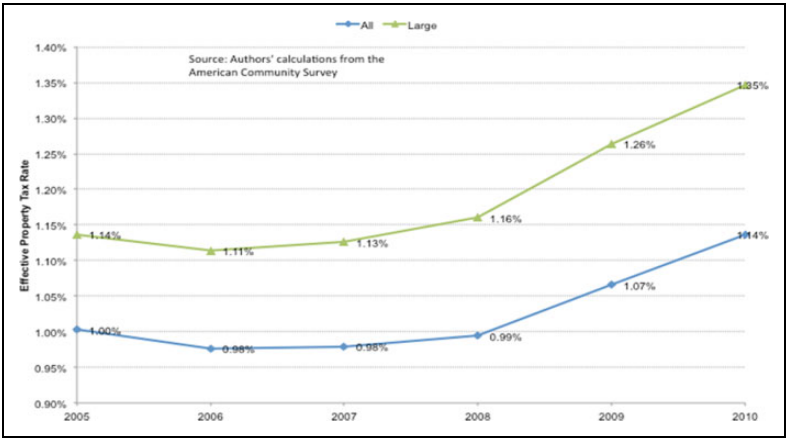

Figure 2. Property tax rates between 2005 and 2010 for groups of Metropolitan Statistical Areas (MSAs).
Source: Authors' calculations.

decomposing the sources of these changes—for example, between reassessment lags and rising millage rates.

Exacerbating Bubbles and Busts

Practices that act to stabilize property tax revenues may exacerbate bubbles and busts, along with their associated costs. This possibility can be illustrated using the canonical user cost of capital model, often considered to be a strong driver of housing demand and house prices. User cost is defined as the imputed rental value of a house, R, divided by the price of the house, P. The user cost model implies that the price demanded for owner-occupied housing, where the owner itemizes deductions, can be expressed such that

$$p = \frac{R}{(1-\tau)(i+\tau_p)+\beta+m+\delta-\pi}.$$

In the previously mentioned equation, the denominator represents user cost. The mortgage interest rate, i, and property tax rate, τ_p, are multiplied by $1-\tau$, where τ is the marginal income tax rate, to reflect the fact that these costs are deductible for income tax purposes. β represents the risk premium; m, maintenance; δ, depreciation; and π, inflation. Note that a falling effective property tax rate, τ_p, as the bubble inflates lowers user cost,

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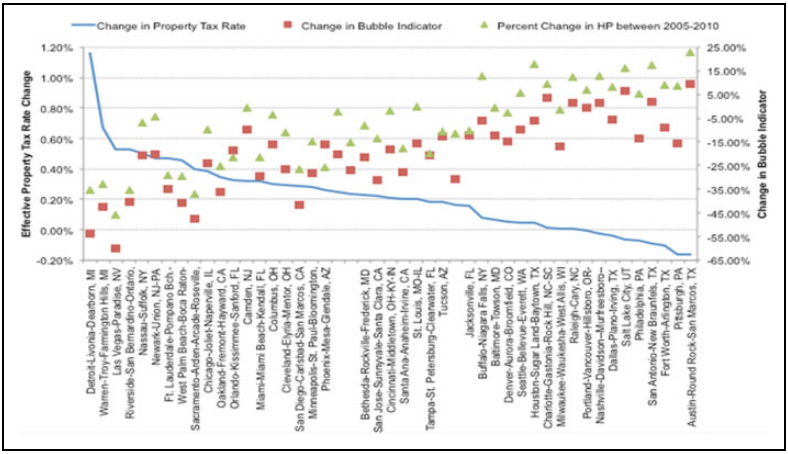

Figure 3. Changes in property tax rate and bubble indicators from 2005 to 2010.
Source: Authors' calculations.
Note: Metropolitan Statistical Areas (MSAs) are in descending order, based on growth in effective property tax rates.

increasing housing demand, and fueling additional increases in house prices. Likewise, the growing effective tax rate during the bust, shown in figure 2, reduces housing demand, slowing the rate of recovery, all else equal.

