Predicting House Price Bubbles and Busts with Econometric Models: What We've Learned. What We Still Don't Know.

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Abstract

This paper builds upon our previous study (Follain and Giertz, 2011b) of the house price bubble and bust that has affected many US metropolitan housing markets in the last several years. Here, data are compiled for a balanced panel of 342 MSAs from 1990–2010. A vector error correction model (with as many as five second stage equations) is employed to estimate the relationship between house prices and an array of economic variables. Out-of-sample house price paths are projected for several different three-year periods, with special focus on projections from 2006:Q3 to 2009:Q2 and from 2008:Q1 to 2010:Q4. The model is also estimated for several additional time periods (such as through 2000:Q4 and 2010:Q4). For each specification, Monte Carlo simulations are conducted to project an array of house price paths. The cumulative three-year price changes from the Monte Carlo simulation are ordered, so as to examine both median projections, as well as low probability events—such as the price path at first or fifth percentile of the distribution. Attention is focused upon the ability of the model to predict actual house price changes from 2008:Q1–2010:Q4. Follain and Giertz (2011b) adequately captured the ranking of the MSAs that were hardest hit during this period, but substantially underestimated the magnitude of the price declines. Here, the predictions from the various models generate much larger declines than the models from our previous work and, in some instances, exceed the actual declines that occurred. Excluding from the in-sample data all periods after 2006:Q2 has a major impact on the three-year projections (and in the forecast error). With only data through 2006:Q2, the cumulative three year projections for house prices generally under predicted what occurred and by a much greater degree than the model with just 18 more months of data. We find some evidence of a growing importance of price momentum in the models estimated using data ending at different points during the first half of the 2000s. This increased momentum appears to reflect the enhanced sensitivity of the housing market to negative shocks in other variables and, especially, to declines in the growth rates of house prices. In effect, an exogenous shock may have started the drop in house prices, but the greater importance of momentum may have led to a snowball effect. The model is also estimated using data through 2010:Q4 and predictions for 2011–2013 are provided. These initial projections suggest the road to recovery is a long way off.

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Section I: Introduction

Andrew Lo (2012) recently reviewed twenty-one diverse books about the recent financial crisis. He concludes that no single and compelling narrative emerges, though he reports that "the sheer variety of conclusions is informative." The root cause of the divergence of the narratives offered in these books is the difficulty of adequately describing and modeling "complexity and human behavior." He also champions an important goal for economists who study the crisis: "establish a single set of facts from which more accurate inferences and narratives can be constructed."

The focus of our paper is upon one important element of the crisis—the substantial and widespread declines in the price of housing within the US. We begin this investigation with what we believe are a two key facts. First, house prices in many parts of the US began a period of sharp and substantial decline around the middle of 2006. The extent of the decline in many metropolitan areas exceeded what had been observed in over thirty years. This fact rests on substantial evidence. Were the declines more substantial and widespread than any occurring in the 20th century? Our guess is that the answer to this question is also "yes," but we stop short of claiming this as fact since data to confirm or reject this claim are limited.[1] A second likely fact is that econometric models of housing markets failed to predict the turmoil within housing markets that has accompanied this crisis. We do not mean that no one was bearish and expressed concerns prior to the bubble bust. Follain and Sklarz (2005), for example, offered estimates of the rising mortgage credit risk in their paper entitled "Pricing Market Specific Bubbles." Many others such as Robert Shiller (2005) and Edward Leamer (2003) raised concerns as well, but, to our knowledge, such concerns were voiced by a small minority of housing market modelers and understated what was to follow.

We use Follain and Giertz (2011b) to exemplify both of these facts. In this earlier paper, we estimate a complex three-equation model of the housing market using data from 1980 through 2010 and encompassing a large number of metropolitan statistical areas (MSAs). Model estimates based upon data through 2007 were used to generate forecasts of housing prices for 2008–2010 for a wide variety of scenarios using Monte Carlo simulation analysis. The model predicted substantial house price declines for many metropolitan areas and did an especially good job of identifying the MSAs that were ultimately the hardest hit, such as Stockton, California. However, the median path of estimated price declines (from the simulation) were often half as large as the actual declines in the worst hit areas. The actual outcomes more closely

[1] One effort to capture the extent of the declines is provided by Follain (2010) in his study of real estate markets in declining cities, which includes an examination of a large number of urban areas and a deep examination of both a traditional declining city, Cleveland, Ohio, and a potentially new type of declining city, Stockton, California. Cleveland is a case in which house prices have been in a state of decline for many years due to the exodus of jobs and population that began decades ago. Stockton is a different case in which house prices peaked in 2006 and have declined dramatically during the current crisis.

mirrored the 5th percentile paths in the simulation for many of the hardest hit areas—although many times, even the 5th percentile paths under-predicted the actual price declines.

A key purpose of this paper is to explore why our earlier model and others understated to the magnitude of house price declines in recent years. One overarching explanation is raised in Lo's characterization of the problem. Capturing the complexity of the housing market, especially the important role of widely varying local market conditions and the special challenges presented by subprime mortgage lending, is a very challenging assignment. Lo, Taleb (2007) and others have encouraged economists to be wary of our ability to predict extreme events. Follain (2012) discusses what Taleb refers to as Black Swan Blindness as a related factor: we have a hard time coming to grips with the possibility of an extreme event that is reflected in models that rest upon many untested yet critical assumptions. Furthermore, most econometric models assume a linear relationship between the covariates—and many nonlinear models still assume a smooth relationship between the covariates. Malcolm Gladwell (1996) describes what can happen when imposing linear thinking to nonlinear problems: "I can remember struggling with these same theoretical questions as a child, when I tried to pour ketchup on my dinner.…I assumed that the solution was linear: that steadily increasing hits on the base of the bottle would yield steadily increasing amounts of ketchup out the other end. Not so, my father said, and he recited a ditty that, for me, remains the most concise statement of the fundamental nonlinearity of everyday life: Tomato ketchup in a bottle—None will come and then the lot'll." Vector autoregression, for example, assumes linear interdependence. As Stock and Watson (2001) note, "that, without modification, standard VARs miss nonlinearities, conditional heteroskedasticity and drifts or breaks in parameters."

A second explanation is that the models we and others estimated omitted important variables that contributed to the decline. Our model focused on three main economic variables: house prices; income per capita; and, employment. MSA and time fixed effects were also incorporated in our three-equation vector error correction model (VECM). Perhaps the model would have performed better if other variables were included such as rent, housing sales, the housing stock, or mortgage lending. Surely there is some truth in such a view, but the drawback from pursuing this approach is that adding more and more variables increases the complexity of the model and, in turn, the ability to identify stable parameters. An important purpose of this paper is to consider a wider variety of additional variables to see which, if any, would have helped provide more accurate estimates the declines of the last few years; or, if not providing more accurate estimates, providing evidence that the housing market was more sensitive to changes in economic conditions, making the pattern of house price declines a more realistic possibility.

A third broad explanation for the steep declines is that certain very difficult to predict events took place beyond the sample period that led to much larger declines than any model would have been likely to incorporate. In one sense, these too could be considered omitted factors, however, here we are referring to unobservable events that one could not hope to capture a priori—e.g., resulting from the confluence of events that have not occurred before (or for which little recorded data exist). Obviously, the events of September 2008 are prime examples. Capturing the effects of these events is very challenging. The emergence of large volumes of distressed real estate data from offers hope that further investigation will add more insight into what caused recent events. Distressed real estate refers to housing units in some element of the foreclosure process and includes potential candidates for foreclosure and those actually foreclosed upon and awaiting return to the private sector. This distressed real estate inventory is both a consequence of the declines in house prices and a contributing factor to the decline and slow recovery. Follain, Miller, and Sklarz (2012) discuss this issue.

A fourth, but not unrelated, explanation is one we consider as a core hypothesis of this paper. That is, housing markets since 2000 underwent two key changes that make them both more sensitive to shocks and increased the potential for such large negative shocks. These two changes present fertile ground for steep and difficult to anticipate declines in house prices. The first change is one widely cited by Shiller (2005) and others: expectations of future house price appreciation increased dramatically in many housing markets. The second change is housing markets have become more interconnected to other important drivers of a local economy and these other sectors became more dependent upon the continuation of a strong housing market. Added leverage due to the boom in subprime mortgage lending contributed to this interconnectedness and the potential of large negative shocks to the system. The interactions among this array of factors may have produced cascading effects that increased the amplitude of price declines. These also appear to have been more pronounced in areas with relatively elastic supply curves like those in eastern California relative to the large price spikes that occurred in the late 1980s.[2]

The primary goal of this paper is to explore and develop models of the housing market to identify the future direction of house prices. A central assumption is that housing is closely connected to other sectors of the local economy; hence, we employ a vector error correction model (VECM) as opposed to a more traditional structural model of housing markets in which exogenous drivers affect housing prices, but where the potential for feedback from housing to the other drivers of the economy is much less. The model is estimated using quarterly data from 1990–2010 for a balanced panel of 342 MSAs. Several additional variables are considered for the model and additional equations are added for each of them. The volume of residential sales and housing rents are featured in this draft, but other variables have been and may be considered for the final version. As before, results from the VECM are used to generate Monte Carlo simulations. A key focus of attention is the changing sizes of the parameter estimates and the resultant sensitivity of the model to as house prices escalate, moving closer to the peak. Impulse response (IR) analyses are also conducted that further test whether the potential for negative shocks and their impacts upon house prices increased around that time.
Several important findings have emerged.

- The predictions for 2008:Q1–2010:Q4 based upon data through 2007:Q4 called for much larger declines (when using 5 or even 3 equations) than were predicted by the model estimated in Follain and Giertz (2011b) for the same period. Adding additional variables to the model actually led, in many instances, to predicted price declines that exceeded what actually happened.

[2] Glaeser, Gyourko, and Saiz (2008) show evidence that bubbles were more pronounced in areas with relatively low supply elasticities. Haughwout et al. (2012) also discuss the complex role that the supply side played in the current bubble and bust.

- The model estimated using data through 2006:Q2, the height of the boom, substantially underestimated the declines between 2006:Q3 and 2009:Q3. In other words, adding six quarters of data led to very different predictions. Furthermore, the model through 2006:Q2 performed worst for the hardest hit MSAs. By many measures, the model based on data through 2007:Q4, did a much better job for the hardest hit MSAs.
- The degree of momentum, which we define as the sum of the coefficients on the lagged values of the dependent variable, is strongest for the house price and employment equations; in addition, the degree of momentum varies over time. For example, the coefficient estimates reveal substantial increases in the momentum effect within the house price equation using data through 2006:Q2 relative to the model estimated with data through 2000:Q4 and data through 2010:Q4. Projections based upon data through 2010:Q4 suggest that bumps remain on the road to recovery for many places.
- The residual from the first-stage error correction equation consistently has a negative impact upon the rate of growth of house prices, though the size of this coefficient varies over time. The residual also tends to reduce the growth in residential sales and increase the rate of growth in rents. It has smaller and less consistent impacts on employment and income per capita.
- The impacts of lagged growth rates in house prices on the other variables vary by the time period of the model and the variable. The most significant and consistent interaction is between sales and house prices; larger growth rates in lagged house prices tend to reduce the volume of sales, all else equal.

These findings are discussed in Section V.

A brief discussion of literature particularly relevant to the goals of this paper is offered in the next section. Section III offers a thorough examination of the data used in the estimation and a number of critical patterns and trends in the data. The VECM model is described in Section IV. A brief discussion of the critical role that the momentum coefficients can play is offered to emphasize one aspect of our core hypothesis. The results of the paper are discussed in Section V. The final section discusses some of the possible next steps that we might follow. Discussions with you about our current results and the link of this work to the second report will help us prioritize which of the many possible directions we might follow. A brief appendix offers a long table with selected results for a large number of MSAs.

Section II: Literature

What follows is a brief overview of some of the enormous and still burgeoning literature analyzing the recent collapse of the housing market. The broad purpose of this section is to highlight selected articles and aspects of the literature that help motivate and position our contributions. We begin with a brief discussion and a few references that position and motivate the central elements of our approach.

The VECM Approach. Follain and Giertz (2011b) and this paper both utilize a VECM framework and seek to highlight the importance of local market conditions. Chen, et al. (2011) provides an excellent example of the VECM approach and underscores our belief that this approach has become a state-of-the art econometric technique for analyzing growth rates in house prices. Chen, et al. use a two equation model. Their first equation relates the level of house prices to variables such as: income per capita; the ratio of total commercial bank assets in home equity lines of credit (HELOCs), which proxies for the wide variety of changes in the mortgage market over the years; a measure of the risk-return tradeoff between the broader stock market and housing; a measure of the age distribution of the population; and population growth of the MSA; and a variety of fixed effects. Their second equation explains growth rates in real house prices and includes the residuals from this first stage regression (i.e., an error correction term) as an explanatory variable along with lagged values of house price growth, income, user cost, the unemployment rate, the change in the foreclosure rate (more on this variable below), and various fixed effects. Another example that highlights how widespread the approach has become is Taipalus (2012), who develops a version of the approach to predict the date of a bubble bust. His focus is upon US stock market data.

Our approach also seeks to model the first stage and use the residuals from this equation in a multiple equation model that explains not just house price growth but other variables as well. The potential benefit of our approach is to capture the interaction between house prices and other measures of the local economy.

Highlight Local Market Conditions. Our approach also continues to highlight the importance of incorporating local market conditions. Chen et al. is surely an example that also rests on this proposition and offers considerable evidence of their importance. We also cite two other papers that take very different approaches to this issue. On one side is Alan Greenspan (2010) who focuses on the relative importance of long- versus short-run interest rates and whether the relatively loose monetary policy of the early 2000s contributed to the boom and bust in house prices. He uses a single equation model of national house prices to argue that the bust was not the result of monetary policy because during the period of study national house prices were much more sensitive to the long interest rate, which was little affected by monetary policy, than short rates, which were the target of monetary policy. While this may be true, utilization of a national house price model with a primary focus upon interest rates omits, in our opinion, the myriad of other factors at work and the enormous heterogeneity among housing markets within the US. On the other side is a recent paper by Landvoigt, Piazzesi, and Schneider (2011). They focus upon house price patterns within one market—San Diego. The title captures an important theme: "The Housing Market(s) of San Diego." Much debate is ongoing about the importance of local market conditions and the limits of treating housing markets in the aggregate. This is a central theme to a series of articles being written by Follain, Miller, and Sklarz under the heading: "Lessons from the Data".[3] The approach taken in this paper is between these two extremes and focuses upon the MSA as the base geographical unit.

Focus on out-of-sample forecasts. Another element of our approach is to estimate the model for different time periods and to examine out-of-sample forecasts. An excellent example of this

[3] These are available at: http://www.homevalueforecast.com/archives/lessons/.

approach, which also uses a VAR approach with MSA-level data, is Wheaton, William and Nechayev (2008). They provide an interesting perspective about the shift from structural models to the VAR approach and also utilize two applications similar to what we do and to what we plan to do. This paper examines the inflation in housing prices between 1998 and 2005 and investigates whether this run-up in prices can be "explained" by increases in demand fundamentals such as population, income growth and the decline in interest rates over this period. They estimate time series models for each of 59 MSA markets and dynamically forecast price changes from 1998 to 2005—using actual economic fundamentals to drive the models. In all 59 markets the growth in fundamentals from 1998–2005 forecasts price growth that is far below that which actually occurred. They also examine the magnitude of the 2005 forecast errors in a cross-section and find that the errors are greater in larger MSAs, in MSAs where 2nd home and speculative buying was prevalent, and in MSAs where indicators suggest the sub-prime mortgage market was most active. Our paper applies variations of the first approach by applying two models estimated with different data to forecast future house price outcomes.

<u>Challenge of Predicting the Current Bubble-Bust</u>. As noted in the introduction, an earlier paper of ours (Follain and Giertz, 2011b) underestimated the declines in house prices for 2008–2010—especially for some of the worst hit areas. Many other papers were written prior to the bust that offered predictions and assessed the potential of a house price bubble. We cite two examples of excellent research and by excellent economists who also failed to predict the extreme change that was to take place: McCarthy and Peach (2004) and Himmelberg, Mayer, and Sinai (2005).

<u>Adding additional variables to our previous model.</u> One key part of this paper is to consider adding other variables to our model that may help to predict house prices or measure their sensitivity to these factors. Here is a list of some that we have been considered and that others have incorporated.

1. <u>Rent.</u> The rent-to-value ratio is widely viewed as a potential indicator of a bubble. A relatively low rent to value ratio typically indicates that investors are expecting relatively more price appreciation to meet their rate of return targets. When the implied rate of expected price appreciation becomes very large, the prospect of a bubble is thought to increase. Several papers in the list of references in our first paper highlight this variable. Examples include as Leamer (2003), Lai and Van Order (2010), Goodman and Thibodeau (2008), Kishor, N. Kundan and James Morleyy (2010), Campbell, Davis, Gallin, and Martin (2006), and Follain and Follain (2007). Ultimately, we did not include this variable because a high quality data series on this variable was not available for our full sample. However, a new research project whose results were just released for public use by Carrillo, Early, and Olsen (2010) has now generated a data set that we can use. It includes rent indexes for 1982 to 2008 for most metropolitan areas. We do incorporate this measure in the current paper.
2. <u>Construction.</u> Rising house prices at some point can exceed the cost of construction, which provides incentives to build more housing. As the housing supply expands, house price growth diminishes and can fall. Indeed, some people believe that the rate of construction was so large as to become the seed of the destruction of the most recent house price bubble in some areas. A number of papers have sought to incorporate supply side considerations into the analysis of the recent and earlier bubbles. These include

Glaeser, Gyourko, and Saiz (2008), Leamer (2007); Hendershott, Hendershott, and Shilling (2010); and, most recently, McCarthy and Peach (2012). A challenge for our paper is to obtain and incorporate data on land prices, construction costs, and regulatory measures for the 342 MSAs we focus upon. We sought to incorporate the role of housing starts and the stock, but the results show little connection. The estimated MSA fixed effects likely capture some of these effects. Follain and Giertz (2012b) are also exploring this issue.

3. <u>Price to Sales Volume.</u> Some believe this is another latent but reliable indicator of an emerging bubble and subsequent bust. This argument rests on the notion that sales volumes tend to rise on the way up and fall substantially on the way down. Clayton, Miller, and Pen (2010) examine this issue. Follain (2010) also highlights the change in the mix of sales—regular versus REO/foreclosure—during the steep decline. In fact, arguments can and have been made both ways about this relationship. Leamer (2010) is a proponent. Follain and Velz (1995) found the relationship was not very stable in previous cycles. We anticipate being able to purchase sales volume data from NAR for a large number of metropolitan areas, but the cost is to be determined. Miller and Sklarz (2011) explore a variety of different measures of regular sales and distressed sales and find they can be good predictors of future house price trends. Our current model incorporates regular sales and further exploration of the role of distressed real estate will be done in a subsequent paper since a long time-series data for more complete measures of all sales types are not readily available or widely available among the MSAs in our study.

4. <u>Mortgage Originations and the Subprime Boom.</u>
    a. This is probably the most widely discussed "cause" of the current bubble. The basic idea is that mortgage credit was greatly expanded to the population and at rates that did not fully reflect credit risk. Excessively generous mortgage lending conditions and the growth in subprime lending surely played a role in the current crisis in many parts of the country. Perhaps the prevalence of the subprime boom was greater in these most affected areas. This factor includes, especially, the prevalence of home equity lending. Excellent examples of the recent literature that highlight and try to capture the influence of the mortgage market include the book by Engel and McCoy (2011) and papers by Wheaton and Nechayev (2008), Glaeser, Gottlieb, and Gyourko (2010), Coleman, LaCour-Little, and Vandell (2008), and Hendershott, Hendershott, and Shilling (2010). Follain and Sklarz (2005) offer estimates of what such risk-adjusted credit spreads might have been at the height of the bubble.
    b. Bokhari, Torous, and Wheaton (2012) use loan level data provided by Fannie Mae to study the role of household leverage as a driving factor for the recent collapse in house prices. Empirically, they estimate an interest rate elasticity of leverage demand of -0.37 or, equivalently, a movement along the demand curve from an r-LTV pair of (10%, 72%) to that of (5%, 85%). They find that leverage demand was cyclical and responsive to economic events but without a general trend. By contrast, leverage supply shifts in the form of lower mortgage interest rates were concurrently associated with higher average loan-to-value ratios. They estimate that a doubling of the conforming loan limit leads to a fall in the average note rate by 4% and an increase in leverage by 12.5 percentage points. In MSAs with

higher house prices, households borrowed more and bought equally more expensive houses. That left leverage unchanged but raised households' risk of illiquidity by increasing their loan-to-income ratios. In MSAs with high house price volatility, both leverage demand and supply were lower. They also identify that younger, poorer and less creditworthy borrowers demand more leverage than their counterparts.[4]

5. Foreclosure Fallout. The mechanism involves the impact of a house price decline upon the loan-to-value ratio of homeowners. When borrowers are highly leveraged, either because of a high initial ratio or the addition of home equity loans, then large price declines can have cascading effects, setting in motion foreclosures that have direct and indirect impacts upon the local housing markets (Geanakoplos, 2010 and 2011). The most recent house price bubble bust occurred during a time in which many home mortgages were more highly leveraged than ever before. Hence, when prices fell, mortgage delinquencies and foreclosures rose to new record levels. This process, which is not yet finished, led to a massive "shadow supply" of housing and great uncertainty about the current value of real estate and its path back to full recovery. This factor most likely affects the depth of the decline in many of the markets with the largest price declines. Examples of papers that explore these forces include LaCour-Little and Yang (2010), LaCour-Little, Rosenblatt, Yao (2010), Khandani, Lo, and Merton (2009), Kiefer and Kiefer (2009). Follain and Follain (2008) also examined the role of home equity extraction. Follain (2010) discusses and documents the magnitude of these foreclosures and REOs in one particular market—Stockton, CA. More data are available than ever before regarding foreclosures; the recent article by Follain, Miller, and Sklarz (2012) highlight these data and their potential value. However, publicly available data for the 20 years focused upon in this study.