Figure 3 plots changes from 2005 to 2010 for effective property tax rates, a bubble indicator (based on our model) and median house price for 47 large MSAs. The MSAs are presented in descending order, based on changes in effective property tax rates over the period. The pattern is clear and unsurprising. MSAs that experienced the largest increases in effective property tax rates also experienced the largest declines in the bubble indicator and house price measures. For example, the effective property tax rate in Detroit increased by about 1.16 percentage points (from 1.55 to 2.72 percent) while the bubble indicator and the level of house prices declined by 53 and 34 percent, respectively. This pattern of property taxes works in oppositions to policies such as countercyclical capital buffers, which is a tool for preventing and managing bubbles.[15] Note also that many of the MSAs on the left side of the axis, ones that experienced the largest increases in the effective property tax rates, are among the areas hardest hit by the recent crisis. Examples include Las Vegas, Riverside, and Fort. Lauderdale. These patterns are consistent with our premise: the rising property tax rate acted to

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deter demand in the aftermath of bursting of the housing bubble. We do not want to overstate our case, however. The property tax is unlikely to have been among the most important factors underlying the housing crisis. However, there is reason to believe that it may have been a catalyst, hindering the recovery in many areas, all else equal.

Policy Implications and Caveats

The propensity for the property tax to exacerbate house price bubbles and busts should be taken into consideration when determining local government policy. Something akin to countercyclical capital buffers may counteract the problem and could be constructed so as to maintain smooth spending (from this revenue source). For example, a component of the property tax (e.g., a buffer tax) could be increased if evidence of bubble formation is detected. This component could then be lowered during the downside of the bubble.

The effectiveness of such a policy rests, in part, on the ability to recognize bubbles in real time. Thus, the ability of a bubble indicator to capture deviation from fundamentals could be critical to the policy's success. The policy would be triggered by prices deviating from prices suggested by fundamentals and not for price changes driven by core fundamentals. The user-cost model suggests that such an approach could counteract the property tax's inherit tendency to exacerbate bubbles and busts. However, in order to maintain the stability of public expenditures, surplus revenues during the bubble would need to be set aside for use in a potential bust. This would allow for the best of both worlds, but many challenges would need to be overcome to make such a plan workable.

Another advantage of such an approach is that it is necessarily local. Housing markets are heterogeneous. Policies at the local level are naturally decentralized and more likely to account for heterogeneity across markets. Additionally, mistakes made in implementing such a policy will also be localized. If such mistakes are independent, then systemic risk may also be reduced. Mistakes made from a centralized model applied throughout the nation are more likely to threaten the broader financial system.

Using the property tax as a tool to counteract bubbles and busts has not previously been explored. There is considerable uncertainty as to how such a program would work in practice. In addition to political obstacles, several economic factors could limit the efficacy of something like a buffer tax. For example,

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- local government services also are capitalized into property values. Thus, the patterns observed in figures 2 and 3 may not necessarily exacerbate price bubbles and busts. Increasing effective tax rates during a bust raises the user cost of housing but spending cuts averted by these effective tax rate increases may counteract the effects of the tax change. The net effect on user cost is indeterminate.
- the impact of a buffer tax may be muted, if it is known that it is temporary. A reserve fund (e.g., built up as bubbles emerge) lowers expected property taxes down the road. Rational foresight could negate capitalization effects.

Normally, these factors would work against the policy objective of containing or preventing house price bubbles. However, the capitalization of these factors may work differently when prices are deviating from long run or rational levels. For example, a buffer tax in conjunction with liquidity constraints may attenuate housing demand on the upside of a bubble, while liquidity constraints may limit borrowers' ability to bid up prices, even if lower taxes are expected on the downside of the bubble. Furthermore, those purchasing houses during the upside of a bubble likely do not expect a bust.

Conclusion

This article is motivated by the role that house price bubbles and busts played in the Great Recession and housing market collapse. More than five years since the 2008 meltdown, mortgage giants Freddie Mac and Fannie Mae remain in government conservatorship. Furthermore, many hard-hit MSAs (and their residents) remain in bad shape. We are in agreement with the views expressed by Bernanke and Dudley (in the opening of this article) that a better understanding of price bubbles can improve regulatory policy. Such policies include measures such as countercyclical capital buffers. However, we argue that house price bubbles also should play a role in our thinking about property taxes at the local level. Previous research has focused on the implications of house price changes on local government revenues. We add to this literature by arguing that the property tax may have a role beyond raising revenue. In its current incarnation, it may be a procyclical element that exacerbates house price cycles.

More broadly, our analysis underscores the complexity of forecasting bubbles. This finding is supported by the broader literature focused on detecting impending financial distress (Borio and Drehmann 2009). Our findings reject the notion of a national housing market. Housing markets are

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heavily influenced by local supply and demand, even in recent years. Approaches that do not allow for this variation across markets make it especially hard to develop sound policies to improve the functioning of the housing, mortgage, and related markets. On the other hand, even with a flexible model that allows for heterogeneous local markets, our projections based on data through 2007 severely underestimated what was to come in every MSA, suggesting that something aberrant and consequential occurred at the national or international level that affected all or many MSAs, albeit to different degrees.