6. Expectations about the future paths of key house prices. Expectations about house price appreciation play a critical role in housing investment decisions. A sharp reduction in these expectations since the house price boom of the early and mid-2000s could lead to substantial declines in demand and house prices. The role of expectations clearly has roots in the work of Case and Shiller (1987, 2003) and their emphasis upon irrational expectations. Leamer (2003) and many others in the behavioral finance school also argues that people sometimes make expectations based on a short but recent historical episode that is unsustainable over a longer period of time. This factor is also broadly consistent with what underlies the notion of a new type of declining city (Follain, 2010). In this story, the traditional declining city experienced substantial declines in population and employment, which lead to years of price decline whereas the new type of emerging declining city is one that has experienced a substantial and enduring decline in "expectations" about the future growth in house prices and population. Some use "average" historical values for this variable, which we have avoided. An alternative we would consider is using our previously estimated model to generate estimates of expected inflation in housing by MSA and multiple years. As of now, we have not examined a specific and separate measure of anticipated inflation or a conceptually similar concept—user cost—because they are subject to substantial measurement error.

[4] Geanakoplos (2010 and 2011) has emerged as one of the biggest proponents for the idea that leverage has been central to the financial crisis and problems in housing markets.

There are other variables that are mentioned in the literature. For example, some have discussed the potential impact of regional migration trends and we have explored some of this literature, e.g. Frey (2009). Other possible omitted variables include rising gasoline prices, which impact the future viability of distant suburbs. Areas in Eastern California like Stockton are good examples of such places that might be affected by such trends. Another possibility that seems relevant but relatively understudied is the fiscal crises facing many states. Perhaps the causation runs from the house price bust to poor fiscal health, but growing property tax burdens may have played a role in stemming the growth of house prices in some areas. One option for local governments to address steep drops in their property tax bases is to increase property tax rates. In some cases, this would require states relaxing regulations that limit the ability of local governments to tax real estate. These too could influence property values. A lot will depend on the difference between the added tax revenue and the value residents place on the services provided with those revenues (as well as how those added taxes and benefits are distributed across different income groups etc.). Though each of these is a potentially important factor, our sense is that these are not the top priorities for further investigation within the framework that we have developed in the first paper.

At the end of the day, many judgments are needed about which of the many possible candidate variables to include in a model. What follows is a discussion of the variables considered and the choices finally made.

Section III: Data and Trends

Several sources are used to create a panel of quarterly pooled time series data for 342 U.S. MSAs. Restricting the sample to those MSAs in which all variables (used in our analysis) appear in every quarter, beginning with 1990:Q1, leaves 342 MSAs.[5] The data begin with the first quarter of 1990 and extend through the end of 2010. We would like to incorporate as long of a time-series as possible. We also would like to include as many MSAs as possible, with more variable options, measured more frequently (i.e., quarterly versus annual). However, several tradeoffs must be balanced in achieving these objectives. A sample extending back to 1976 (see Follain and Giertz, 2011b) or earlier is certainly possible. Economist Robert Shiller has compiled data on home prices and a host of other variables dating as far back as 1890 (Shiller, 2005)![6] But, as one goes back further, information for many variables is available for fewer and fewer MSAs. And, those that are, are often tracked on only an annual basis. And, for a number of variables no data are available for earlier years. Here we have sacrificed additional years of data in exchange for a larger panel and much richer set of variables. Nonetheless, our data still spans 21 years (84 quarters) and include a wide variety of swings in housing market conditions, some of which were experienced by a large number of MSAs and some of which were more geographically focused.

For this study, data are collected from both government and private sources. Some were obtained from Moody's Analytics Economy.com web site: http://www.economy.com/default.asp. A key

[5] It is primarily smaller MSAs that are lost when moving to a balanced panel.

[6] However, whether these data are measured with enough precision to be meaningful is debated. See http://online.wsj.com/article/SB124051414611649135.html. The data are available at: www.econ.yale.edu/~shiller/data/Fig2-1.xls.

variable throughout the analysis is the median house price index, which is from Federal Housing Finance Agency (FHFA). Other government data are from sources such as the Census, Bureau of Labor Statistics (BLS) and Bureau of Economic Analysis (BEA). Variables from various sources obtained via Economy.com include:

1. employment;
2. income (per capita and household);
3. housing sales;
4. housing starts and stock
5. construction employment;
6. unemployment and unemployment rate;
7. population and population over 65;
8. number of households;
9. personal bankruptcies;
10. net migration; and,
11. the value of mortgage originations.

A rental housing price index is from Carrillo, Early and Olsen (2011). Quarterly rent data are imputed from the annual rent variable using the housing component from the Consumer Price Index. While we considered a great many variables, we focus primarily on the first three listed above, as well as the FHFA house price index and the rental housing index.

The average FHFA median house price index (weighted by MSA employment) increased by 17.7 percent from 1990:Q1 to 2010:Q1. Real per capita household income over this same time period was flat, going from $57,278 in 1990:Q1 to $56,149 in 2010:Q1. By contrast, per capita income increased by roughly 20 percent, $34,553 to $42,051. Dollar values are in real 2010 terms (as adjusted by the Consumer Price Index for urban consumers).[7] Average population was over 534 thousand in 1990 and 675 thousand in 2010.

Overall trends, relating house prices to a host of other variables, are presented in Figures II-1 and III-2. For comparison purposes, many variables are normalized to 1.0 in 1990. Figure III-1 compares trends for the FHFA house price index, employment, income per capita, and rent. All values (other than employment) are weighted by MSA employment. The average FHFA index shows real house price appreciation beginning in the second half of the 1990s and accelerating in the 2000s. From 2000:Q1 to 2006:Q3, this measure increases by 52 percent. After peaking, the price index drops by 24 percent from 2006:Q3 through 2010:Q4, with the declines accelerating in 2007 and 2008.

The only other variable in Figure III-1 showing this much volatility is single-family home sales. Sales roughly double from trough to peak before dropping sharply from 2005 to 2008. The sales

[7] All dollar values in this paper are in real 2010 values, unless otherwise stated.

pattern is roughly similar, but more exaggerated than the pattern for house prices. Changes to sales often precede price changes. No strong relationship between the house price trends and the trends for the other variables is apparent. Even the rental index increases by just 10 percent from 1990 to its peak and finishes 2010 at 7 percent above the 1990 level. As noted earlier, a persistent divergence between per capita income and median household income continues throughout the full time period. By 2010, median real household income is below its 1990 level, while household per capita income is more than 25 percent higher than in 1990. The growth in per capita income is much greater than the growth in household median income mainly because of a widening income distribution and a reduction in household size over this time period.

Figure III-2 compares housing stock variables to single family sales. The stock measures increase at a nearly uniform rate from 1990 to 2007, before leveling off. The total number of single family sales transactions is even more volatile than house prices.

Figures IIIA to IIIC show tremendous volatility in the value of mortgage originations (including refinances). From 2000 to 2003, the value of origination increases by over 3 fold. Note that the value of originations peak several years before prices. The value of originations may be a good measure for the fragility of the housing market, since a drop in house prices has the greatest likelihood of pushing the most recent purchasers under water. This would be magnified to the extent that originations grew because of declining lending standards. (This would not apply to refinances.)

Figure III-2 compares employment, construction employment and population. Construction employment enjoys great growth from 1992 to 2006 before falling sharply beginning in 2008. For markets where speculation was rampant, construction employment may have been a major sector of the economy. The bursting of the bubble and end of the construction boom magnified the hardship faced by some of these MSAs.

For each group, house prices fluctuate much more than employment or income. However, great fluctuations are observed in some of the financial variables and for some of the other more detailed housing market variables. At least on an aggregated level, it is clear that correlation between house prices and employment, income and even rental housing values are relatively weak during the run-up and of the housing bubble.

A correlation matrix containing the five key variables, that are the focus of the analysis in the following sections, is presented in Table III-1. In all instances, the correlation coefficient is positive—indicating a positive covariance. House prices are most strongly correlated with income per capita. The correlation coefficient is 0.51. The correlation with rent is also fairly strong. For house prices, somewhat surprisingly, correlations are weakest with employment and single-family sales. The correlation coefficient is largest (0.83) between single-family sales and employment. A strong direct relationship is also observed between rent values and income per capita.

Grouping MSAs

The data are divided into groups based on 2010 population and on population growth rates since 1990. MSAs with fewer than 250 thousand residents in 2010 are in the low population group. Those with more than 250 thousand but fewer than 750 thousand residents in 2010 are in the medium group. MSAs with more than 750 thousand residents in 2010 are in the high group. With respect to population growth, MSAs that have grown by less than 15 percent from 1990 to 2010 are in the low growth group. MSAs that have grown in population by more than 15 percent but less than 33 percent are in the medium growth groups. MSAs that have grown by more than 33 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. Tables III-2 and III-3 show considerable variation across these groups, both in the levels for the core variables and for their growth rates. For example, as can be seen in Table III-2, house prices and per capita income increase monotonically with population. Within each population group, there is no general pattern. Among low population MSAs, high population growth MSAs have the highest house prices. Among medium and high population MSAs, medium population growth MSAs have seen the greatest house price appreciation since 1990. It is important to remember that most of these variables are endogenous. For example, slow growth is likely to depress house price appreciation; however, “affordable” housing is a selling point for individuals and businesses considering relocating.

The results in Table III-3 and Table III-4 also show that the growth rates in total employment vary widely among the nine groups. For example, the average annual growth rates in employment (Table III-3) vary between 2.4 and 24.3 percent among the nine groups. The cumulative growth in employment (Table III-4 Panel B) varies between 0.9 and 39.5 percent from 1990 to 2010.[8] Within a population group, employment growth varies tremendously between low and fast population growth MSAs. Because of the Great Recession, employment growth measured since 2000 is poor across the board (Panel B). In fact, low population growth MSAs experienced *drops* in employment of between 3.6 and 4.3 percent.

Growth rates in the real house price index (RPI) totaled between and 17.1 and 27.9 percent across the nine total groups (Table III-3). All groups experienced net increases in the real prices, as measured by FHFA’s house price index. Once again, high population growth does not necessarily imply rapid real house price appreciation. In addition to the endogeneity issue mentioned above, housing supply elasticities have been shown to vary across these groups (Glaeser and Gyourko, 2005, and confirmed by Follain, 2010). 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 relatively larger increases in housing prices, but only modest population growth.

Section IV: Methodology

A vector error correction model (VECM), employing as many as five equations, is used to examine the relationship between housing prices and other economic variables. As just

[8] Average growth numbers in Table III-2 use the average of the start and end year in the denominator, instead of the start year.

discussed, the data used by the model begins in 1990. The analysis is performed running through different end years to test whether the relationship between housing prices and the covariates changes over time. Results from the VECM are central to a simulation exercise used to project out-of-sample house price paths. Additionally, impulse response (IR) paths are produced after imposing negative shocks to key explanatory variables. The IR analysis is used to highlight the sensitivity of house prices over time. It is hypothesized that prices are more unstable and more responsive to shocks in the midst of a bubble. A related measure used to gauge whether conditions are ripe for a bubble and bust is the momentum component from the regression analysis. This idea is discussed in greater detail in the following section.

To start, an error correction equation is estimated in log form (as opposed to differences in logs) and is used to estimate residuals (i.e., for the error correction term, ε_{it}^{EC}). These estimated residuals are then included as a regressor in the multi-equation model. The equation can be expressed such that

$$\log\left(HP_{it}\right) = \alpha_i + \beta_{2j}\log\left(Emp_{it}\right) + \beta_{3j}\log\left(Inc_{3,it}\right) + \beta_{4j}\log\left(x_{4,it}\right) + \beta_{5j}\log\left(x_{5,it}\right) + \delta_1(TB10_{t-1} - TB1_{t-1}) + \delta_2 TB10_t + \varepsilon_{it}^{EC}. \quad \text{(VI-1)}$$

Real (annual) median house prices (*HP*) for MSA *i* in year *t* are regressed against concurrent values of the other endogenous exogenous variables. Each specification includes house prices (*HP)*, employment (*Emp*) and income per capita (*Inc*). Some specifications include one or two additional endogenous variables. Also included among the regressors is the ten-year Treasury rate (*TB*10) because it is correlated with mortgage interest rates and is also exogenous (i.e., not influenced by changing lending practices etc.). And, a one-year lag of the yield spread ($TB10_{t-1} - TB1_{t-1}$) is included because it has been shown to be a good predictor of real economic activity (e.g., see Estrella and Hardouvelis, 1991 and 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 (IV-1), attention turns to estimating the system of autoregressive equations. Equation (IV-2) is estimated in first differences and can be expressed such that

$$\log\left(Y_{it}\right) = \alpha_t + \alpha_{group} + \alpha_{EC}\hat{\varepsilon}_{it}^{EC} + \sum_{k=1}^{5}\left(\sum_{j=1}^{12}\beta_{kj}\log\left(\frac{x_{k,it-j}}{x_{k,it-1-j}}\right)\right) + \delta_1(TB10_{t-1} - TB1_{t-1}) + \delta_2 TB10_t + \varepsilon_{it}. \quad \text{(IV-2)}$$

The (up to) five endogenous variables, whose lags are included on the right-hand side, are represented by x_k.[9] For each specification, x_k represents the same variables as in equation (IV-1). All of the variables represented by x_k are also used as dependent variables, and except when serving as dependent variables, they are measured in concurrent (as opposed to lagged) logged

[9] A requirement for the classical linear regression model is that the right-hand-side variables are exogenous. In vector autoregressive models, both exogenous and endogenous variables are included on the right-hand-side. However, the endogenous variables are included in lagged form, which are assumed exogenous.

differences, i.e., a separate equation is estimated for each endogenous variable. Thus, Y_{it} is a vector of dependent variables such that

$$Y_{it} = \begin{bmatrix} \left(\dfrac{HP_{it}}{HP_{it-1}}\right) \\ \left(\dfrac{Emp_{it}}{Emp_{it-1}}\right) \\ \left(\dfrac{Inc_{3,it}}{Inc_{3,it-1}}\right) \\ \left(\dfrac{x_{4,it}}{x_{4,it-1}}\right) \\ \left(\dfrac{x_{5,it}}{x_{5,it-1}}\right) \end{bmatrix} . \text{(IV-3)}$$

In addition to median house prices, employment and per capita income, which are included in all specifications, variables x_4 and x_5 represent, depending on specification, housing stock, single-family home sales, rent, personal bankruptcies, net migration and foreclosures. Year (α_t) and MSA group dummies (α_{group}) are included in order to absorb unobserved factors. Year and group fixed effects measure the influence of factors that are not explicitly included in the estimation — and which often are not available in sufficient detail over a long period of time. Year fixed effects control for unobserved factors whose impact is homogeneous across MSAs. Group dummies (defined in the previous section) control for mean differences between the groups of MSAs whose impact is time invariant.

As an alternative to group dummies, full MSA fixed effects could be included again here (as in equation (IV-1)). This would impose stronger controls for heterogeneity across MSAs, but would reduce degrees of freedom and wash away the influence of time-invariant within-group cross-sectional variation. $\hat{\varepsilon}_{it}^{EC}$, the estimated error correction term from equation (IV-1), is also included among the regressors in equation (IV-2). Equation (IV-1) represents the 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. MSA fixed effects, conditional on the other covariates, allow for long run equilibriums that differ by MSA. These fixed effects are incorporated to account for a variety of local market conditions without imposing a structural relationship or additional and difficult to measure factors.

Estimated coefficients on lagged growth in house prices and employment can help distinguish between markets characterized by price momentum and those where mean reversion is more prominent. When including house price growth as the dependent variable, positive estimated coefficients on the house price lags would suggest momentum (or self-reinforcing) effects. This would include bubbles, where behavior such as speculation can lead to periods of rapid price increases and, after peaking, rapid price decreases. Lags in employment and per capita income growth are intended to pick up more traditional changes in housing demand. National factors, such as interest rates and the lagged term structure, are part of the model, but much of their influence will be absorbed by the year fixed effects—thus these variables will be left to measure the influence of within-year variation in these variables.

The momentum component in the house price equation is potentially an important indicator of the sensitivity of the economic environment. The larger the momentum effect, all else equal, the greater the impact will be from a shock to the error term. Consider a simple model where the change in house prices is function of the lagged change plus an error term, such that

$$dHP_t = a \cdot dHP_{t-1} + u_t. \quad \text{(IV-4)}$$

Now consider two scenarios, one where modest momentum is present, so that $a = 0.45$, and another scenario with stronger momentum, so that $a = 0.9$. Suppose that in the initial period, an exogenous shock to the error term lowers *HP* by one percent. When $a = 0.45$, the cumulative effect after ten additional periods of this one time shock will be a 1.82 percent (i.e., the initial 1 percent drop plus an additional 0.82 percent from the momentum effect). When $a = 0.9$, the analogous drop in prices is 6.51 percent (i.e., the initial 1 percent drop plus an additional 5.51 percent from the momentum effect). Thus, in this example, the scenario with greater momentum resulted in a cumulative price drop that of 3.6 time the scenario with modest momentum.

In a more complex model, a shock to any of the variables has the potential of snowballing when momentum is large. A fragile housing market (one susceptible to large price swings) could be characterized by a large momentum factor, along with strong (and positively correlated) interconnectedness to other variables. In such instances, a shock could throw the system out of balance. The basic idea is this. Bubble detection requires looking carefully at the coefficients and how they change over time. One possible indicator on which we focused is the momentum coefficients in the house price equation, i.e. the sum of the 12 lagged values of lagged house price change. All else equal, the larger the size of this momentum effect, the more sensitive will be the model's predictions of future price changes. A large negative shock, for example, might be expected to generate a steeper in a model with a large momentum effect than in a model with little or no momentum effect. We show a simple model of this point above in equation IV-4. However, there are other parts of the VAR model that may be relevant as well. For example, if the various equations show a closer and more interdependent relationship over time, then house prices may be more susceptible to shocks in other variables. Alternatively, perhaps the relationships with the other variables may be such that a shock to one of the other variables is substantial enough to offset the momentum effect of a negative shock. We investigate one specific hypothesis via the impulse response analysis: is the model's sensitivity to a negative shock in housing prices larger as the momentum effect increases. To this end, we examine impulse response paths for two periods in which the momentum effects are different. The evidence will also provide insights about whether the net effect of the momentum effect is enhanced or diminished by changes in the coefficients of the other variables in the system.

Simulating House Price Paths

Our model imposes little structure on the interaction between the variables. Furthermore, the dynamic properties of the model obfuscate calculations of the long-run elasticities. Thus, a simple review of the coefficients does not reveal the model's predictive power. Insights about the long-run interactions among the core variables in the model can be helpful in gauging the potential onset of a house price bubble or bust. To this end, we produce out-of-sample forecasts based on our regression results and then employ a Monte Carlo simulation that is based on a similar approach that we developed in an earlier paper in order to construct a severe house price stress test that can be used to analyze portfolios of mortgages, such as those held by Freddie Mac and Fannie Mae (Follain and Giertz, 2011a). This approach captures the interactions among the dependent variables and the fixed effects. In so doing, it also generates three-year (12 quarter) projections for each of the dependent variables, which are then used to assess the model's performance.

Each set of simulated projections uses the estimated regression coefficients for the respective specifications. For each of the specifications, 100 paths (i.e., for house prices, employment etc.) are simulated for each MSA. When using all 342 MSAs, 34,200 house price paths are simulated for each specification. The simulated paths are used to compute the cumulative three year projected change for each of the dependent variables. This approach incorporates interactions among the endogenous variables into the projections. Random variation is added to the process to produce distributions of projected outcomes. The first source is from the year fixed effects. The second source is based on the RMSE (root mean squared error) of the estimated equation. Thus, predicted (or projected) values based on equation (IV-2) can be expressed such that

$$\begin{aligned}\log(Y_{it}) = {} & \hat{\alpha}_{t=U(a,b)} + \hat{\alpha}_{group} + \hat{\alpha}_{EC}\hat{\varepsilon}_{it}^{EC} + \sum_{j=1}^{3}\hat{\beta}_{1j}\log\left(\frac{HP_{it-j}}{HP_{it-1-j}}\right) + \sum_{j=1}^{3}\hat{\beta}_{2j}\log\left(\frac{Emp_{it-j}}{Emp_{it-1-j}}\right) + \\ & + \sum_{k=3}^{5}\left(\sum_{j=1}^{12}\beta_{kj}\log\left(\frac{x_{k,it-j}}{x_{k,it-1-j}}\right)\right) + N(0,\hat{\sigma}_t).\end{aligned} \quad \text{(IV-5)}$$

The first distinctions between this and traditional predicted values is that, for each simulated path, the time dummy, $\hat{\alpha}_t$, is chosen at random. That is, $U(a, b)$ is a discrete uniform random variable that ranges from the earliest year included in the regression (a) to the final year of data (b). These time fixed effects capture important unobserved factors that influence the dependent variable. This approach assumes that these unobserved conditions will occur in the future at the same rate at which they occurred in the past (i.e., over the time frame of the underlying sample). The other distinction is the random variable, $N(0,\hat{\sigma}_t)$, added to the equation. This variable is normally distributed with mean 0 and standard deviation equal to the regression RMSE. Also, note that the lagged values or starting conditions are the actual historical values of the endogenous variables in the 12 quarters just prior to the end of the sample. The VEC residual term is held constant throughout the simulation.

Impulse Response Paths

One approach used to identify the effects from exogenous shocks in a VEC or VAR (vector autoregressive regression) model is traditional impulse response (IR) analysis. This consists of estimating the impact of a shock to one of the error terms upon the final long-run predictions of the model for each dependent variable. For example, one might impose a negative shock to the house price equation and the IR analysis would generate estimates of the net change in the long-run forecast or equilibrium levels for each of the variables taking account of the interactions among them. This approach is straightforward with a single time series. With a panel and with two stages of estimation, however, such analysis is much more complex. Here, we conduct a variation of an IR analysis for panel data that is in the spirit of the more traditional approach. This process begins with the estimated regression coefficients. Predicted values for the out-of-sample quarters are imputed iteratively, in the usual manner. However, the lags that feed into the model for one or more of the endogenous variables are reduced (i.e., negatively shocked), usually by two standard deviations. Specifically, for one of the dependent variables in the system, the twelve lags that start the simulation plus each projected growth rate is reduced by two times the standard deviation of the three-year (i.e., 12 quarter) in-sample growth rate. (Note that only the lags are shocked not valuations in the projection period.) Given a normal distribution, negative shocks of a two standard deviation magnitude or greater would be expected to occur with a 2.3 percent probability. The IR analysis is repeated for alternative end periods to assess the sensitivity of shocks over time. The response to the shock can be thought of as a bubble indicator. Accurately making out-of-sample forecasts may prove quixotic. However, our hypothesis is that during a bubble, house prices are more sensitive to a negative shock. Thus, if the model works, the impact from the IR should be larger in a bubble environment, all else equal.

Section V: Results

Our discussion begins with an overview of regression results from various specifications. This includes a detailed presentation of estimation results for one full model. This is followed by an overview of results from several different specifications and for four different time periods. Later in the section attention turns to our Monte Carlo simulations and various comparisons of the model predictions to actual outcomes. The section concludes with a discussion of the 2011–2013 house price predictions of the five equation model estimated with data through 2010:Q4 Appendix Table 1 contains estimates of the first stage VEC equation for the five equation model estimated using the entire sample.

Five-Equation VEC Model Regressions results, 1990–2010

Table V-1 presents regression results for a five equation VECM model, where the five equations include median house prices, employment, income per capita, single-family home sales, and rent values. These endogenous variables are all converted to quarter-over-quarter differences in logs. Exogenous variables in each regression include year dummies, quarterly dummies, as well as national interest rate variables. Finally, an error correction term is included among the exogenous variables. Recall from Section IV, that prior to estimating the system of equations, a stage one error correction equation for median house prices is estimated in log form. The error correction term is the predicted residual from this equation. To allow for greater variation in equilibrium house prices across MSAs (and in recognition that equilibrium prices across MSAs may vary substantially due to unobserved factors), MSA fixed effects are included in the first stage regression.

The estimated coefficients for the (time and quarter) dummy variables are suppressed in Table V-1. However, it is important to note that these variables are controlling for unobserved factors that are similar across MSAs, but vary over time (or by quarter). The interest rate variables are also not presented in the table. The estimated coefficients on these variables are effectively zero. That is not to say that interest rates are not important. This result is a reflection of the inclusion of the year and quarter dummies, which absorb almost all of the variation in national variables.[10]

To begin, notice the complexity of this process and all of the moving parts. The model is quite flexible and allows for complex interactions between variable and over time. On the downside, a clear picture does not always emerge from the estimation results. Even looking at the influence of one variable for one equation requires reviewing 12 separate coefficients. This is in contrast to a more traditional regression model (or two-stage-least squares approach), where one can turn to a single coefficient for a key elasticity estimate.

Some inferences can be made, however, from Table V-1. The sign on the error correction term is negative and statistically significant for the median house price equation. This is consistent with theory, in that the error correction variable is positive when the observed median house price exceeds the price predicted by the model—i.e., prices tend to fall when the model predicts that prices are above their equilibrium level. The lags of the house price variable appear important, especially for the most recent three quarters. These estimated coefficients are large, positive and statistically significant. For the house price equation, thus, momentum appears to be important—meaning past price changes tend to be reinforced or amplified in future periods. This is consistent with price bubbles, but could be explained by other factors. For more distant lags, statistical significance is often maintained, but the size of the estimated coefficients drops off substantially (and occasionally turns negative).

The relationship between house price growth and employment growth lags is not so clear. Estimated coefficients are often substantial, however, so are standard errors. And, the lags vary greatly from quarter to quarter. The estimated coefficient on the first quarter lag is -0.28. However, for the second quarter lag, the estimate is 0.39. Lagged coefficients range from a high of 3.58 to a low of -2.78. In aggregate, the lagged coefficients are positive, suggesting that MSAs follow a price trend, rather than immediately shifting to a new equilibrium.

Estimated coefficients for lagged rent growth are more modest and estimated with greater precision. The lags fluctuate from positive to negative. Negative values could suggest that increases in rental housing costs are associated with increases in house prices, as consumers

[10] If a dummy were included for every quarter, the effect of any national variable would be totally wiped out.

substitute towards owner-occupied housing. However, increasing rents could be a sign of increased demand for housing more broadly and thus also associated with rising house prices.

The relationship between house prices and lagged per capita income growth varies greatly from quarter to quarter. Levels of statistical significance are generally high and the overall influence appears to be positive. However, the estimated coefficient for the first lagged quarter is -0.12.

Estimated coefficients for growth in lagged single family home sales are modest and fluctuate between positive and negative estimates. Overall, the relationship appears to be modestly positive. Sales could change due to either a shift on the supply or on the demand side, so the expected sign on this variable is ambiguous. By definition, all of these lagged variable are endogenous, thus there is not unambiguous theoretical relationship that should be expected. This issue is discussed more in comparing the different specifications.

In turning to the other equations, a few observations jump out. In each instance, the lags of the dependent variable appear to have the greatest influence. In the case of employment, little else (among the other endogenous variables) seems to matter. Of course, this is aside from the year and quarterly dummies, which absorb much information. Not surprisingly, lagged employment is often strongly correlated with income. However, this relationship fluctuates greatly across the lags, from strongly negative to strongly positive. The same is true regarding lagged employment in the single-family home sales equations—although the quarter-to-quarter fluctuations are not as large here. Lagged growth in employment and income per capita also appear to be important in the rent equation. Again, the estimates on the lagged coefficients fluctuate and are only modestly positive on average.

Comparing Coefficient Estimates across Specifications and Time Periods

The VEC model described in Section IV is estimated for four different time periods. Each time period begins with 1990:Q1 and the four ending periods are 2000:Q4, 2006:Q2, 2007:Q4, and, 2010:Q4. The models use combinations of three, four and five endogenous variables. In order to make comparisons between these specifications and time periods, we first produce summary measures from each regression. Comparing the five, four and three equation models for four different time periods requires information from 48 different regressions (excluding the 12 first stage regressions). These 48 regressions are summarized in Table V-2, which we refer to as a "dashboard." In addition to the coefficient of determination and estimated coefficient on the error correction term, the table includes the sum of lagged coefficient estimates for each endogenous variable. This summary allows one to easily compare the cumulative impact of the lagged terms across regressions and this information can fit in a single table. Additional information can be gained from looking at the dynamics of the coefficient over the 12 quarters, as seen in Table V-1. However, additional insight from the full regression results appears to be small.

All specifications presented in the dashboard include house prices, employment and per capita income. Different candidates for the other two equations are explored. While a number of alternatives were explored, the additional endogenous variables focused on here are rent and single-family home sales. In a previous paper (Follain and Giertz, 2011b), we employ a three equation model that includes house prices, in addition to employment and personal income. Here we build on this earlier work, in part, by exploring additional variables that were not available for the period examined in the earlier study. Examining the regression results gives us a better idea about what variables may prove to me important and whether their inclusion has much impact on the estimated coefficients on the three variables used in our earlier work.

The Three-Equation Model

Results from the three-equation model—which includes house prices, employment and per capita income as endogenous variables—are summarized in panel 3 of Table V-2. For the house price equation, the estimated coefficient on the error correction term is negative for all time periods. This supports the notion that the first stage regression is measuring the departures of the level of prices from the levels predicted by the steady state relationship embodied in the first stage regression and that such departures affect future price growth. The absolute value for this coefficient is largest for the 1990s. It may have been that deviations from equilibrium values were "corrected" more quickly during this earlier period.

Note that the sum of lagged estimated coefficients for the house price variable is large for all four time periods. Large estimated coefficients are consistent with momentum. I.e., previous house prices feed on themselves leading to further increases—and likewise, if a drop in prices occurs, this too has to potential to snowball. Thus, large coefficients on the house price variables would be consistent with a price bubble and, all else equal, should imply that house prices are more sensitive to shock. However, large lagged coefficients are not prima facie evidence of a bubble. They may also be consistent with a market where unobserved fundamentals tend to follow multi-period trends. Consider a declining city such as Detroit, where house prices have fallen sharply over a long period of time. While a poor economy will be reflected by stagnant or declining employment and incomes, changes to these variables may understate shifts in expectations about the local economy and future demand for housing. In such cases, large coefficients on the house price variables could be capturing changes in longer-term expectations for the housing market due to fundamental changes to the economy, as opposed to a bubble, where prices are driven more by herd behavior.

Sums of estimated coefficients on the employment lags are positive and vary little across the time periods. One possibility is that during a bubble, fundamentals, such as employment, may be less important. The results do not reflect this, however. Employment is likely a key demand side factor and this appears to hold through varying economic conditions. In fact, the effect of employment on house prices is smallest for the period ending in 2000:Q4 (prior to bubbles in most markets) and was 50 percent larger for the other three time periods. As such, perhaps the negative shock to employment in many MSAs in the post-bubble period may have contributed to the substantial price declines. In terms of the language used in Section IV, the negative impact of a decline in employment in concert with a larger momentum effect in the house price equation may have been a strong contributor to the house price declines that followed, especially those with substantial fractions of employment in the construction industry. In fact, despite steady employment growth through the middle part of the first decade of the 2000s, overall employment growth for the decade was dismal (see section III and Irwin, 2010). However, disentangling the effects of the housing price bubble (on employment) from other factors that contributed to the

Great Recession and collapse of financial markets is incredibly complex, and beyond the scope of this paper.

From the three-equation model, the estimated coefficients on personal income fluctuate the most across time periods. For the 1990s, the sum of these lags is 0.39, consistent with a strong demand side influence. Extending the data through 2006:Q2 and through 2007:Q4 leads to very different estimates. The first of these sums is -0.10. When going through 2007:Q4, the sum is -0.19. If a causal interpretation were applied, this would imply that housing is an inferior good! However, when including data through 2010:Q4, the sum is up to 0.29—moving towards its position in the 1990s. The changes in lending standards during the 2000s may explain the odd findings for this variable. During the first half of the first decade of the 2000s, income may have become less important, as lending standards became lax, exemplified by phenomena such as "liars' loans," where loan applicants state their incomes with no verification process. At the time, recent history suggested that these loans were safe. However, recent history had been dominated by substantial house price appreciation with few declines.

Turning to the employment equation, lagged employment growth variables show a strong positive relationship with current employment growth. This relationship is remarkably stable across the time periods, with the sum of lagged coefficients equaling 0.97. Momentum in employment would not be considered a bubble, since employment is not a price. However, the strength of the lagged coefficients suggests that local economic conditions often produce multi-period trends in employment. For example, a city on the rise may not have a one period jump to a new steady state employment level, but may rather have strong employment growth for many quarters. Likewise, employment in a declining city may not collapse at once, but may fall over a number of quarters until a new steady state is reached. The income and house price variables appear to have only a very weak relationship to current employment growth. And, the error correction term (from the first stage house price equation) appears to be irrelevant in the employment equation.

For the income equation, lagged income growth shows a strong positive correlation with current income growth. This is analogous to the results from the employment equation, in that MSAs appear to move between different steady states over a number of periods. Lagged employment growth is also positively correlated with income growth. It may be that increased demand for labor yields both higher incomes and employment. In other words, a city may have to offer higher wages to attract additional employees in order to grow. While the influence of lagged income appears strongest for the 1990s, the reverse is true for employment. The relationship between employment and income is strongest with data extending to 2006:Q2 or through 2007:Q4, and weakest for the 1990s. The influence of the error correction term is very modest for the income equation. This variable's importance is strongest (0.01) for the period extending through 2006:Q2. The positive relationship suggests that MSAs with house prices above long-run equilibrium levels tended to have slightly faster income growth. It could be that house price growth in these markets had positive feedback effects for the overall local economy. Another possibility is that a short period high-income growth was contributing to the bubble, pushing house prices above long-run equilibrium levels. Thus, places with more rapid income growth tended to have median house prices that exceeded equilibrium levels, but the higher house prices were not a driving factor for income growth.

The Four-Equation Model

Adding a fourth equation, single-family home sales, appears to add little to the model. For the three variables used in the three-equation model, the sum of lagged coefficients for the house price equation change very little. Estimated coefficients on the error correction term are also robust to adding the fourth equation. And, the sum of coefficients on the single-family home sales lags is modestly positive for all four time periods. This general pattern holds for the employment and income equations as well. i.e., single-family sales appear to add little.

Turning to the single-family sales equation, the lags for this variable appear to dominate the other variables. The sum of lagged coefficients is stable across time periods, ranging from 0.87 to 0.89. Lagged income is negatively correlated with sales. For the 1990s, this negative relationship is strongest. The negative relationship is somewhat surprising, as one would expect increases in income to result in greater sales. The relationship between sales and house prices is as expected, though, with lagged house price increases associated with a slight drop in sales. Lagged employment is positively correlated with sales, consistent with its proxy for housing demand. The estimated coefficient on the error correction term is slightly negative for all time periods (and is largest in absolute value for the 1990s). The negative coefficient is consistent with a scenario in which home sales slow as prices move above longer-run equilibrium levels.

The Five-Equation Model

Adding a fifth equation, rent, has a modest impact on the other variables, but the magnitudes and patterns are pretty similar to those from the three and four equation models. Estimated coefficients on the error correction term are virtually unchanged (for all four equations included in the previous specification). Rent does appear to have a substantial negative relationship with house prices, however. As mentioned earlier, all else equal, increasing rents should increase demand for owner-occupied housing, pushing up prices. Here, though, all else is not held equal. It appears that either rising rents are a proxy for a rising demand for housing in general, which would include rental and owner-occupied. Or, rental prices could rise if demand shifts from owner-occupied to rental—which would also be consistent with the negative sum of lagged coefficients.

Once again, for the other equations, the addition of lags of growth in rent has only a modest impact on the estimated coefficients. For the employment equation, lagged employment growth still dominates everything else, and the impact of changes in rent appears to be minimal. For the income equation, the rent lags show a negative relationship for the 1990s and for the full period, extending to 2010:Q4. For the full period, the influence is greatest, with a sum of lagged coefficients equal to -0.16. When including data to 2006:Q2 or through 2007:Q4, the relationship is modestly positive. It may be that during the bubble years, rent is proxying for strong demand in all housing sectors, yielding the positive estimates. For the other periods, the fact that rental and owner-occupied housing are substitutes appears to dominate.

For the rent equation itself, lagged rent growth is strongly positive throughout. This is consistent with multi-period trends and with relationships from the other equations. Employment and income also show a positive relationship with rent across all time periods. This is consistent with income and employment as key demand side factors. The summed coefficients on the income lags are much greater for the full period than for any of the sub-periods. The sum of employment lags is much smaller for the 1990s than for the longer periods. Estimated coefficients on the error correction term are positive throughout. These estimate range from 0.009 for the 1990s and for the full period to 0.014 for the periods ending with 2006:Q2 and 2007:Q4. Positive coefficients suggest that, when house price exceed long-run equilibrium levels, rent cost rise with increased demand for rental housing.

Regression Standard Errors

Another set of regression results important for the Monte Carlo simulations are the regression standard errors (i.e. root mean squared errors or RMSE). As discussed in section IV, the RMSE from each equation is a key component in generating distributions of possible house price paths—as opposed to the most likely scenario. For out-of-sample projections, a normally distributed random variable with mean zero and standard deviation equal to the RMSE of the respective equation is added to each predicted value. Other things equal, larger RMSEs are associated with greater uncertainty concerning future price paths.

As shown in Table V-3, the RMSEs show almost no variation among models estimated for the same time period, though they do vary across time periods. One hypothesis is that the RMSEs may be larger during bubbles, since the future paths of the variables are more uncertain. Looking across time periods, one finds modest support for this hypothesis. RMSEs for the house price equations are somewhat larger for the regressions extending through 2006:Q2 and 2007:Q4. RMSEs for income are smaller for the 1990s than for the later periods. In general, however, variation in the RMSE across specifications is modest and is capturing little of the uncertainty that is associated with a price bubble.

Predictions from the Model

Follain and Giertz (2011b) compared out-of-sample house price projections for 2008-2010 to actual outcomes. Those results were estimated using the same general model employed here, but with annual data (instead of quarterly) from 1980 (instead of 1990:Q1) through 2007. The projected and actual outcomes were generated for each of the MSAs in the sample. A striking conclusion emerged. The ranking of MSAs by projected house price changes were highly correlated with the rankings based on actual outcomes. In other words, the model accurately predicted the MSAs in which house prices would decline the most. However, the model substantially understated the magnitude of the actual decline in house prices, especially among the worst hit MSAs.

As noted in the introduction, there are two broad explanations for such a gap between the model predictions and the actual outcomes. One is that the model necessarily omitted certain unpredictable events that negatively impacted house prices. These might include, for example, the banking crisis, the severity and length of the Great Recession that become more apparent well into 2008 and 2009, and the secondary effects of the large increase in the distressed real estate inventory. Another possibility is that the model itself and estimates of its key parameters failed to incorporate relevant evidence and information available prior to 2008. The previous model focused upon house prices, employment, and income per capita. Perhaps such a three equation model omitted other important variables that affect the housing market. As noted above, this paper estimates models with these same variables and two additional ones—the level of rents and the volume of single-family home sales.

This section revisits this issue with the current model and data. One exercise is similar to that conducted in the previous paper. Out-of-sample estimates of house price changes are generated for 2008:Q1-2010:Q4 using the regression estimates based on data extending through 2007:Q4. One difference is that five alternative specifications are estimated. This includes projections based on models ranging from a single equation to as many as five equations. A purpose is to see whether adding more variables to the model reduces the gap (between the projections and actual outcomes). This exercise is then repeated for different points in time. For example, additional three year house price forecasts are generated based on data extending through 2000:Q4, 2006:Q2 and 2010:Q4. 2006:Q2 was chosen because it is at or near the peak of the house price boom. In addition to comparing the 2008:Q1-2010:Q4 results to those from Follain and Giertz (2011b), we also seek to determine whether the accuracy of the model's predictions varied significantly from the results from the 2007:Q4 specification, i.e., a model with just six additional quarters of data. The short answer is that the models based upon data through 2006:Q2 severely understated the declines that were to come in many MSAs, whereas the estimates of the new models using data through 2007:Q4 generated much larger declines than were generated by our previous 3 equation model and were often much worse than what actually happened. Adding equations to the model has mixed results. In some instances it improves the projections. In some instances, the projections are worse with the additional equations.

Predictions for 2008–2010

The projections for 2008:Q1–2010:Q4 are quite different from those reported in Follain and Giertz (2011b). Here, predicted house price appreciation from 2008:Q1–2010:Q4, based on data through 2007:Q4, yields systematically larger price declines than what actually occurred during this period! This performance is best depicted by comparing the actual and baseline house price projections reported in Figure V-1. Predicted price appreciation projections are presented for the largest MSAs. MSAs are ordered based on actual price appreciation and the "baseline" projections are from the five-equation model. In stark contrast to the predictions in Follain and Giertz (2011b), here predictions are generally below the actual outcomes. This is true even for most of the hardest hit MSAs. The largest gap is found for the West Palm Beach MSA, where predictions called for a decline of 83 percent; prices actually declined by 36 percent. The five equation model predictions were quite close to the actual outcomes for Phoenix, San Jose, and Tucson and actually modestly under predicted the declines for Las Vegas and the San Francisco MSA. These cities were all hard hit by the bubble's collapse—Phoenix and Tucson especially so. A summary of these results for this period and the impact of adding equations to the model are included in column (3) of Table V-4, with more details in Table V-5. Like Follain and Giertz (2011b), the actual percentage changes in 2008 to 2010 are quite dire in most MSAs and similar to those reported in Follain and Giertz (2011b). For example, the average cumulative decline in house prices from 2008 to 2010 for the full set of MSAs was 14 percent. Twenty-five percent of MSAs experienced declines of at least 19 percent and 5 percent of MSAs experienced declines in excess of 40 percent.