Acknowledgment

Barbara Follain provided valuable editorial assistance throughout the project. Brent Ambrose provided helpful comments at the January AREUEA conference. Susan Wachter and Jim Alm provided valuable comments. We also appreciate the efforts of Jan Ondrich to organize the conference and those of the conference participants. All errors and omissions are our own.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Financial support for this project was provided by the Lincoln Institute of Land Policy. Greg Ingram and Yu-Hung Hong of the Lincoln Institute of Land Policy provided substantial input to the design of this research and many helpful suggestions on earlier drafts. Tom Follain, Jeff Barnhart, Steve Wendelboe, and Juan Montoya of FI Consulting (http://www.ficonsulting.com)—provided substantial assistance in developing the database for the project.

Notes

1. See our Lincoln Institute Working Paper for more extensive estimation results and a longer literature survey than is included in this article: http://www.lincolninst.edu/pubs/1928_A-Look-at-US-House-Price-Bubbles-from-1980-2010-and-the-Role-of-Local-Market-Conditions.
2. Of course, the ability to predict house price bubbles has applications that extend well beyond local government finances. For example, see Follain and Giertz (2011a) for an examination of the stress scenarios applied by regulators to Fannie Mae and Freddie Mac.
3. Note that price bubbles are commonplace in controlled laboratory experiments, where these types of explanations for price deviations can rationally be ruled

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out. See Caginalp, Porter, and Smith (2000). It may be that people "invent" explanations in cases where such explanations are clearly implausible. Ed Leamer poses an alternative explanation he terms "Survivor Investing." During a bubble, money can be made by purchasing at prices above those suggested by fundamentals, so long as one sells before the bubble bursts. With Survivor Investing "It's the greater fool and the last man in who loses . . . Survivor investing is a zero-sum game, which can transfer a massive amount of wealth from losers to winners" (Leamer 2002).

4. All dollar values in this paper are in real 2009 values unless otherwise stated.
5. Again, note that these are averages from an unbalanced panel and that growth rates for dollar values are weighted by employment.
6. Data on New Orleans are included only through 2005, which was the year in which Hurricane Katrina hit the area and generated massive changes in population and housing and are considered extreme outliers. Employing a simpler model, Follain (2011) reports estimates of house price growth that are quite sensitive to the inclusion of New Orleans data post-Katrina.
7. The simulation exercise yields estimates for the full distribution of median house price paths for each MSA. Details on this approach and results from the process can be found in Follain and Giertz (2011b). Details on the procedure are not included here because this article relies primarily on the projected median price paths.
8. Projected house price paths, are important inputs for financial models that evaluate the credit risk in mortgage lending—and output capital requirements necessary to withstand various scenarios. Follain and Sklarz (2005) provide an example of this type of extension.
9. Note that we report changes in the natural logs and not actual percentage changes. In many cases, the two measures are very close. However, this is not always the case. For example, consider the case of a US$200,000 house that declined in value to US$80,000. The difference in the natural log of these two values is $\ln(80{,}000) - \ln(200{,}000) = 11.29 - 12.206 = -.92$. We label this as a 92 percent decline in value. We do this primarily because we use differences in the natural log as the metric for the estimation. Also, percentage changes are very sensitive to the base when changes are huge. For example, the percentage change from 200,000 to 80,000 using the peak value as the base is -60 percent. Using the ending value as the base yields a decline of -150 percent. Note that an "arc" measure, which uses the average of the values from two periods for the denominator, yields a decline of $-.86$, which is much closer to our measure.
10. The ten MSAs with the largest projected median price declines are all in California. Because table 3 is abridged, it does not include some of these other hard-hit MSAs.
11. Note that we report changes in the natural logs as percentage changes.

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12. Time dummies control for factors that vary over time but do not for factors that vary across MSAs.
13. For the period he examines, most house price declines are modest, and Lutz cautions that his estimates are not nearly as precise for periods of declining prices.
14. As an historical anecdote, Robert Caro (1974) notes that, during the depths of the Great Depression and following years of rapid increases in real estate values that had begun to level and then decline, New York City responded to massive budget imbalances with a "record increase in the real estate tax rate" (327). As Caro details, the city's budget woes were partly to the Great Depression, but were also, to a large extent, the result of gross mismanagement and widespread corruption.
15. For more background on this issue, see Follain and Giertz (2013).

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