Turning again to column (3) of Table 4, including only house prices as an endogenous variable, the average predicted decline is 20 percent. The projected and actual price decline for the median MSA for 2008:Q1–2010:Q4, also reported in Table V-4, are systematically smaller (in absolute magnitude) than the means. Note that the overall mean (or the median) across MSAs, by itself, is a poor measure of model performance. This is partly because both actual and projected price paths very tremendously across MSAs and cannot be captured by an average. Furthermore, projections that are way off for each MSA may, on average, appear to do a good job of tracking actual outcomes. In our figures and some of our tables, we look at the performance for particular MSAs (or the performance at particular points in the actual distribution of price appreciation) to better assess model performance. Additionally, in order to better assess the predictions, Table V-4 also presents the root mean squared error (RMSE). The RMSE is the square root of the average of the sum of squared deviations between the (cumulative three-year) projected and actual three-year price changes.

Adding employment as an endogenous variable does very little to the average projected decline and only marginally improves projections based on the RMSE. Adding a third equation, income per capita, yields a sharper drop of -22 percent. Once again, the model predicts much larger declines than actually occurred! The paths at the 5th percentile decline by 57 percent.

In preparing Table V-5, MSAs are ordered based on actual house price outcomes over the projection period. Thus, while the 5th percentile of the three-equation projections (for 2008:Q1–2010:Q4) shows a price decline of 57 percent, the MSA at the 5th percentile of *the actual price distribution*, as reported in Table V-5, has a projected decline of 72 percent. Alternatively, in creating tables, one could independently order the actual price appreciation and each set of projections for the MSAs. Such an approach, however, can yield misleading conclusions. For example, suppose the actual and projected price appreciation have very similar distributions. One might conclude that the model performs very well. However, it may be the case that the ordering of MSAs is very different for actual and projected price appreciation. Thus, the model may in fact have performed poorly for every MSA. The approach taken here is not without drawbacks either. Moving across a row for a particular percentile in Table V-5 provides information for the same MSA. This is a plus. But, the fact that the model performs well at, for example, the MSA whose actual decline was at the 5th percentile, says nothing about what happened for the MSA at the 4th or 6th percentile. Again, since MSAs are ordered by actual three-year price appreciation, moving a percentile will make little difference for the actual measure, but the predicted measure could vary greatly.

Turning to the four and five equation models, the gaps between the actual and predicted declines are even more pronounced. For example, the five-equation model predicted an average decline of 27.6 percent and declines in the hardest hit areas of more than 60 percent. Projections after adding a fourth equation, single-family sales and a fifth equation, income per capita, are quite similar. In fact, the correlation between these two sets of predictions is 98 percent.[11] While the 5-equation model seems more closely correlated with actual outcomes, the two-equation model actually performs best for this period, when comparing RMSEs. Adding equations three through five results in larger under predictions, and thus larger RMSEs.

[11] The appendix contains a table with the actual outcomes and the predictions using the three models for each of the largest MSAs, which consists of MSAs in MSA groups 7, 8, and 9.

The differences among groups of MSAs also reveal an interesting pattern (See Table V-6). The gaps between the predictions and the actual outcomes are largest for the subgroups whose populations have grown most rapidly over our sample period. For example, the fastest growing MSAs among the MSAs with the largest populations were predicted to have declines by 36 percent with the five equation model, yet they experienced declines of a (mere) 21 percent. An alternative presentation of the results features graphs of the actual versus predicted outcomes ranked by the actual outcomes, which is able to better handle this issue by including information on many MSAs. For example, the tendency for the five equation model to predict more severe outcomes than the three equation model is captured in Figure V-2, which focuses upon the largest MSAs in the sample. Nine exceptions to this general pattern are apparent among this group of MSAs. Like the exceptions noted above, these are also concentrated in California and include Bakersfield, Fresno, Los Angeles, Oakland, Sacramento, San Diego, San Francisco, Santa Ana, and San Jose. A tentative conclusion is that incorporating total sales and residential rents generally leads to more severe outcomes than a model without them, although the exceptions to this rule may be worth further consideration.

The out-of-sample forecasts for 2008:Q1–2010:Q4 are predicted forecasts. As discussed earlier, we also perform Monte Carlo simulations to produce a distribution of potential house price paths.[12] (The median path from the simulation is akin to the predicted path—i.e., projections that are not from the simulation. In practice, median simulated paths and the predicted paths are quite similar, but not identical.) In examining outcomes from the Monte Carlo simulation, we use the median path as a point of reference. For example, see Figure V-3, which presents projections at the 5th based on the five-equation model for the largest MSAs. Scenarios such as this are often used to develop and define stress tests.

Two key and important patterns emerge from Figure V-3. First, the relationship between the two scenarios is quite close. A simple regression of these two series indicates that the stressful scenario is about 175 percent of the median forecast (assuming a zero constant term). The R^2 for this simple regression is 96 percent.

Second, the notion of a stress test varies widely among markets, which is a consistent theme of our work and earlier work by Follain, such as Follain and Sklarz (2005). Indeed, this pattern seems relevant to an ongoing debate about Basel III, which defines capital standards for financial institutions.[13] A key part of the proposed rules is to make capital rules more sensitive to the business cycle. During periods of growth capital requirements will be higher than during periods of decline. The hope is to build up excess reserves during the good times in order to provide a larger capital cushion for declining periods and to avoid the need to raise additional capital

[12] Most of the analysis is based on projections using out-of-sample predicted values. Because year dummies are included in the underlying regressions, average year dummies are assumed for the forecast period. I.e., the average of unobserved time-varying factors is assumed for the projection period. In contrast, Figure V-3 is based on the Monte Carlo simulation approach described in Section IV. The simulation yields an array of price paths. Each iteration selects a year dummy at random and adds to each quarterly projection a stochastic term with mean 0 and standard deviation equal to the standard error of the underlying regression. Thus, average and median projections across MSAs for the two approaches, while generally very close, are usually not exactly the same.

[13] The proposed rules are discussed at the BIS web site: http://www.bis.org/press/p110928.htm.

during declining periods, which can work to further slow down the economy. We believe that using estimates of a stress test based upon the experiences of MSAs can be a helpful tool in developing these counter-cyclical capital rules. For example, our results suggest that the stress test scenarios for many of the MSAs experiencing the largest increases in house prices during the mid-2000s would have led to more substantial capital requirements than those experiencing much milder house price appreciation. For example, many places in Florida and California would have been forced to pass a more severe stress test and have more capital than Texas MSAs at the other end of the spectrum.

Comparing the Model Predictions from the Bubble Peak

Next, model predictions for two alternative time periods are compared. One is the 2008:Q1–2010:Q4 period just discussed, while the other uses data through 2006:Q2 to project through 2009:Q2. For many MSAs, 2006:Q2 represented the peak of house prices. Two questions are addressed: First, did the model as of 2006:Q2 predict the declines that were to follow in 2006:Q3 through 2009:Q2? Second, if not, then what factors seem to be driving the differences in the model predictions? For example, can changes in the coefficient estimates be identified as a possible explanation or, alternatively, perhaps the differences can be attributed to differences in the recent historical trends in house prices associated with each model.

Consider, first, the actual changes in house prices in the two different (but overlapping) three-year projection periods. Figure V-4 highlights a close correlation between actual outcomes for the two overlapping periods. House prices declined substantially in most of the large MSAs over both 2006:Q3–2009:Q2 and 2008:Q1–2010:Q4. However, actual price declines from 2008:Q1–2010:Q4 were substantially greater than for the slightly earlier period. Average price appreciation for the three years ending with 2009:Q2 was -9.5 percent (-5.1 for the median) versus -13.8 percent (-10.1 for the median) for the three years ending in 2010:Q4. Wide variation across MSAs in the two historical periods is also vivid.

Comparing Figures V-1 and V-5 shows that, for the later period, projections from the five-equation model did a much better job of capturing the trend across MSAs. That is, the model overestimated price declines, but did so by roughly similar magnitudes across the distribution. As mentioned earlier, this is particularly surprising at the left tail of the distribution, where Follain and Giertz (2011b) under-predicted price declines by a huge margin. By contrast, the performance of the model for 2006:Q3–2009:Q2 (see Figure V-5) is more in line with the 2008–2010 projections from Follain and Giertz (2011b). I.e., on average, projections from the five-equation model are closer to actual averages for this earlier period, but the model's performance varies greatly across the distribution. And like Follain and Giertz (2011b), it, for the most part, misses by a huge margin what occurs in the left tail of the distribution. For these worst hit MSAs, the model greatly under-predicts declines (even predicting growth in prices for some of the hardest hit MSAs). Consider, for example, the 5th percentile of the actual distribution of price appreciation for 2006:Q3–2009:Q2. As Table V-5 reports, the actual price decline was 41 percent, whereas the model predicted a 21 percent price *increase*. This suggests that the model massively over-predicted house price appreciation for this MSA at the 5th percentile (of the actual distribution of price appreciation). By contrast, average projected price appreciation for this three-equation model was just -3.6 percent.[14]

The fact that projected appreciation for the MSA at the 5th percentile of the actual distribution is four times larger than mean projected appreciation suggests that the MSA at the 5th percentile may be an aberration. The fact that the projection grossly overestimates price appreciation suggests that this model did not perform well, but looking at the mean and at some of the other percentiles suggests that model did not generally over predict by this margin. In fact, in this case, the same three-equation model predicts a smaller price increase (17 percent) for the MSA at the 95th percentile of the actual distribution than it does for the 5th percentile.

In addition to the model's poor performance in the left tail, the performance when moving from MSA to MSA through the distribution shows that the model's performance is all over the map. For example, actual declines for Cleveland, Ohio and Tacoma, Washington from 2006:Q3–2009:Q2 were very similar (12 percent and 10 percent declines, respectively. However, Cleveland is projected to experience a 34 percent *decline* in its median house price, while the value for Tacoma is projected to *increase* by 3 percent. Such huge differences in model performance for MSAs with similar actual experiences are very unusual for 2008:Q1–2010:Q4, but fairly common for 2006:Q3–2009:Q2. In fact, projections for this earlier period appear almost random.

From Figures V-1 and V-4, it appears that the model captured what was to occur much better for 2008:Q1–2010:Q4. However, as we have noted, differences between average actual and projected price appreciation are greater for the later period. And, the RMSE calculations suggest that, over the full distribution, the model's performance was about the same for the two periods. In fact, since on average the 2008:Q1–2010:Q4 projections missed what actually occurred by 18 percentage points compared to just 6 percentage points for 2006:Q3–2009:Q2, it may seem surprising that the RMSE is similar for both periods. As is borne out by Figures V-1 and V-5, this is largely because for 2008:Q1–2010:Q4 the model over-predicted declines throughout the distribution whereas the 2006:Q3–2009:Q2 projections tend to both over- and under-predict. The under- and over-predictions tend to cancel each other out in calculating the average—which of course is not true when calculating the RMSE. The fact that the model performs well for 2006:Q3–2009:Q2 on average appears to be dumb luck.

For 2006:Q3–2009:Q2, now consider how the model performed using fewer equations. The one-equation model, with house prices as the endogenous variable, predicted flat prices (mean appreciation of -0.8 percent). See column (2) of Table V-4. Adding employment yielded predicted mean price appreciation of -1.6 percent. For these models, the RMSE (measured in percentages) is 25.5 and 23.6, respectively. These RMSEs are well over twice as large as those for the corresponding 2008:Q1–2010:Q4 estimates. In comparing the two time-periods, the same general story remains: the 2008:Q1-2010:Q4 projections overestimate price declines, while the 2006:Q3-2009:Q2 estimates underestimate declines. Adding variables only modestly changes average projections for the earlier period. For the later period, moving from three to five

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[14] While the five-equation model performed very poorly in this instance, the three-equation model performed considerably worse. Also, note that for 2008:Q1-2010:Q4 the difference between the baseline projections and actual price appreciation is much closer to the difference between the averages of these numbers.

equations lowers projected declines by more than ten percentage points, on average. For the one-, two- and three-equation models, average performance across MSAs once again provides an incomplete and potentially misleading picture. For these models, the RMSE is often twice as large for 2006:Q3–2009:Q2 versus 2008:Q1–2010:Q4. This suggests that with fewer equations (and as with the five-equations), the model continues to project price appreciation that is substantially lower than what some MSAs experienced and substantially larger than what others experienced.

More details for the three-, four- and five-equation models are included in Table V-5. Once again, with fewer equations, projections for the earlier period are much greater in the lower tail of the distribution. Again, the 5th percentile for 2006:Q3–2009:Q2 provides a good example. While the five-equation model overstates price declines by 24 percentage points, the three-equation model overstates declines by 32 percentage points. Another striking example is Las Vegas. Prices were to decline by over 40 percent from 2006:Q3–2009:Q2, but the five-equation model was predicting a future with flat prices and the three-equation model predicted a 14 percent increase in prices. In many instances, 2006:Q3–2009:Q2, moving from three to five equations improved projections for the hardest hit MSAs. However, as was noted with Las Vegas, the five-equation model still often mixed the mark on these MSAs by a wide margin. Other examples of hard hit MSA include: Phoenix with three- and five-equation models projecting house price growth of 32 and 18 percent, respectively; Ft. Lauderdale with three- and five-equation models projecting house price growth of 25 and 10 percent, respectively; and, Miami with three- and five-equation models projecting house price growth of 32 and 18 percent, respectively. On the other hand, for Bakersfield, which had a three-year price drop of 42 percent, the three-equation model was somewhat less bad, predicting price increases of 8 percent versus 14 percent with the five-equation model. More generally, the model predictions were relatively similar for the large MSAs and, when including all five equations, often called for price increases or decreases in the range of plus or minus 10 percent. The actual cumulative price decline at the 25th percentile (of the actual price distribution) was 19.2 percent. The three-, four- and five-equation models called for price *increases* ranging between 24 and 35 percent.

In sum, compared to Follain and Giertz (2011b), the estimates based upon quarterly data through 2007 with and without more variables does a better job of predicting what happened in 2008–2010 (at least for the hardest hit MSAs) than the model estimated in that paper using annual data. The predictions of the 2006:Q2 model are actually more similar to those with the annual model. This suggests that at or near the peak it is important to examine data with higher frequency in order to better capture the potential of sudden changes. Our analysis suggests that the likely culprit was the wide difference in house price patterns in the last year of data used to estimate the models. Figure V-6 captures this pattern. Note that many of the large MSAs in Arizona, California, and Florida had experienced substantial growth rates in house prices in the second half of 2005 and the first half of 2006 (notice the right hand part of the chart). MSAs in these places began to experience price declines in 2007. The combination of a substantial momentum effect and rising prices in the four quarters prior to a forecast period likely lead to positive price forecasts for the first part of the forecast period, all else equal. This was the case for the 2006:Q3 model whereas prices had begun to decline in the year or so prior to the end of 2007:Q4, which allowed the 2007:Q4 model to foresee a rapid unraveling and reversal of house prices in the near term.

Model Predictions from the Beginning of the Bubble (2001:Q1–2003:Q4)

Lastly, projections are also produced for a third period, 2001:Q1–2003:Q4, using data through 2000:Q4. This earlier period is characterized by a soft economy in the midst and aftermath of the bursting of the tech bubble and the attacks on 911. However, in sharp contrast to the Great Recession, where housing has been seen as ground zero of the crisis, during the early 2000s, housing was seen as keeping the economy afloat. In fact, while employment and the stock market were weak, it was argued that consumers continued to spend and borrow, in no small part, because of the wealth effect from rising property values. How does the model perform under these circumstances? In short, not very well.

Column (1) of Table V-4 shows the strength of the housing market. Despite a weak economy, median house prices rose at an average of 14 percent from 2001:Q1 to 2003:Q4. In contrast to the actual performance, the models took the weakness of economic indicators as portending declining house prices. The one-equation model project house prices to fall by 10.6 percent—i.e., it over-predicted growth in house prices by more than 24 percentage points. Adding equations to the model results in worse predictions. The full five-equation model predicts an average decline in median house prices of 22.7 percent.

Table V-7, which presents projections at different points in the distribution, reinforces this narrative. For example, even at the 5th percentile of MSAs, actual prices rose by 3 percent, while the models predicted price declines of 22 percent. This period appears to be an aberration within the data. The housing market is usually positively correlated with the business cycle. This was especially true of the Great Recession, when the housing market and the broader economy appeared to form a vicious circle. Weaknesses tended to exacerbate each other. In the early 2000s, the reverse was true. Some argued that the sharp drop in the stock market, rather than reducing demand for housing, led, and was in part due to, investors shifting income from stocks to housing, where many expected higher returns. Others argued that housing market was "catching up" after a period of relative slow price appreciation. In any event, for the early 2000s, the models' projections were based on historical relationships that failed to hold. Because correlations had reversed, adding more variables made predictions worse, rather than better. Finding a measure that could account for experiences of the early 2000s and for the Great Recession is a major challenge that has not been resolved.

Another point is that these projections would have implied higher capital requirements for financial institutions, when, for this period, such measures did not turn out to be necessary. The implications of higher capital requirements could have added to the weakness in other sectors of the economy and resulted in a more severe recession. On the other hand, such measures may also have made borrowing more difficult (especially for those with poor credit and low down payments). It is possible that this could have stifled the impending house price bubble before it gathered steam.

The Road Ahead, 2011–2013

Table V-9 presents projected house price appreciation for 2011:Q1–2013:Q4 using data through 2010:Q4. These projections suggest that housing market will remain weak, but that price declines will moderate. Using a single endogenous variable (house prices), the model predicts an average increase in median house price 4.4 percent over the period. However, the five-equation model, which includes rent, pushes the mean prediction back to -4.8 percent. At the 5th percentile, projected cumulative price declines range from 1 percent for the one-equation model to a decline of 21 percent for the four-equation model.

Figure V-7 presents the projected three-year percent change in house prices for the MSAs in our sample, based on median projections from the Monte Carlo simulation. MSAs are ordered by projections from the five-equation model. Across MSAs, projections range from a 26.7 percent decline for Brunswick (Georgia) to a 14.6 percent increase for Williamsport (Pennsylvania). What stands out is the variation in projections from the different models. In particular, and consistent with Table V-4, simulation results from the four equation model are much more pessimistic than the other two. Median Projections based on the four equation model predict an employment-weighted drop in house price of 6.9 percent. For many of the MSAs where the five-equation model projects price declines, the four equation model projects much more severe declines. Again, see Figure V-7. Thus, adding single-family sales to the three equation model leads to a much more pessimistic forecast. Adding rent, when moving from the four to five equation model, mitigates this effect.

Focusing upon the predictions of the 5 equation model offers a sense of the near term future, which is not bright. The median predicted change in house prices for the 2011–2013 period from the 5 equation model is -3.4 percent. The 25th percentile is -8.1 percent. The 75th percentile is only 1.1 percent. No obvious pattern has been discerned regarding which ones will recover most quickly or most slowly. The correlations among the other five variables are only about 10 percent. Overall, these suggest a very modest and slow recovery of house prices. Indeed, if attention is focused upon the level of prices at the start of the boom, few if any of the MSAs will reach that level over the next ten years. See Appendix Table 2.

Market Sensitivity over Time: Momentum and Impulse Response Results

The IR analysis is designed to show how a severe shock to one or more of the endogenous variables, during the final 12 quarters of the in-sample data, affects the three-year out-of-sample projections. The IR projections can be viewed as low probability scenarios. Additionally, the difference between baseline projections (without any shocks) and those of the impulse response analysis may measure the sensitivity of house prices (or other variables) to a negative shock. As the spread between the IR and baseline paths widens, the market may be more fragile. This does not predict a bubble or bust, but is warning that markets are more volatile. An exogenous shock that might have a relatively benign effect in “normal” times may have major economic implications during fragile periods.

The IR analysis and the sensitivity to exogenous shocks also relate to the discussion of momentum and to the estimated regression coefficients. Recall from Table V-2 that the sum of the lagged coefficient estimates was used to proxy for the momentum effect. The focus was primarily on the house price lags and whether changes in house prices tend to snowball (i.e., the sums are large and positive), or whether mean reversion dominates (i.e., the sums are negative). For the three-, four- and five-equation models, the momentum proxy for the house price equation is strongest when the data extends to the peak in house prices (2006:Q2) and is weakest for the full period (through 2010:Q4). The differences across the time periods are most pronounced for the three-equation model. Note that while this measure of momentum was strongest at the bubble peak, the subsequent three-year drop in house prices was greatest following 2007:Q4. For example, the sum of house price lagged coefficients peaked at .893 in 2006:Q2 using the five equation model and then declined to .791 and .735 in the next two periods (See Table V-2. However, that does not necessarily nullify the measure, since latter period includes more of the financial crisis, which represented a huge exogenous shock. Had the financial crisis hit (six quarters) earlier, maybe house prices would have fallen even further or more rapidly.

Of course, house prices are only one component of the model. Feedback effects from the other equations and other variables could be even more important. For the house price equation, recall the changes to the sum of lagged coefficients on income per capita, single-family sales and rent during the two middle end periods. Turning to the income per capita equation, notice that the relationship between employment and income strengthens in the years leading up to the Great Recession, while the relationship between current and lagged income growth weakens. The income equation is the only one where the relationship between current values and lags of the dependent variable change markedly across the time periods. For the single-family sales the importance of lagged employment rises while the importance of lagged rent diminishes as the Great Recession approaches. For the rent equation, the importance of lagged employment shows a similar pattern. Because of the interconnectedness of the system of equations, changing relationships in these other equations could have important effects on house price growth. However, the complexity of the system means that such relationships are generally not self-evident. The IR analysis can shed some light on the overall influence of these moving parts.

Our IR analysis considers the response of the predictions to a large negative shock equal to two standard deviations in the 12 quarter growth rate (for each of the core or endogenous variables in the model. For example, the HP shock is applied to each of the twelve lagged coefficients in the equation that predicts house price growth and the employment shock is applied to each of the twelve coefficients in the employment equation. The key results are summarized in Table V-8. The results show the actual house price changes, the amount predicted by the baseline model without a shock, and the changes in house price changes generated by shocks to each of the variables in the five equation model. The changes include the mean, median, six percentiles, and the interquartile range of the impacts of the shocks. The top panel provides results of shocks to the model estimated with projections from 2006:Q3 through 2009:Q2 and the bottom panel to the model estimated with projections from 2008:Q1 through 2010:Q4.[15] These results can be used to test the hypothesis described earlier in the paper is that the impact of a negative shock upon future house prices would be larger in a model marked by a higher momentum effect than in a

[15] As discussed earlier, the shock is imposed during the last 12 quarters of in-sample data. The shock is imposed smoothly over this period. That is the growth rate for the 12 quarter lag is reduced by 1/12th of the 12-quarter standard deviation. Each subsequent lag is lowered by 1/12th of the previous lag. Thus, the growth rate for the 1-quarter lag is a full two standard deviations lower than what actually occurred.

model with a smaller momentum effect, all else equal. In fact, these two data periods provide an opportunity to test this hypothesis since the momentum effect was estimated to be larger in the model with data through 2006:Q2 than in the model with data through 2007:Q4. For example, the momentum effects are 0.893 and 0.791 in these two models using the five equation model. (See Table V-2.)

On average, the mean projected effect of the house price shock is to lower house prices by 20 percent for 2006:Q3–2009:Q2, which is about17 percentage points lower than the mean projection of the baseline model (without a shock). For 2008:Q1–2010:Q4, the mean projected effect is to lower house prices by 45 percent, or 14 percentage points lower than the baseline projection. The same ordering of these effects can be seen by comparing Figure V-1 and V-2. Thus, the IR results are consistent with the hypothesis: house prices were more sensitive to a house price shock in the earlier period (2006:Q3–2009:Q2) than in the latter period (2008:Q1–2010:Q4). The impulse response analysis also highlights the complexity of the system of equations and the need to take account not just of the house price momentum, but also the coefficients in the other four equations in the model. For example, the lagged income and rent coefficients could be playing an important role. The lagged per capita income coefficients sum to 0.03 with data through 2006:Q2 and to -0.09 with data through 2007:Q4. So, the effect of changes to per capita income (resulting from the shock to house prices) is much larger in the latter period and carries the opposite sign. That lagged rent terms sum to -0.27 for the earlier period and -0.10 for the latter.[16] These effects on per capita income growth and rent appreciation feed back into the house price equation, affecting the house price projections. As such, the test of the hypothesis suggests that the net effect of the larger momentum effect and the other coefficients in the model suggested modestly larger sensitivity to a negative shock in the 2006:Q2 model versus the 2007:Q4 model. Sorting out the net or marginal effect of the momentum coefficients relative to other factors is a very complex analysis that we did not undertake.

Now turn to the effects that shocking the other four variables have on house price projections. Shocks to employment growth have the second biggest effect. Results from shocks to single-family sales are very similar to the results from shocking employment—although the effect of sales is a little bit smaller. Note, however, that house prices appear much more sensitive to both employment and sales during 2008:Q1–2010:Q4 (as opposed to 2006:Q3–2009:Q2). Shocks to rent and income have virtually no effect on house price projections, thus are not included in Figures V-1 and V-5. Sales are also not presented because the line is so similar to the employment plot.

For both periods and for each of the variables, the negative shock (applied to the 12 quarterly lags feeding into the projections), does not appear to improve the fit of the projections. The shocks either have virtually no effect on the predictions or they shift the projections downward,

[16] The lagged coefficients from the other equations are also important. Here we focus on lags from the house price equation. However, the magnitude of the changes to lags of the other four variables is a function of the lagged coefficients from the other equations. Thus, while the relationship between the dependent variable house prices and independent variable per capita income, for example, may differ between the two time periods, the relationship between the dependent variable per capita income and the independent variable house prices also changes. Thus, the process is even more complex.

but do not change the shape of the picture. Since the baseline projections for 2008:Q1–2010:Q4 already predict larger declines than what actually occurred, the shocks, to the extent they have an effect, move the projections farther from the actual. Since the baseline projections for 2006:Q3–2009:Q2 understated what actually occurred, the shocks often move the projections closer to the actual. For 2006:Q3–2009:Q2, this would suggest a better fit, if the baseline projections systematically under-predicted declines. However, the error margin is all over the map for the baseline projections. While a negative shock to employment growth, for example, improves projections, the model fit is still very poor.

Section VI: What Next?

The subtitle of this paper raises two questions. They both relate to the challenge of detecting house price bubbles with econometric models. The specific type of model used in a VEC model estimated using quarterly data from 1990 through 2010 for 342 MSAs. Three different types of models are estimated that differ in the number of variables modeled as dependent variables. The three equation model focuses upon the growth rate in the real price of housing as measured by the FHFA all transactions price indexes, the growth in employment, and the growth in income per capita. The four equation model adds the volume of residential sales and the five equation model adds residential rents. The right hand side variables in each model include lagged values of the growth rate in house prices and lagged values of the other variables in the system. Each equation in each system also includes a measure of a residual generated in a first stage reduced form equation designed to measure departures of the level of house prices from the amounts predicted by the other variables and fixed effects. The growth rate equations also include time and fixed effects and two interest rates. Estimates of each model were computed for four different time periods and then used to predict house prices for each MSA for three years beyond the sample used to estimate the model. The periods were 1990 Q1 through 2000 (time period 1):Q4: 1990 through 2006 (time period 2): Q2; 1990 through 2007:Q4 (time period 3); and 1990 through 2010:Q4 (time period 4). Monte Carlo simulation and impulse response analysis were conducted to gain insights about the sensitivity of the results to various factors.

Several patterns are apparent among the various estimates. First, the estimation strongly confirms the importance of momentum in each variable, which we define as the sum of the coefficients on the lagged values of the dependent variable, though they can vary substantially over time. For example, the estimates of the momentum effect in the house price equation in the five equation model were 0.851 for the first time period, 0.893 with the second; 0.791 for the third; and, 0.733 using the fourth model and the full sample. These estimates do not vary substantially among the models with fewer variables. The sizes of the momentum effects are similar for employment and sales but smaller for the other two variables. Second, the residual consistently has a negative impact upon the rate of growth of house prices, though the size of this coefficient varies over time as well. The residual also tends to reduce the growth in residential sales and increase the rate of growth in rents. It has smaller and less consistent impacts on employment and income per capita. Third, the impacts of lagged growth rates in house prices on the other variables vary by the time period of the model and the variable. The most significant and consistent interaction is between sales and house prices; larger growth rates in lagged house prices tend to reduce the volume of sales, all else equal.

Question #1: What have we learned about the challenges of predicting house price bubbles using models of this type? We wish to highlight six specific findings before offering our broad answer to this question.

1. The models estimated with data through 2007:Q4 (time period 4) do a very good job of capturing the extent of the actual decline in house prices experienced in 2008 through 2010. Indeed, the model typically overstates the decline. This is different than the results obtained in Follain and Giertz (2011b) in which their model generally under predicted what was to happen in 2008–2010, especially in the MSAs most hard hit by the crisis. The finding is potentially important because it suggests that quarterly or shorter duration models may be more appropriate for bubble detection than annual models. Also, it likely reflects the fact that the decline was well underway in most places in the latter half of 2007 and an annual model was less able to detect the fast changing environment.
2. The model estimated with data through 2006:Q2 (time period) generated results more similar to Follain and Giertz. The three year out of sample predictions of this model underestimated by substantial amounts the actual declines by substantial amounts. There was a tendency to be more off the mark in the worst hit areas, but this was not as evident in this model as in Follain and Giertz. The critical implication of this point and the last is the sensitivity of model estimates and predictions at or near the peak.
3. Adding more variables and equations to the process probably helped but did not eliminate the failure to miss the crash at the height of the boom. Indeed, the first two points are relatively robust among the three, four, and five equation models.
4. The Monte Carlo simulations suggest that a reasonable 5th percentile stress test at the MSA level Stress test from Monte Carlo: 30 percent but varies from declines between negative 60 and negative 10 percent.
5. Evidence regarding the sensitivity of the predictions to negative shocks in house prices to the size of the momentum coefficient is mixed. Clearly, a negative shock to house prices leads to a larger decline in house prices in a model with a larger momentum effect, all else equal. Of course, all else is not equal. The interdependencies among the equations in the model also change. The impulse response analysis sought to take these into account; when it did, the predictions of the model did not show the kind of unambiguous change in the distributions of the predictions that we had hoped to see.
6. The path to recovery of house prices seems a long way off. The average predicted growth rate for the 342 MSAs is negative 3 percent for 2011 through 2013. The majority of MSAs are predicted to have negative growth. A very small number are predicted to have modest positive growth of 10 percent or more: Sumter, SC; Waco, TX; El Centro, CA; Miami, FL; Anderson, SC; Merced, CA; and Williamsport, PA. Those in which substantial declines in excess of 20 percent are predicted include Brunswick, GA; Albuquerque, NM; Redding, CA; Couer d'Alene, ID; Dalton, GA; Eau Claire, WI; Fresno, CA; Las Vegas, NV; and Gainesville, FL. Time will tell how accurate these prove to be.

More generally, the analysis suggests that bubble detection requires frequent updating of estimated models and careful attention to changes in the coefficient estimates and the predictions of the model. This is especially important as prices rise well above levels suggested by the cast of fundamental values. The models should also include a variety of variables and notions of equilibrium; no single set should be considered sacrosanct. Nonetheless, our broad judgment is that this approach can add value to a complex and challenging problem for economists.

Question #2: What we still do not know. Three issues seem most important and at the frontier of explorations in this area.

1. We still do not have a firm hand on the role of momentum and the complex interactions between housing and other sectors of the economy. On the other hand, the "truth" almost certainly includes trying to capture the interaction between housing and other markets. The simple structural model of housing market that makes a fine distinction between endogenous and purely exogenous is hard to justify.
2. Local conditions play an important role in the predictions judging by the wide variety of forecasts of future house prices among MSAs. Also, the importance of the MSA fixed effects in the first stage regressions also highlights this point. Models that focus on the US aggregate housing market seem increasingly out of date. On the other hand, uncovering the factors that drive the MSA fixed effects requires more work.
3. The subprime mortgage market undoubtedly played an important role in the latest boom and bust. Unfortunately, a lengthy time series with information that might highlight the role of subprime lending is not available. Some insights on this issue may be obtained by utilizing information about high cost lending in HMDA, which began in 2004. But even this will not fully capture the complex nature of the subprime loans relative to the traditional types that dominated the market prior to this bubble and bust. Further insights on this likely require loan level data with substantial characteristics. Data of this type do exist but are typically proprietary.

a. Distressed real estate plays a major role in today's housing market. However, like mortgage data, lengthy time series data about this factor is not available. What is available strongly suggests that the size and prevalence of the distressed inventory goes well beyond anything experienced in US history. Additional research is needed to highlight the importance of this complex issue.

More caveats and limits could be offered, but these seem sufficient to capture a key theme—there is much we still do not know about bubble prediction and we are wise to be aware of this limitation.

The results are relevant to a number of ongoing policy debates. One pertains to the specification of capital requirements for banks. Basel III calls for higher capital during a period thought to be a boom. The estimates of this model with its emphasis upon a cross-section of MSAs shed light on how capital rules might be measured. The sizes of the bubbles and busts varied widely. This would greatly benefit from additional information about the cost and availability of credit, but models that do not incorporate widely varying market conditions seem well off the mark of what is needed for an effective bubble protection capital rule.

Another pertains to the need to focus on local market conditions to develop policies to work out way out of the current malaise. All places were not hit equally hard. Some may have experienced near "knock out" punches that will take many years to overcome. Policy will have to make some tough decisions about where to provide assistance and how to structure the assistance to the local market conditions. These include the HAMP program and other federal state policies that are trying to unplug the severely clogged drain adversely affecting the path of recovery in many housing markets. One size surely does not fit all markets.

Lastly, the results in this paper strongly underscore the need for sound and often subjective judgments regarding the process of detecting bubbles. This involves the search for extreme events where evidence is seldom going to be definitive and without serious caveats. One wonders whether this message alone may be helpful in protecting against future bubbles!

References

1. Bokahri, Sheharya, Walter Torous, and William Wheaton (2012). "Why did Household Mortgage Leverage Rise from the mid-1980's until the Great Recession?" (Preliminary).

2. Campbell Sean D., Morris A. Davis, Joshua Gallin, and Robert F. Martin (2006). FRB Working Paper, "A Trend and Variance Decomposition of the Rent-Price Ratio in Housing Markets", Federal Reserve Board. April. http://www.federalreserve.gov/pubs/feds/2006/200629/200629pap.pdf.

3. Carrillo, Paul E., Dirk W. Early, and Edgar O. Olsen (2010). "A Panel of Price Indices for Housing, Other Goods, and All Goods for All Areas in the United States 1982–2008". http://www.virginia.edu/economics/Workshops/olsen/CEOFinalDecember2010.pdf

4. Case, K.E. and R.J. Shiller (1987). "Prices of Single-Family Homes since 1970: New Indexes for Four Cities". *New England Economic Review*: 45–56.

5. ——. (2003). Is There a Bubble in the Housing Market? *Brooking Papers on Economic Activity* 2: 299–342, http://cowles.econ.yale.edu/P/cp/p10b/p1089.pdf

6. Chen, Celia, Andres Carbacho-Burgos, SunaYana Mehra, and Mike Zoller (2011) "Moody's Analytics Case-Shiller Home Price Index Forecast Methodology" January, *Moody's Analytics.* http://www.economy.com/home/products/samples/case-shiller-methodology.pdf.

7. Clayton, Jim, Norman Miller and Liang Peng (2010). "Price-volume Correlation in the Housing Market: Causality and Co-movements," *The Journal of Real Estate Finance and Economics*, vol. 40(1), pages 14–40, January.

8. Coleman, Major D., Michael LaCour-Little, and Kerry D. Vandell (2008). "Subprime Lending and the Housing Bubble: Tail Wags Dog?" *Journal of Housing Economics*, 17(4), 272–290. http://ssrn.com/abstract=1262365 .

9. Engel, Kathleen C. and Patricia A. McCoy (2011). The Subprime Virus: Reckless Credit, Regulatory Failure, and Next Steps, Oxford University Press.

10. Follain, James R. (2010). "A Study of Real Estate Markets in Declining Cities," Research Institute for Housing America, Special Report. http://www.housingamerica.org/Publications/AStudyofRealEstateMarketsinDecliningCities.htm.

11. Follain, James R. (2007). "The Search for Capital Adequacy in the Mortgage Market: A Case of Black Swan Blindness". Paper to be presented at the 2012 ARES Meetings.

12. Follain, James R. and Barbara Follain (2007). "Are We There Yet?" http://www.ficonsulting.com/node/17.

13. Follain, James R. and Barbara Follain (2008). "Under the Hood of New Fed Plan for Homeowners". http://www.ficonsulting.com/node/17.

14. Follain, James R. and Mike Sklarz (2005). “Pricing Market Specific Bubbles,” *Mortgage Banking Magazine*, October.

15. Follain, James R. and Orawin Velz (1995). "Incorporating the Number of Existing Home Sales into a Structural Model of the Market for Owner-Occupied Housing," *Journal of Housing Economics*, 4, 93–117.

16. Follain, James R. and Seth H. Giertz (2011a). “Using Monte Carlo Simulations to Establish a New House Price Stress Test,” *Journal of Housing Economics*, 20(2):101–119

17. Follain, James R. and Seth H. Giertz (2011b). “A Look at US House Price Bubbles from 1980–2010 and the Role of Local Market Conditions,” Lincoln Institute of Land Policy, (July 2011) working paper WP11JF1. http://www.lincolninst.edu/pubs/download.asp?doc_id=1251&pub_id=1928.

18. Frey, W., A. Berube, A. Singer, and J. H. Wilson (2009). “Getting Current: Recent Demographic Trends in Metropolitan America”. Brookings Institution, Metropolitan Policy Program, Washington D.C.

19. Geanakoplos, John (2011). “What’s Missing from Macroeconomics: Endogenous Leverage and Default,” *Approaches to Monetary Policy Revisited—Lesson from the Crisis*, Sixth ECB Central Banking Conference 18–19 November 2010, European Central Bank, 2011, 220–238.

20. Geanakoplos, John (2010). “The Leverage Cycle." *NBER Macroeconomic Annual 2009*, 24: 1–65, University of Chicago Press, 2010.

21. Gladwell, Malcolm (1996). “The Tipping Point: Why is the city suddenly so much safer—could it be that crime really is an epidemic?” *New Yorker.* June. http://www.gladwell.com/1996/1996_06_03_a_tipping.htm.

22. Glaeser, E. L. and J. Gyourko (2005). “Urban Decline and Durable Housing,” *Journal of Political Economy* 113(2):345–375.

23. Glaeser, E., J. Gyourko and R. Saks (2005). “Why Have Housing Prices Gone Up?”*American Economic Review* 95: 329–333.

24. Glaeser, Edward L., Joshua D. Gottlieb, and Joseph Gyourko (2010). “Can Cheap Credit Explain the Housing Boom?” NBER Working Paper No. 16230. http://www.nber.org/papers/w16230.

25. Glaeser, Edward L., Joshua D. Gottlieb, and Joseph Gyourko (2010). “Can Cheap Credit Explain the Housing Boom?” NBER Working Paper No. 16230. http://www.nber.org/papers/w16230.

26. Goodman, Allen C. and Thomas G. Thibodeau (2008). “Where are the speculative bubbles in US housing markets?” *Journal of Housing Economics*, Volume 17, Issue 2: 117–137.

27. Greenspan, Alan. (2010). “The Crisis,” *Brookings Papers on Economics Activity*, 201–246. http://www.brookings.edu/~/media/files/programs/es/bpea/2010_spring_bpea_papers/spring2010_greenspan.pdf.

28. Haughwout, Andrew, Richard W. Peach, John Sporn, and Joseph Tracy (2012). “The Supply Side of the Housing Boom and Bust of the 2000s.” Federal Reserve Bank of New York Staff Reports, no. 556.

29. Hendershott, Patric, Robert Hendershott, and James Shilling (2010). “The Mortgage Finance Bubble: Causes and Corrections”, Journal of Housing Research, Volume 19, 1.

30. Himmelberg, Charles, Christopher Mayer, Todd Sinai (2005). “Assessing High House Prices: Bubbles, Fundamentals, and Misperceptions,” *Journal of Economic Perspectives*, 19(4). http://www.nber.org/papers/w11643.

31. Khandani, Amir E., Andrew W. Lo, and Robert C. Merton (2009). “Systemic Risk and the Refinancing Ratchet Effect,” Working Paper. http://hbswk.hbs.edu/item/6291.html

32. Kiefer, Hua and Leonard C. Kiefer (2010). “The Co-Movement of Mortgage Foreclosure Rate and House Price Depreciation: A Spatial Simultaneous Equation System”. Paper presented at the Mid-Year American Real Estate and Urban Economics Association, Washington DC. http://www.areuea.org/conferences/papers/download.phtml?id=2570.

33. Kishor, N. Kundan and James Morleyy (2010). “What Moves the Price-Rent Ratio: A Latent Variable Approach”. Working paper. http://apps.olin.wustl.edu/MEGConference/Files/pdf/2010/48.pdf .

34. LaCour-Little, Michael and Yang, Jing (2010). “Pay Me Now or Pay Me Later: Alternative Mortgage Products and the Mortgage Crisis”. *Real Estate Economics*, Vol. 38, No. 4, pp. 687–732.

35. LaCour-Little, Michael, Eric Rosenblatt, and Vincent Yao (2010). “Home Equity Extraction by Homeowners: 2000–2006”. *Journal of Real Estate Research* 32(1): 23–46.

36. Lai, Rose Neng and Robert Van Order (2010). “Momentum and House Price Growth in the U.S. Anatomy of a Bubble,” *Real Estate Economics*, 38 (4).

37. Landvoigt, Tim, Monika Piazzesi, and Martin Schneider (2012) “The Housing Market(s) of San Diego” NBER Working Paper No. 17723 http://www.nber.org/papers/w17723

38. Leamer, Edward (2003). “Bubble Trouble? Your Home Has a P/E Ratio Too,” UCLA Anderson Forecast Report. http://www.uclaforecast.com/ and the update: http://www.anderson.ucla.edu/documents/areas/ctr/forecast/PE_ratio_update.pdf

39. Leamer, Edward. (2007). “Housing IS the Business Cycle,” NBER Working paper 13428. http://www.nber.org/papers/w13428.

40. Leamer, Edward (2010). “Tantalus on the Road to Asymptopia, *Journal of Economic Perspectives*. http://www.springerlink.com/content/u514743kg0114584/fulltext.pdf.

41. Lo, Andrew W. (2012). “Reading about the Financial Crisis: A Twenty-One-Book Review,” *Journal of Economic Literature*, 50(1): 151–178. http://www.aeaweb.org/articles.php?doi=10.1257/jel.50.1.151 or http://ssrn.com/abstract=1949908.

42. McCarthy, Jonathan and Richard W. Peach (2004). “Are Home Prices the Next Bubble’? FRBNY Economic Policy Review at: http://www.newyorkfed.org/research/epr/04v10n3/0412mcca.pdf.

43. Miller, Norman and Michael Sklarz (2011). “Integrating Real Estate market-Based Indicators into Fundamental Home Price Forecasting Systems” Western Economic Association International’s 86th Annual Conference

44. Shiller, Robert (2005). Irrational Exuberance, 2nd edition, Princeton University Press: Princeton, NJ.

45. Sinai, Todd, “House Price Moments in Boom-Bust Cycles,” *Housing and the Financial Crisis*, Edward Glaeser and Todd Sinai (eds.), *forthcoming*, University of Chicago Press.

46. Stock, James H. and Mark W. Watson (2001). “Vector Autoregressions,” *Journal of Economic Perspectives*, 15(4):101–115

47. Taipalus, Katja (2012). “Signaling asset price bubbles with time-series methods,” Bank of Finland Research Discussion Paper 7-2012, http://www.suomenpankki.fi/en/julkaisut/tutkimukset/keskustelualoitteet/Documents/BoF_DP_1207.pdf

48. Taleb, Nicolas (2007). The Black Swan: The Impact of the Highly Improbable, Random House.

49. Wheaton, William and G. Nechayev (2008). “The 1998–2005 Housing ‘Bubble’ and the Current ‘Correction’: What’s Different this Time?” *Journal of Real Estate Research* 30(1):1–26. http://ssrn.com/abstract=1028895.

Table III-1. Correlation Matrix for 342 MSAs: 1990:Q1-2010:Q4

	HP	Employment	Income/ Capita	Rent	Sales
HP	1.00				
Employment	0.18	1.00			
Income/Capita	0.51	0.39	1.00		
Rent	0.42	0.45	0.67	1.00	
Sales	0.18	0.83	0.37	0.34	1.00

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Table III-2. Averages by MSA Group for Potentially Key Variables

Populuation Group	Population Growth	Real HPI	Employment[1]	Income Per Capita	Households[1]	Population[1]	Construction Employment[1]	Unemp. Rate	Housing Stock[1]	Existing Single-family Sales[1]	Mort Originations (Mil. $)
All Unweighted		167.82	290.80	33,966	226.29	606.98	13.74	5.84	247.66	9.49	2,793.1
All Employment Weighted		179.03		39,181	910.24	2489.86		5.67	982.28	30.84	12,809.4
low	low	161.50	62.92	30,927	52.20	136.03	2.54	6.07	58.38	2.03	293.2
medium	medium	163.33	64.71	31,949	51.00	134.37	3.07	5.39	57.03	2.24	362.0
low	high	167.55	60.39	30,437	48.28	129.57	2.94	6.57	54.80	2.55	415.3
medium	low	164.66	196.18	33,899	161.85	419.02	8.51	5.92	177.01	6.41	1,191.3
medium	medium	169.63	187.80	34,914	146.79	386.66	8.79	5.32	161.21	6.60	1,456.5
medium	high	168.73	165.84	33,272	133.48	356.95	8.69	6.14	151.94	7.47	1,478.2
high	low	177.99	1,180.05	43,172	925.69	2,501.07	45.19	5.66	993.11	26.82	11,812.1
high	medium	179.10	790.27	40,498	593.79	1,599.43	38.30	5.18	639.93	25.93	10,405.3
high	high	171.87	839.78	36,465	637.91	1,730.26	48.34	6.08	706.22	32.69	8,219.7

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.
1. Measured in Thousands.
2. Number of units.

Table III-3. Averages Growth Rates by MSA Group for Potentially Key Variables

Pop. Group	Pop.Growth	Real HPI	Employment	Income Per Capita	Housing Stock	Construction Employment	Unemp. Rate	Housing Stock
low	low	0.171	0.030	0.163	0.073	0.125	0.040	0.073
low	medium	0.216	0.108	0.192	0.155	0.208	0.052	0.155
low	high	0.264	0.243	0.170	0.270	0.358	-0.008	0.270
medium	low	0.179	0.024	0.152	0.072	0.107	0.045	0.072
medium	medium	0.231	0.114	0.164	0.150	0.226	0.121	0.150
medium	high	0.257	0.225	0.167	0.269	0.339	0.058	0.269
high	low	0.260	0.029	0.162	0.065	0.170	0.042	0.065
high	medium	0.279	0.092	0.174	0.142	0.223	0.137	0.142
high	high	0.262	0.211	0.163	0.256	0.360	0.109	0.256

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Table III-4. Total Percent Change in Variable from 2000-2010

Panel A

Populuation Group	Population Growth	Real HPI	Employment	Income Per Capita	Construction Employment	Unemp Rate	Housing Stock
low	low	8.9	-3.6	13.8	-21.4	71.3	5.8
low	medium	15.4	4.3	14.8	-12.4	70.8	14.0
low	high	14.2	13.0	12.0	-20.3	76.2	24.0
medium	low	9.4	-4.0	12.0	-18.9	77.5	6.1
medium	medium	12.9	2.5	9.4	-17.7	81.1	13.1
medium	high	9.0	10.5	9.4	-21.6	86.8	24.0
high	low	17.9	-3.8	9.5	-18.6	82.2	5.9
high	medium	12.8	-0.4	7.3	-24.5	90.5	12.5
high	high	11.8	10.2	7.0	-18.6	86.5	23.0

Total Percent Change in Variable from 1990-2010

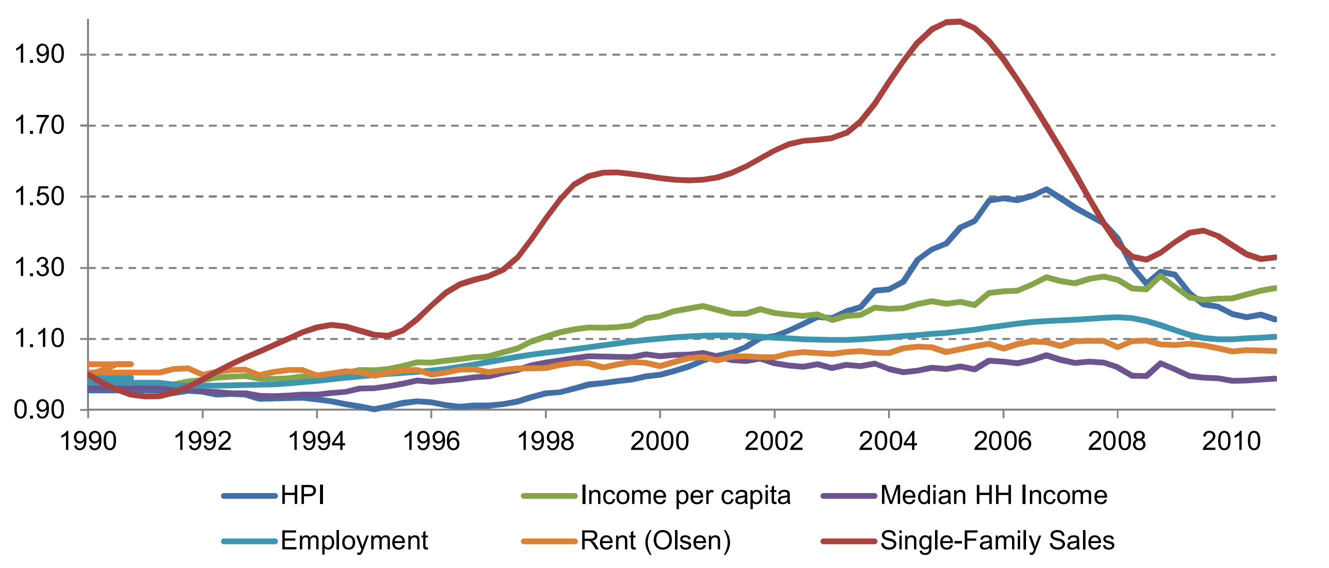
Panel B

		Real HPI	Employment	Income Per Capita	Construction Employment	Unemp Rate	Housing Stock
low	low	18.5	3.2	27.7	3.7	40.5	12.8
low	medium	27.9	19.8	31.9	20.2	37.8	27.7
low	high	25.0	39.5	26.1	21.6	47.9	48.3
medium	low	14.9	2.8	25.9	0.0	47.1	12.6
medium	medium	18.2	16.5	25.8	5.6	55.0	26.9
medium	high	19.4	35.8	25.2	20.0	54.9	46.4
high	low	12.4	0.9	24.9	-14.0	59.1	11.7
high	medium	18.4	13.3	26.3	-1.5	63.1	24.5
high	high	18.1	35.4	24.4	20.3	59.7	44.0

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

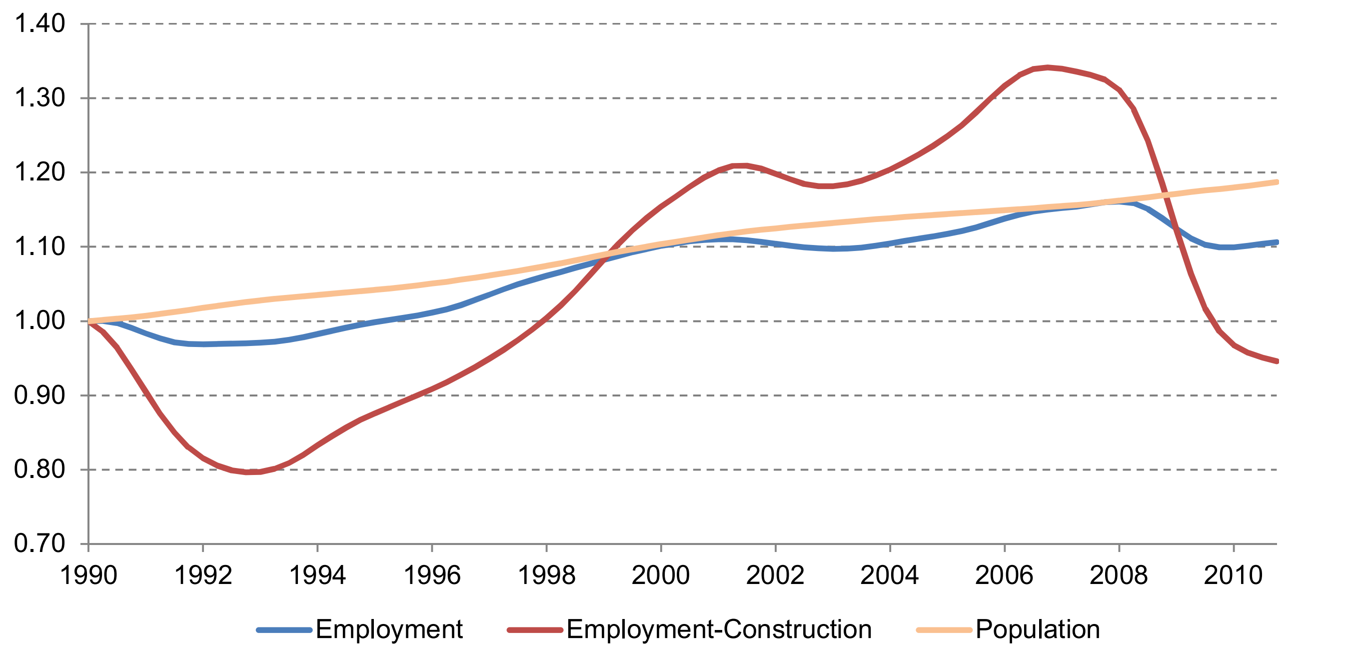
* Percent changes are measured using the average of the two end points as the denominator (similar to an arc elasticity).

Figure III-1. Trends for Key Variables



Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.
All variables are indexed to 1 for 1990:Q1.

Figure III-2. Employment and Population Trends



Source: Authors' calculations based on Bureau of Labor Statistics and Census data available from Moody's Analytics.
All variables are indexed to 1 for 1990:Q1.

Table V-1. 5 Equation VEC Model: 1990-2010
(All endogenous variables are in log difference form)

	HP	Employment	Inc/capita	Single Family Sales	Rent
error correction term	-0.027	0.00013	0.004	-0.004	0.009
	(0.003)	0.00006	(0.001)	(0.001)	(0.002)
House Price					
lag 1	0.150	0.001	-0.121	-0.016	-0.044
	(0.031)	(0.000)	(0.012)	(0.003)	(0.008)
lag 2	0.150	a	0.000	-0.013	0.017
	(0.014)		(0.004)	(0.004)	(0.006)
lag 3	0.278		0.100	-0.023	0.038
	(0.014)		(0.008)	(0.004)	(0.008)
lag 4	0.096		0.028	-0.009	-0.052
	(0.025)		(0.012)	(0.004)	(0.008)
lag 5	0.120		0.056	0.001	0.046
	(0.012)		(0.006)	(0.004)	(0.007)
lag 6	0.051		-0.009	0.017	0.045
	(0.013)		(0.006)	(0.004)	(0.006)
lag 7	-0.131		-0.102	-0.011	-0.028
	(0.013)		(0.008)	(0.004)	(0.008)
lag 8	0.088		0.028	-0.035	0.023
	(0.014)		(0.007)	(0.006)	(0.008)
lag 9	0.061		0.059	-0.002	-0.021
	(0.013)		(0.005)	(0.006)	(0.007)
lag 10	-0.097		-0.032	0.000	-0.017
	(0.011)		(0.006)	(0.005)	(0.005)
lag 11	-0.045		-0.037	0.008	-0.040
	(0.011)		(0.006)	(0.004)	(0.008)
lag 12	0.015		0.014	0.033	0.010
	(0.014)		(0.007)	(0.006)	(0.009)
Employment					
lag 1	-0.276	2.735	0.257	0.402	-0.305
	(0.376)	(0.015)	(0.127)	(0.103)	(0.175)
lag 2	0.353	-2.787	0.244	-0.433	1.132
	(1.049)	(0.053)	(0.337)	(0.296)	(0.534)
lag 3	0.051	1.023	-2.189	-0.237	-2.141
	(1.293)	(0.084)	(0.478)	(0.415)	(0.609)
lag 4	-0.593	-0.565	3.115	0.241	1.466
	(1.083)	(0.080)	(0.428)	(0.429)	(0.548)
lag 5	1.429	1.773	-0.396	0.840	0.984
	(1.055)	(0.074)	(0.341)	(0.508)	(0.646)
lag 6	-0.424	-1.717	-2.740	-1.207	-0.998
	(1.119)	(0.083)	(0.396)	(0.548)	(0.433)
lag 7	-2.783	0.177	1.684	0.398	-1.785
	(1.207)	(0.081)	(0.417)	(0.491)	(0.622)
lag 8	3.577	0.522	1.133	0.204	2.570
	(1.057)	(0.059)	(0.400)	(0.419)	(0.568)
lag 9	-0.114	-0.127	-0.579	-0.075	-0.465
	(0.955)	(0.043)	(0.373)	(0.463)	(0.698)
lag 10	-2.240	-0.072	-1.532	-0.131	-0.721
	(1.041)	(0.037)	(0.471)	(0.427)	(0.594)
lag 11	1.389	-0.051	1.578	0.090	0.268

	(0.904)	(0.025)	(0.333)	(0.255)	(0.410)
lag 12	-0.068	0.055	-0.400	-0.009	0.118
	(0.341)	(0.009)	(0.117)	(0.076)	(0.160)
Rent					
lag 1	0.153	0.004	-0.221	-0.033	-0.097
	(0.041)	(0.001)	(0.020)	(0.007)	(0.009)
lag 2	-0.058	0.000	-0.190	-0.007	-0.072
	(0.030)	(0.001)	(0.016)	(0.009)	(0.013)
lag 3	-0.273	0.002	-0.029	0.015	-0.070
	(0.039)	(0.001)	(0.018)	(0.007)	(0.017)
lag 4	-0.130	0.000	0.018	0.009	0.410
	(0.046)	(0.001)	(0.019)	(0.009)	(0.047)
lag 5	-0.091	-0.002	0.133	0.019	0.006
	(0.033)	(0.001)	(0.028)	(0.007)	(0.011)
lag 6	0.041	-0.002	0.111	-0.012	0.012
	(0.031)	(0.001)	(0.016)	(0.010)	(0.010)
lag 7	0.247	-0.002	0.054	-0.010	0.068
	(0.056)	(0.001)	(0.026)	(0.006)	(0.017)
lag 8	-0.279	-0.005	-0.204	0.019	-0.038
	(0.039)	(0.001)	(0.020)	(0.010)	(0.034)
lag 9	-0.131	-0.001	-0.071	-0.023	-0.028
	(0.025)	(0.001)	(0.019)	(0.009)	(0.018)
lag 10	-0.050	0.000	-0.021	-0.002	-0.008
	(0.039)	(0.001)	(0.012)	(0.009)	(0.008)
lag 11	-0.075	-0.002	0.066	0.000	0.038
	(0.037)	(0.001)	(0.016)	(0.009)	(0.014)
lag 12	0.333	0.004	0.202	-0.041	0.179
	(0.035)	(0.001)	(0.017)	(0.011)	(0.030)
Income Per Capita					
lag 1	0.185	0.006	0.503	0.004	-0.056
	(0.039)	(0.001)	(0.030)	(0.009)	(0.012)
lag 2	0.102	-0.003	0.183	-0.013	-0.005
	(0.031)	(0.001)	(0.013)	(0.009)	(0.016)
lag 3	-0.232	-0.001	-0.068	-0.009	0.152
	(0.029)	(0.001)	(0.014)	(0.007)	(0.021)
lag 4	-0.085	0.003	-0.167	0.026	-0.263
	(0.032)	(0.001)	(0.015)	(0.006)	(0.028)
lag 5	0.159	0.003	-0.097	0.035	0.244
	(0.027)	(0.001)	(0.014)	(0.008)	(0.018)
lag 6	-0.062	0.000	-0.123	-0.061	-0.034
	(0.024)	(0.001)	(0.012)	(0.007)	(0.016)
lag 7	-0.135	-0.005	0.113	0.015	-0.074
	(0.041)	(0.001)	(0.021)	(0.007)	(0.017)
lag 8	0.389	-0.001	0.249	0.033	0.108
	(0.033)	(0.001)	(0.015)	(0.009)	(0.025)
lag 9	-0.139	0.007	-0.044	-0.047	0.029
	(0.036)	(0.001)	(0.021)	(0.012)	(0.024)
lag 10	-0.319	-0.001	-0.185	0.003	-0.060
	(0.043)	(0.001)	(0.014)	(0.010)	(0.014)
lag 11	0.135	-0.006	0.016	0.060	0.018
	(0.035)	(0.001)	(0.015)	(0.007)	(0.013)
lag 12	0.242	0.005	0.124	-0.059	0.139
	(0.026)	(0.001)	(0.012)	(0.010)	(0.015)

Single Family Home Sales					
lag 1	0.019	0.004	0.033	2.202	0.007
	(0.024)	(0.001)	(0.011)	(0.027)	(0.010)
lag 2	0.017	-0.006	-0.010	-1.685	-0.003
	(0.053)	(0.001)	(0.022)	(0.074)	(0.024)
lag 3	-0.004	0.003	-0.008	0.063	0.062
	(0.052)	(0.002)	(0.021)	(0.110)	(0.028)
lag 4	-0.042	0.002	-0.071	0.324	-0.149
	(0.053)	(0.001)	(0.021)	(0.060)	(0.033)
lag 5	0.031	-0.002	0.118	0.285	0.087
	(0.044)	(0.002)	(0.024)	(0.044)	(0.024)
lag 6	0.175	0.000	0.034	-0.382	0.078
	(0.054)	(0.001)	(0.019)	(0.040)	(0.023)
lag 7	-0.167	0.002	-0.133	-0.071	-0.093
	(0.050)	(0.001)	(0.029)	(0.046)	(0.027)
lag 8	0.027	0.001	0.022	0.357	-0.003
	(0.050)	(0.001)	(0.017)	(0.035)	(0.021)
lag 9	0.011	-0.004	0.073	-0.289	0.025
	(0.037)	(0.002)	(0.025)	(0.042)	(0.018)
lag 10	0.084	0.003	0.011	0.008	0.019
	(0.043)	(0.002)	(0.024)	(0.029)	(0.021)
lag 11	-0.079	0.000	-0.083	0.151	-0.030
	(0.043)	(0.001)	(0.029)	(0.032)	(0.021)
lag 12	0.009	0.000	0.037	-0.087	0.004
	(0.020)	(0.001)	(0.015)	(0.015)	(0.011)
Constant	0.034	0.000	-0.003	-0.007	0.009
	(0.004)	(0.000)	(0.001)	(0.001)	(0.002)
Observations	24,258	24,258	24,258	24,258	24,258
R-squared	0.649	0.997	0.689	0.983	0.461

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Seasonal and year dummies are included in the regressions, but not presented.

a. In nearly all cases, estimated coefficients on the lagged house price term for the employment equations are 0 out to three or more decimal points. These estimates are supressed in this table.

The 10-year Treasury rate and the 4-quarter lagged difference between the 10-year and 1-year rate are also include. These estimated coefficients are very close to 0. Nearly all of their impact is likely absorbed by the year dummies.

Table V-2: Dashboard of Selected Output for Various Models and Equations

	5 Equations				4 Equations				3 Equations			
House Price Growth	1990-2000	1990-2006Q2	1990-2007Q4	1990-2010Q4	1990-2000	1990-2006Q2	1990-2007Q4	1990-2010Q4	1990-2000	1990-2006Q2	1990-2007Q4	1990-2010Q4
N	10,602	18,120	20,166	24,258	10,602	18,120	20,166	24,258	10,602	18,120	20,166	24,258
HP	0.851	0.893	0.791	0.735	0.877	0.885	0.796	0.696	0.861	0.902	0.829	0.631
Employment	0.262	0.352	0.380	0.301	0.192	0.351	0.371	0.231	0.214	0.349	0.356	0.312
Inc/capita	0.420	0.028	-0.093	0.240	0.352	-0.055	-0.133	0.252	0.392	-0.104	-0.194	0.290
Single Family Sales	0.049	0.063	0.101	0.081	0.061	0.070	0.108	0.097				
Rent	-0.230	-0.267	-0.100	-0.314								
ehat	-0.062	-0.012	-0.015	-0.027	-0.061	-0.011	-0.012	-0.024	-0.065	-0.018	-0.024	-0.027
R^2	0.553	0.626	0.629	0.649	0.545	0.618	0.621	0.622	0.547	0.617	0.622	0.619
Employment Growth												
HP	0.003	0.000	0.001	0.001	0.003	-0.001	0.000	0.001	0.003	-0.001	0.000	0.000
Employment	0.972	0.970	0.968	0.968	0.971	0.970	0.969	0.966	0.972	0.970	0.970	0.968
Inc/capita	-0.008	-0.001	0.000	0.005	-0.009	0.000	0.002	0.007	-0.009	-0.001	0.001	0.007
Single Family Sales	0.003	0.002	0.003	0.003	0.003	0.003	0.003	0.003				
Rent	-0.007	-0.004	-0.003	-0.004								
ehat	-0.001	0.000	0.000	0.000	-0.001	0.000	0.000	0.000	-0.001	0.000	0.000	0.000
R^2	0.995	0.996	0.995	0.997	0.995	0.996	0.995	0.997	0.995	0.996	0.995	0.997
Income/capita Growth												
HP	0.028	-0.041	-0.034	-0.017	0.034	-0.083	-0.078	-0.032	0.038	-0.070	-0.069	-0.046
Employment	0.041	0.231	0.222	0.175	0.039	0.283	0.270	0.150	0.038	0.267	0.257	0.159
Inc/capita	0.710	0.471	0.496	0.506	0.687	0.505	0.522	0.389	0.678	0.469	0.479	0.376
Single Family Sales	0.011	0.005	0.014	0.022	0.011	-0.003	0.002	0.020				
Rent	-0.035	0.047	0.044	-0.153								
ehat	-0.004	0.013	0.011	0.004	-0.005	0.014	0.013	0.002	-0.007	0.011	0.009	0.000
R^2	0.884	0.731	0.699	0.689	0.877	0.712	0.680	0.644	0.876	0.707	0.673	0.639
Single Family House Sales Growth												
HP	-0.023	-0.094	-0.072	-0.049	-0.030	-0.057	-0.047	-0.051				
Employment	0.039	0.085	0.066	0.082	0.027	0.050	0.039	0.078				
Inc/capita	-0.072	-0.007	0.049	-0.013	-0.142	-0.081	-0.014	-0.050				
Single Family Sales	0.866	0.879	0.880	0.877	0.871	0.883	0.886	0.873				
Rent	-0.249	-0.031	-0.069	-0.067								
ehat	-0.013	-0.006	-0.006	-0.004	-0.016	-0.009	-0.008	-0.005				
R^2	0.976	0.978	0.981	0.981	0.976	0.978	0.981	0.981				
Rent Growth												
HP	0.004	-0.019	0.000	-0.022								
Employment	0.059	0.162	0.173	0.124								
Inc/capita	0.094	0.086	0.068	0.198								
Single Family Sales	0.001	-0.007	-0.012	0.002								
Rent	0.560	0.572	0.530	0.401								
ehat	0.009	0.014	0.014	0.009								
R^2	0.618	0.496	0.483	0.461								

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Table V-3. Regression Standard Errors for All Specifications and Time Periods

Dependent Variable			
1990-2000	5 Eq	4 Eq	3 Eq
HP	0.0087	0.0088	0.0088
Employment	0.0004	0.0004	0.0004
Per Capita Income	0.0024	0.0024	0.0024
Single-Family Sales	0.0045	0.0045	
Rent	0.0034		
1990-2006Q2			
HP	0.0104	0.0105	0.0106
Employment	0.0004	0.0004	0.0004
Per Capita Income	0.0047	0.0049	0.0049
Single-Family Sales	0.0046	0.0046	
Rent	0.0053		
1990-2007			
HP	0.0130	0.0134	0.0134
Employment	0.0004	0.0004	0.0004
Per Capita Income	0.0062	0.0065	0.0066
Single-Family Sales	0.0052	0.0052	
Rent	0.0062		
1990-2010			
HP	0.0107	0.0109	0.0109
Employment	0.0004	0.0004	0.0004
Per Capita Income	0.0051	0.0052	0.0053
Single-Family Sales	0.0048	0.0048	
Rent	0.0053		

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.
Regressions are conducted using logged first differences.

Table V-4. Cumulative Out-of-Sample House Price Projections
Adding Variables to the Model

		Added Variables	(1) 2001:Q1-2003:Q4	(2) 2006:Q3-2009:Q2	(3) 2008:Q1-2010:Q4	(4) 2011:Q1-2013:Q4
Actual	Mean		14.0	-9.5	-13.8	?
	Median		8.9	-5.1	-10.1	?
1-equation	Mean	House Prices	-10.8	-0.8	-19.7	4.4
	Median		-13.4	-2.7	-14.7	4.8
	RMSE		26.6	25.5	12.0	
2-equation	Mean	Employment	-8.9	-1.6	-18.7	1.2
	Median		-11.5	-3.2	-13.8	1.8
	RMSE		24.6	23.6	10.1	
3-equation	Mean	Income/ Capita	-15.9	5.2	-22.1	-3.6
	Median		-18.5	3.4	-16.9	-2.9
	RMSE		25.4	25.4	13.4	
4-equation	Mean	Single-Family Sales	-20.2	1.2	-29.6	-7.7
	Median		-21.8	0.1	-26.1	-6.8
	RMSE		20.9	20.9	19.3	
5-equation	Mean	Rent	-22.7	-3.6	-31.3	-4.8
	Median		-23.8	-4.6	-27.5	-4.7
	RMSE		37.6	19.3	21.2	

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.
Ordering is based on actual house price appreciation.

Table V-5. Cumulative Projections for Two Periods

2006:Q3-2009:Q2	(1) Actual	(2) 3 eqn	(3) 4 eqn	(4) 5 eqn	(5) 5 eqn - actual
Mean	-9.5	5.2	1.2	-3.6	5.9
Median	-5.1	3.4	0.1	-4.6	0.4
p25	-15.4	34.9	26.9	24.2	39.6
p75	0.1	-3.1	-4.4	-6.1	-6.2
p05	-40.5	21.4	6.2	3.2	43.7
p95	5.4	16.6	16.3	12.5	7.0
IQR	15.5	-38.0	-31.4	-30.3	

2008:Q1-2010:Q4	Actual	3 eqn	4 eqn	5 eqn	5 eqn - actual
Mean	-13.8	-22.1	-25.8	-31.4	-17.7
Median	-10.1	-16.9	-21.6	-27.6	-17.5
p25	-19.2	-7.0	-25.8	-27.5	-8.2
p75	-4.9	-21.2	-24.4	-25.5	-20.6
p05	-39.8	-71.8	-61.7	-64.0	-24.2
p95	-0.4	-16.9	-16.1	-17.4	-17.1
IQR	14.4	-14.2	1.4	2.0	

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.
Ordering is based on actual house price appreciation.

Table V-6: Comparison of the 5 equation Predictions to the Actual HP Outcomes for 2008:Q1-2010:Q4

	Smaller MSAs			MidSize MSAs			Largest MSAs		
	Slow Growing	Modest Growth	Fast Growing	Slow Growing	Modest Growth	Fast Growing	Slow Growing	Modest Growth	Fast Growing
Actual HP Growth	-6.4%	-7.5%	-19.5%	-8.2%	-12.7%	-20.3%	-13.1%	-15.6%	-21.0%
5 Eqn Predictions	-22.0%	-19.7%	**-37.3%**	-24.2%	-29.6%	**-43.0%**	-27.1%	-30.4%	**-35.6%**
Difference	-15.6%	-12.2%	-17.9%	-16.0%	-16.9%	-22.7%	-14.0%	-14.9%	-14.6%

Source: Authors' calculations based on data from sources including the Federal Housing Finance Agency, Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Table V-7: Model Projections

Cumulative House Price Appreciation: 2001:Q1-2003:Q4

	(1) Actual	(2) 3 eqn	(3) 4 eqn	(4) 5 eqn	(5) 5 eqn - actual
mean	14.4	-15.6	-19.8	-22.3	-36.7
median	9.4	-18.2	-21.1	-23.6	-33.0
std dev	11.6	10.2	9.9	9.9	8.6
p25	6.0	-18.5	-23.7	-27.3	-33.3
p75	20.6	-3.4	-7.3	-9.9	-30.5
p05	2.8	-22.3	-22.3	-22.1	-24.9
p95	40.8	1.7	-6.2	-12.0	-52.8
IQR	14.5	15.1	16.4	17.4	2.8

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Ordering is based on actual house price appreciation.

Table V-8. Impulse Response Analysis: Cumulative House Price Projections
Two Standard Deviation Shock to Each Endogenous Variable

2006:Q3-2009:Q2

	Actual	Baseline	Projected House Price Appreciation after a Shock to: HP	Employment	Income/ Cap	Sales	Rent
Mean	-9.5	-3.6	-20.1	-10.5	-2.4	-6.7	-1.4
Median	-5.1	-4.6	-21.3	-11.6	-3.5	-7.8	-2.4
p25	-15.4	24.2	-13.7	-33.2	-23.5	-28.6	-22.2
p75	0.1	-6.1	-23.0	-13.2	-4.9	-9.3	-3.9
p05	-40.5	3.2	-12.2	-3.3	4.3	0.2	5.2
p95	5.4	12.5	-1.5	-13.9	-5.5	-9.9	-4.5
IQR	15.5	-30.3	-9.3	20.0	18.5	19.3	18.4

2008:Q1-2010:Q4

	Actual	Baseline	Projected House Price Appreciation after a Shock to: HP	Employment	Income/ Cap	Sales	Rent
Mean	-13.8	-31.4	-45.2	-41.0	-30.1	-39.5	-29.8
Median	-10.1	-27.6	-40.9	-36.8	-26.2	-35.4	-26.0
p25	-19.2	-8.2	-52.8	-48.4	-36.9	-46.9	-36.7
p75	-4.9	-20.6	-40.2	-36.1	-25.6	-34.7	-25.4
p05	-39.8	-24.2	-81.1	-75.8	-62.2	-74.0	-61.9
p95	-0.4	-17.1	-43.7	-39.5	-28.7	-38.1	-28.5
IQR	14.4	-12.4	12.6	12.3	11.3	12.1	11.3

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.
Ordering is based on actual house price appreciation.

Table V-9: Model Projections

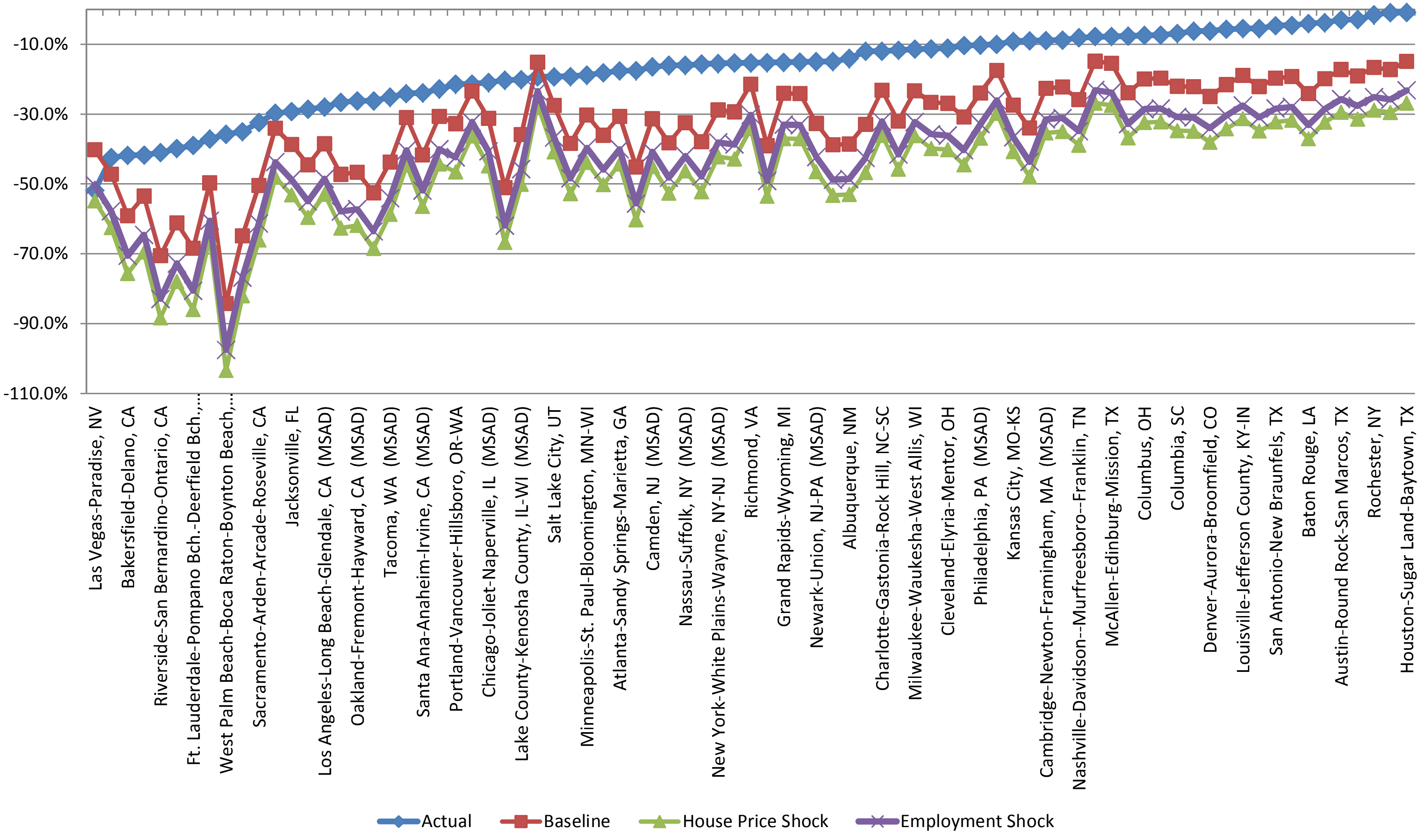
Cumulative House Price Appreciation: 2011:Q1-2013:Q4

	(1) 1 eqn	(2) 2 eqn	(1) 3 eqn	(2) 4 eqn	(3) 5 eqn
mean	4.5	1.5	-3.3	-7.3	-4.4
median	4.9	2.0	-2.8	-6.6	-4.4
std dev	2.9	4.2	4.9	7.6	6.9
p25	2.7	-1.2	-6.4	-12.4	-9.0
p75	6.4	4.3	0.0	-2.2	0.1
p05	-0.8	-6.9	-12.6	-21.1	-17.4
p95	8.6	7.5	4.2	4.0	6.4
IQR	3.7	5.4	6.4	10.2	9.1

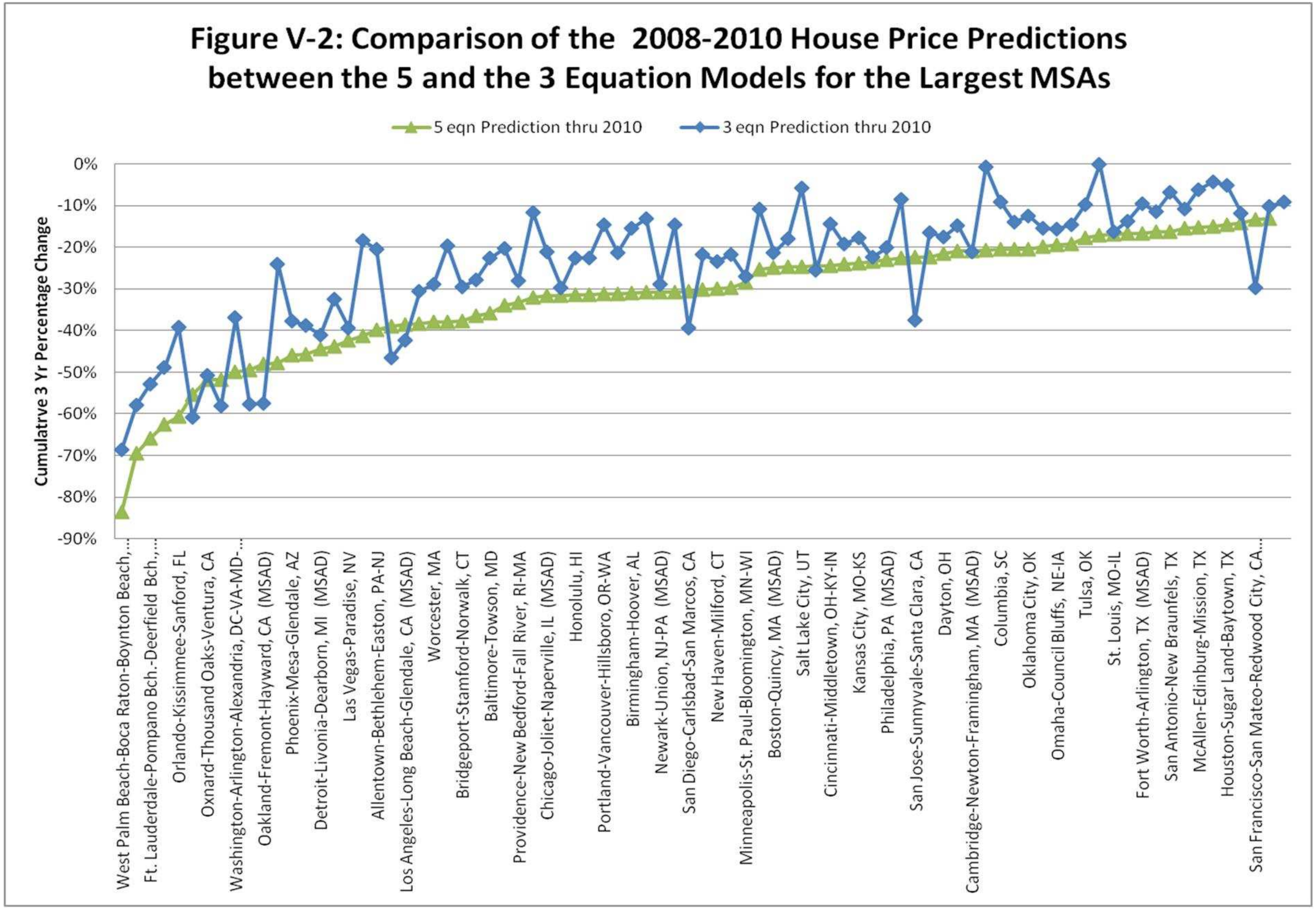
Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Percentiles are calculated independently for each column.

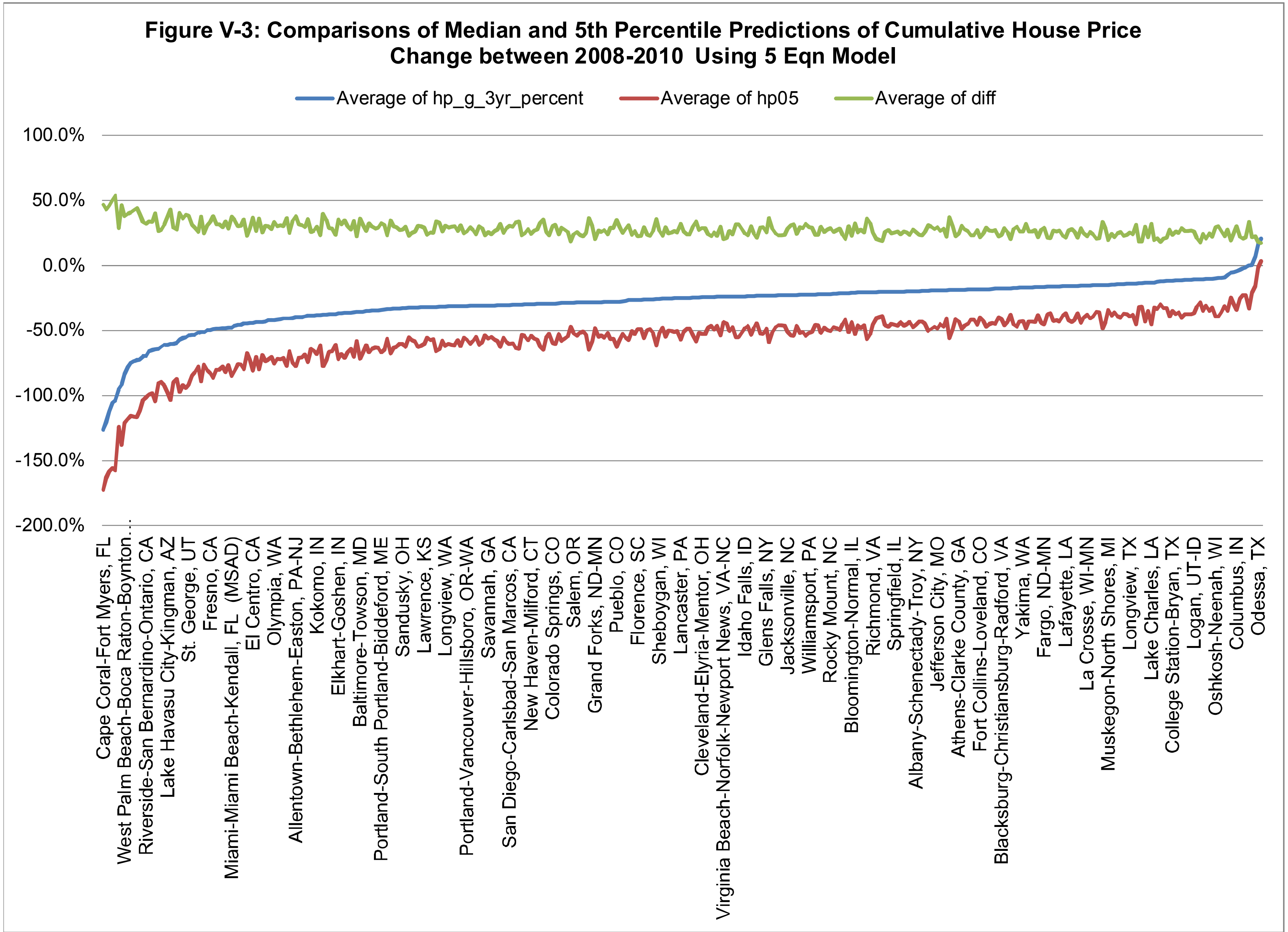
Figure V-1: House Price Appreciation Comparison for 2008:Q1-2010:Q4
Actual, Baseline and Impulse Response Projections for the Largest MSAS



Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

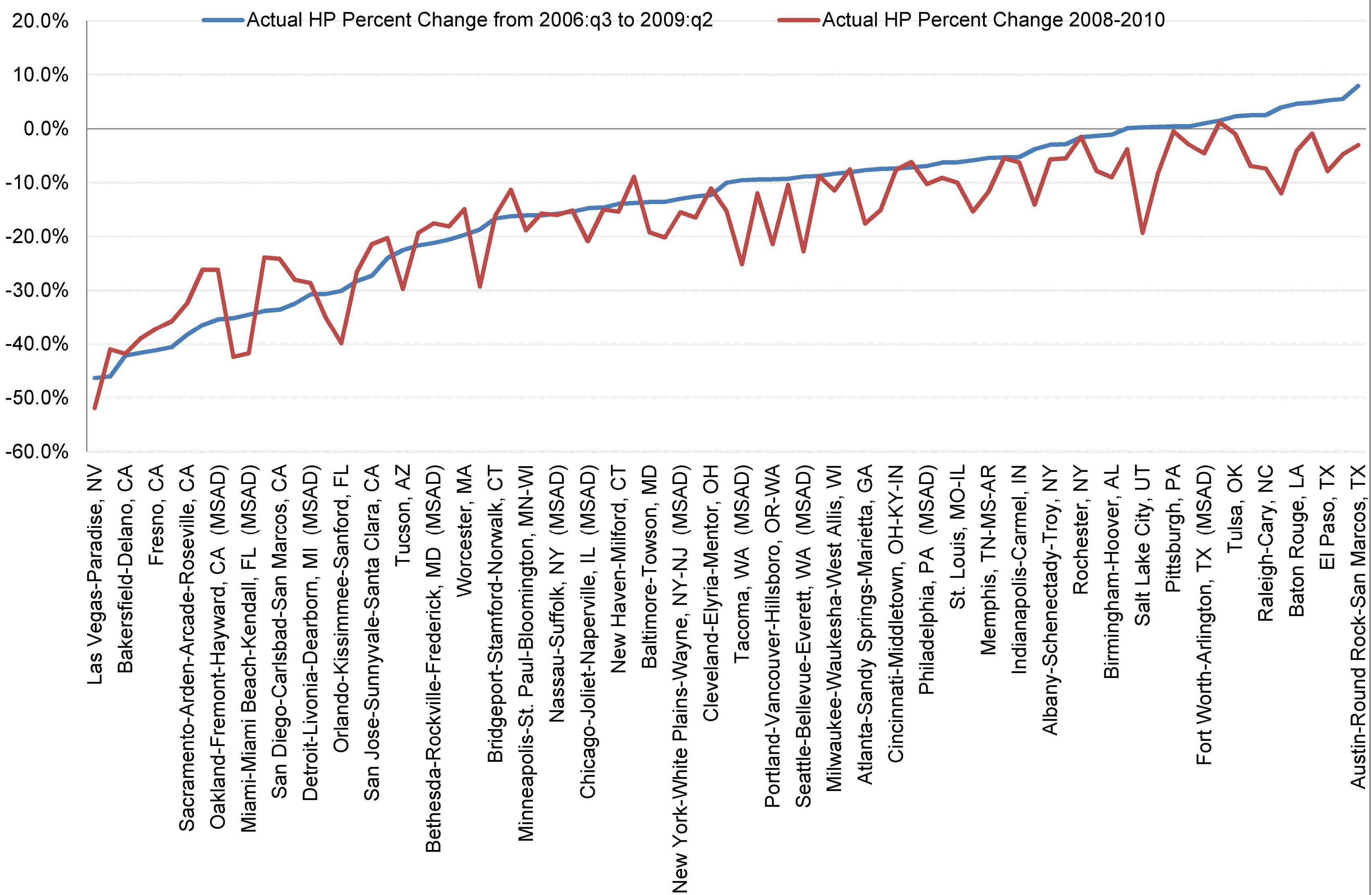


Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.



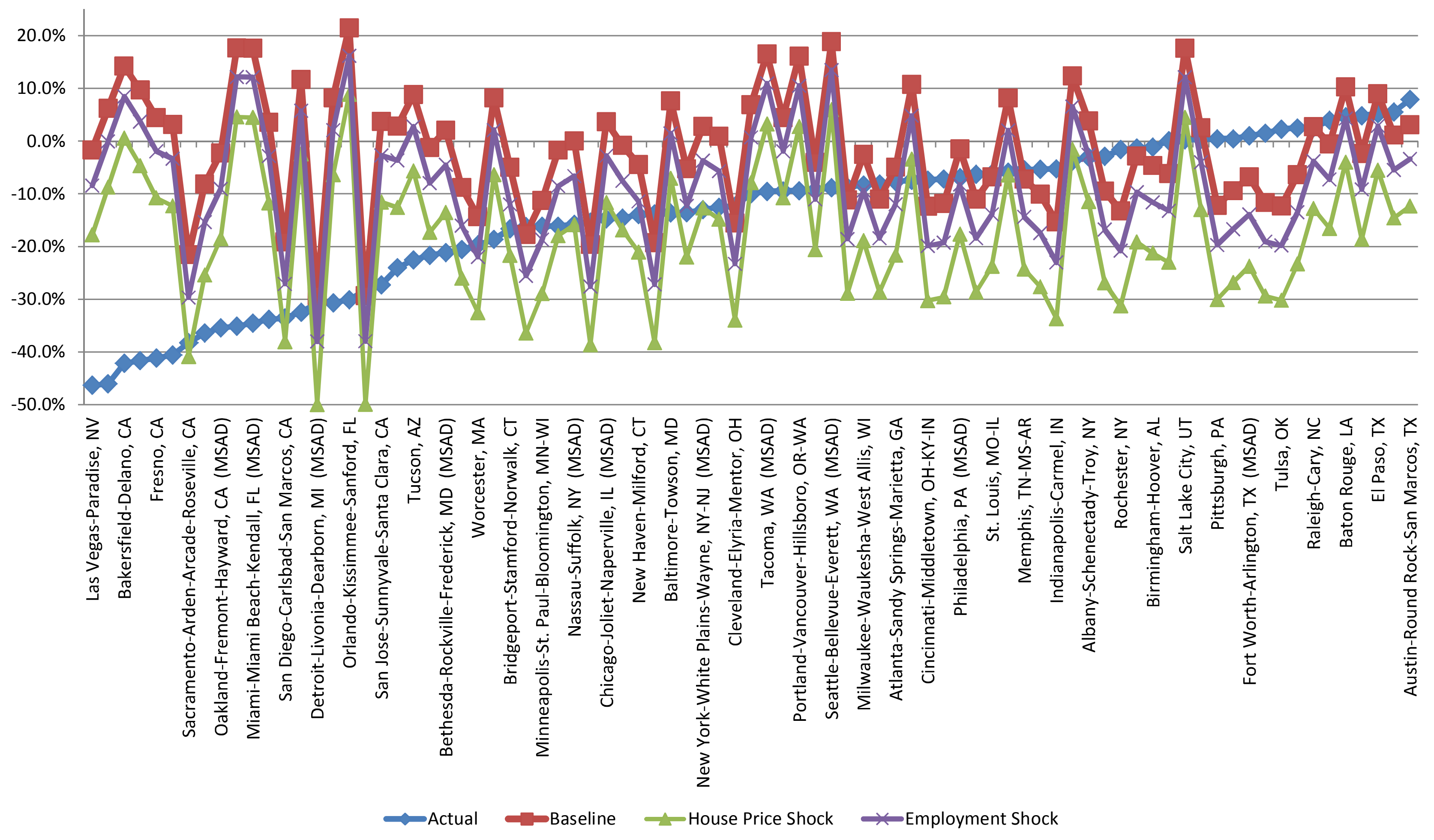
Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Figure V-4: Comparison of Actual House Price Changes for 2006:q3 through 2009:q2 and 2008-2010 for Large MSAs



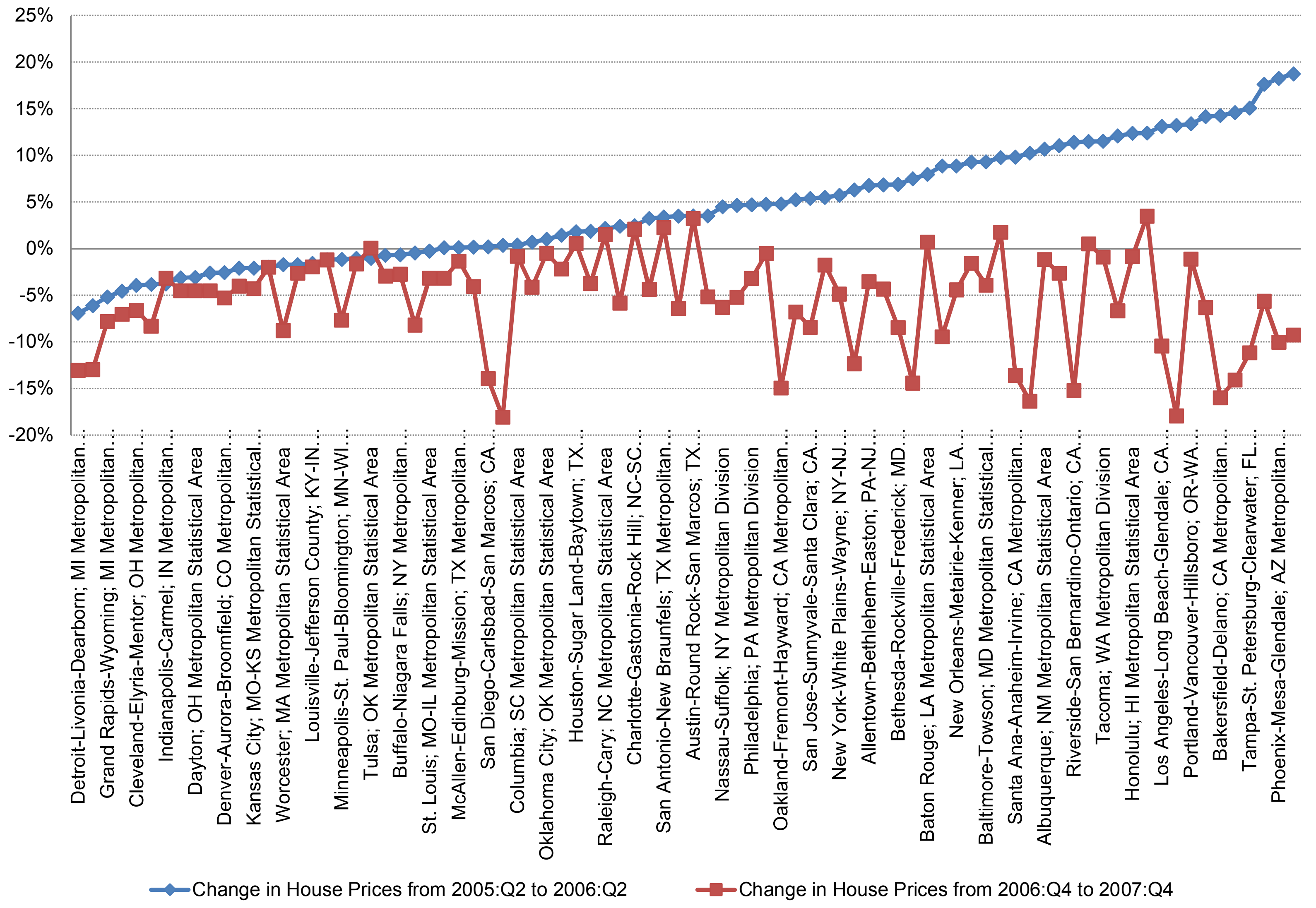
Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Figure V-5: House Price Appreciation Comparison for 2006:Q3-2009:Q2
Actual, Baseline and Impulse Response Projections for the Largest MSAS



Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Figure V-6: Cumulative House Price Change in the Four Quarters Prior to the Beginning of the Model Predictions



Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Appendix Table 1. First Stage VEC Equation

Dependent Variable: log(house price)				
	1990-2000	1990-2006Q2	1990-2007Q4	1990-2010Q4
Employment	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
Rent	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
Income/Capita	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
Single-Family Sales	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
t10	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
L4.tbdiff	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
quarter 2 dummy	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
quarter 3 dummy	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
quarter 4 dummy	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
Constant	0.358	0.584	0.761	0.576
	(0.013)	(0.015)	(0.013)	(0.012)
Observations	13,680	21,198	23,244	27,336
R-squared	0.567	0.748	0.784	0.741
Number of MSAs	342	342	342	342

Source: Authors' calculations based on data from various sources including the Federal Housing Finance Agency and Moody's Analytics. Moody's Analytics. Data from Moody's includes variables that they have compiled from sources such as the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Appendix Table 2: Ranking of Actual HP Outcomes and the Predictions of Each Model for Largest MSAs				
msa_name	Actual HP Percent Change 2008-2010	3 eqn Prediction thru 2010	4 eqn Prediction thru 2010	5 eqn Prediction thru 2010
Albany-Schenectady-Troy, NY	-6%	-15%	-20%	-20%
Albuquerque, NM	-14%	-20%	-37%	-38%
Allentown-Bethlehem-Easton, PA-NJ	-15%	-20%	-39%	-40%
Atlanta-Sandy Springs-Marietta, GA	-18%	-15%	-31%	-31%
Austin-Round Rock-San Marcos, TX	-3%	-4%	-16%	-15%
Bakersfield-Delano, CA	-42%	-61%	-58%	-55%
Baltimore-Towson, MD	-19%	-22%	-38%	-36%
Baton Rouge, LA	-4%	-9%	-24%	-23%
Bethesda-Rockville-Frederick, MD (MSAD)	-18%	-32%	-45%	-44%
Birmingham-Hoover, AL	-9%	-15%	-33%	-31%
Boston-Quincy, MA (MSAD)	-11%	-21%	-31%	-25%
Bridgeport-Stamford-Norwalk, CT	-16%	-30%	-39%	-38%
Buffalo-Niagara Falls, NY	1%	-14%	-19%	-17%
Cambridge-Newton-Framingham, MA (MSAD)	-9%	-21%	-27%	-21%
Camden, NJ (MSAD)	-16%	-21%	-30%	-31%
Charlotte-Gastonia-Rock Hill, NC-SC	-12%	-1%	-25%	-21%
Chicago-Joliet-Naperville, IL (MSAD)	-21%	-21%	-37%	-32%
Cincinnati-Middletown, OH-KY-IN	-8%	-14%	-20%	-24%
Cleveland-Elyria-Mentor, OH	-11%	-25%	-30%	-25%
Columbia, SC	-7%	-9%	-21%	-21%
Columbus, OH	-8%	-15%	-22%	-19%
Dallas-Plano-Irving, TX (MSAD)	-4%	-11%	-24%	-15%
Dayton, OH	-9%	-17%	-25%	-22%
Denver-Aurora-Broomfield, CO	-6%	-18%	-24%	-25%
Detroit-Livonia-Dearborn, MI (MSAD)	-29%	-41%	-42%	-45%
Edison-New Brunswick, NJ (MSAD)	-16%	-31%	-38%	-38%
El Paso, TX	-8%	-10%	-15%	-13%
Ft. Lauderdale-Pompano Bch.-Deerfield Bch., FL(MSAD)	-39%	-53%	-61%	-66%
Fort Worth-Arlington, TX (MSAD)	-5%	-10%	-19%	-17%
Fresno, CA	-37%	-58%	-44%	-50%
Grand Rapids-Wyoming, MI	-15%	-22%	-27%	-23%
Hartford-West Hartford-East Hartford, CT	-10%	-22%	-34%	-30%
Honolulu, HI	-12%	-23%	-32%	-31%
Houston-Sugar Land-Baytown, TX	-1%	-5%	-14%	-15%
Indianapolis-Carmel, IN	-6%	-15%	-23%	-21%
Jacksonville, FL	-29%	-28%	-39%	-37%
Kansas City, MO-KS	-9%	-18%	-30%	-24%
Lake County-Kenosha County, IL-WI (MSAD)	-20%	-20%	-39%	-34%
Las Vegas-Paradise, NV	-52%	-39%	-37%	-42%
Los Angeles-Long Beach-Glendale, CA (MSAD)	-28%	-42%	-33%	-39%

Louisville-Jefferson County, KY-IN	-5%	-11%	-20%	-16%
McAllen-Edinburg-Mission, TX	-8%	-6%	-18%	-15%
Memphis, TN-MS-AR	-12%	-12%	-34%	-32%
Miami-Miami Beach-Kendall, FL (MSAD)	-42%	-24%	-49%	-48%
Milwaukee-Waukesha-West Allis, WI	-11%	-16%	-25%	-22%
Minneapolis-St. Paul-Bloomington, MN-WI	-19%	-27%	-39%	-28%
Nashville-Davidson--Murfreesboro--Franklin, TN	-8%	-11%	-27%	-25%
Nassau-Suffolk, NY (MSAD)	-16%	-23%	-32%	-31%
Newark-Union, NJ-PA (MSAD)	-15%	-29%	-29%	-31%
New Haven-Milford, CT	-15%	-23%	-31%	-30%
New York-White Plains-Wayne, NY-NJ (MSAD)	-15%	-22%	-27%	-30%
Oakland-Fremont-Hayward, CA (MSAD)	-26%	-57%	-44%	-48%
Oklahoma City, OK	-3%	-13%	-19%	-20%
Omaha-Council Bluffs, NE-IA	-5%	-16%	-23%	-19%
Orlando-Kissimmee-Sanford, FL	-40%	-39%	-60%	-61%
Oxnard-Thousand Oaks-Ventura, CA	-26%	-51%	-52%	-52%
Philadelphia, PA (MSAD)	-10%	-20%	-22%	-23%
Phoenix-Mesa-Glendale, AZ	-42%	-38%	-46%	-46%
Pittsburgh, PA	0%	-9%	-16%	-13%
Portland-Vancouver-Hillsboro, OR-WA	-21%	-15%	-30%	-31%
Providence-New Bedford-Fall River, RI-MA	-18%	-28%	-36%	-33%
Raleigh-Cary, NC	-7%	0%	-23%	-17%
Richmond, VA	-15%	-14%	-21%	-21%
Riverside-San Bernardino-Ontario, CA	-41%	-58%	-61%	-69%
Rochester, NY	-2%	-12%	-18%	-14%
Sacramento-Arden-Arcade-Roseville, CA	-32%	-58%	-49%	-52%
St. Louis, MO-IL	-10%	-16%	-21%	-17%
Salt Lake City, UT	-19%	-6%	-23%	-25%
San Antonio-New Braunfels, TX	-5%	-7%	-19%	-16%
San Diego-Carlsbad-San Marcos, CA	-24%	-39%	-31%	-31%
San Francisco-San Mateo-Redwood City, CA (MSAD)	-19%	-30%	-14%	-13%
San Jose-Sunnyvale-Santa Clara, CA	-21%	-38%	-21%	-22%
Santa Ana-Anaheim-Irvine, CA (MSAD)	-24%	-46%	-38%	-39%
Seattle-Bellevue-Everett, WA (MSAD)	-23%	-13%	-30%	-31%
Tacoma, WA (MSAD)	-25%	-18%	-41%	-41%
Tampa-St. Petersburg-Clearwater, FL	-35%	-49%	-62%	-63%
Tucson, AZ	-30%	-30%	-33%	-32%
Tulsa, OK	-1%	-10%	-16%	-18%
Virginia Beach-Norfolk-Newport News, VA-NC	-15%	-19%	-25%	-24%
Warren-Troy-Farmington Hills, MI (MSAD)	-27%	-39%	-46%	-46%
Washington-Arlington-Alexandria, DC-VA-MD-WV (MSAD)	-20%	-37%	-45%	-50%
West Palm Beach-Boca Raton-Boynton Beach, FL (MSAD)	-36%	-69%	-86%	-83%
Worcester, MA	-15%	-29%	-39%	-38%