Recent Price and Quantity Volatility in Metropolitan Housing Markets: A First Look

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 DRAFT Results are far from final.

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This paper is a working draft, and will be revised extensively. Comments and criticisms are especially welcome.

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This presentation draws heavily on past work with Dr. Yongping Liang, including our 2005 paper, presented to the 2005 ASSA meeting in Philadelphia. This paper does not represent the views of Fannie Mae or any other institution.

Contents

Abstract

This paper extends the analysis of metropolitan housing markets in several directions. One contribution is to integrate market adjustment in prices and quantities. Many papers have analyzed one or the other, but relatively few papers have examined them together. Here we present our first data analysis, which suggests markets with supply constraints (regulation and physical geography) adjust more on the price side to demand shocks, while less constrained markets adjust more with quantities; prices remain relatively stable. We are currently solving some final data matching problems and will then apply regime switching regression models, based on the strength of supply-side constraints (physical geography and the stringency of land use and development regulation) as a more granular test of which markets in the U.S. adjust in terms of quantities versus prices, in both the short and long-run.

Our current paper is available at http://reudviewpoint.blogspot.com/ and in due course our full econometric results and supporting data will be available there as well.

Introduction

A growing number of papers have examined metropolitan housing prices in a panel supply and demand framework, e.g. Follain and Giertz (2012), Glaeser, Gyourko and Saks (2005), Glaeser, Gyourko and Saiz, Leung (2014), and Malpezzi (1999), among others. A smaller number of papers have examined housing production in a similar localized framework, e.g. Green, Malpezzi and Mayo (2005), and McDonald and McMillen (2000). Still fewer papers have examined them together, e.g. Hwang and Quigley (2006) and Saks (2008).

Of course in a shorter run we would observe both adjustment in prices and quantities (Samuelson 1949); further, in metropolitan areas with varying supply conditions, the mix of price adjustment and quantity adjustment could vary. Focus on simply prices, or quantities, in isolation can lead to anomalies, as pointed out recently by Davidoff (2013); e.g. panel price models don't predict recent behavior very well in markets like Las Vegas or Phoenix.

This paper is a preliminary draft of work in progress. Model specification is incomplete. We are still collecting and refining and checking data. You won't find much discussion of endogeneity in this draft, but trust us that there is no lack of endogeneity in our data. Please take these results as a first draft to stimulate discussion. Results will surely change in future versions.

Some Simple Descriptive Motivating Analysis

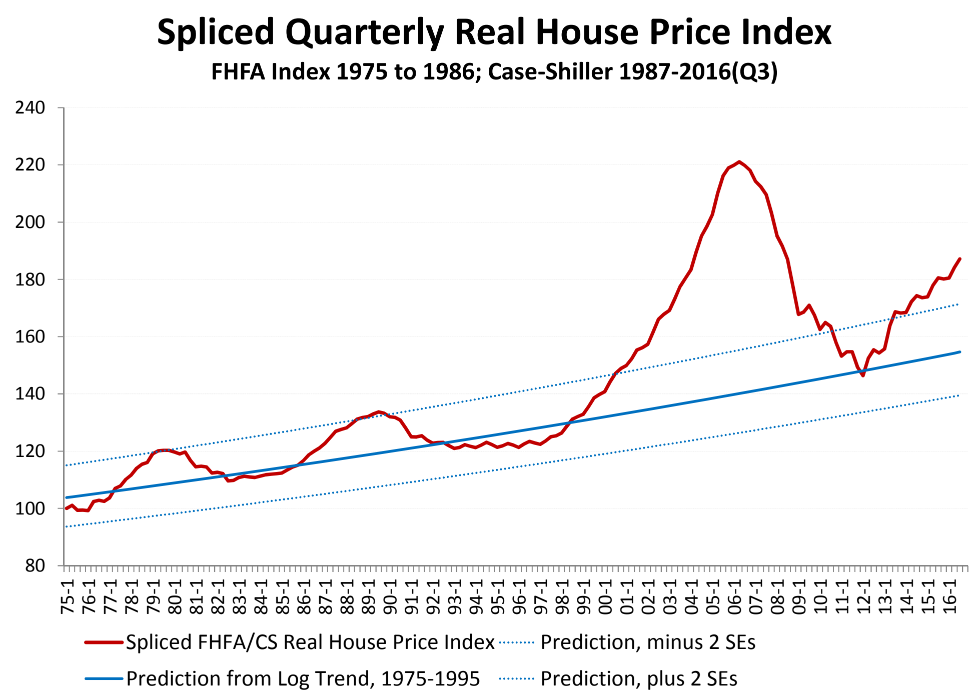


Exhibit 1

Ask any economist where to begin studying almost any market and the likely answer is, "prices." Exhibit 1 represents an "average" time path of typical U.S. housing prices. This particular representation is based on Case-Shiller prices from 1987 forward, and based on Federal Housing Finance Agency prices before that. The blue logarithmic trend line is based on data from 1975 to 1995, i.e. before the boom and bust of the 2000s. The dotted lines show the trend plus and minus two standard errors. We don't claim that a simple trend analysis is an especially good forecast of housing prices, but the pattern of modest increases and apparently mild cycles prior to the late 90s followed by a very unusual boom and bust is hard to miss.

In this data from 1975 to 1995 real house prices grew at slightly less than one half of 1% per year. From 1996 to the peak in 2006 real house prices grew at about 7% a year, inflation-adjusted. One did not need much of a model to understand that the price of a large fraction of our tangible capital stock could not increase by 7% annually in real terms indefinitely. (Unless one were willing to believe that asymptotically housing would eventually become the entire capital stock!)

As all readers of this paper know, after the 2006 bust, the U.S. housing market bottomed in 2012. Since then average housing prices have shown a strong recovery, and have now once more broken the two standard error trend barrier that preceded modest downturns circa 1979 and 1990. The annual real growth rate over this 3 year period is back up to 6 percent. While clearly less of a boom than we experienced in the early 2000s – 3 years of 6 percent growth is very different from a decade of 7 percent growth – a number of housing market observers have begun to discuss the possibility of a new "bubble" (Kusisto 2015; La Monica 2015; Vasel 2015). We will return to this question of a "bubble" below.

Exhibit 1 is a national average price index. Of course, no one buys or sells or rents a house in the United States. We buy, rent or sell in Chicago, or New York, or Harrisburg, or Memphis. A major theme of this paper (and many others cited) is that metropolitan housing markets vary markedly in their market conditions and in their market outcomes. But a quick look at a national average is a reasonable way to start us off.[1]

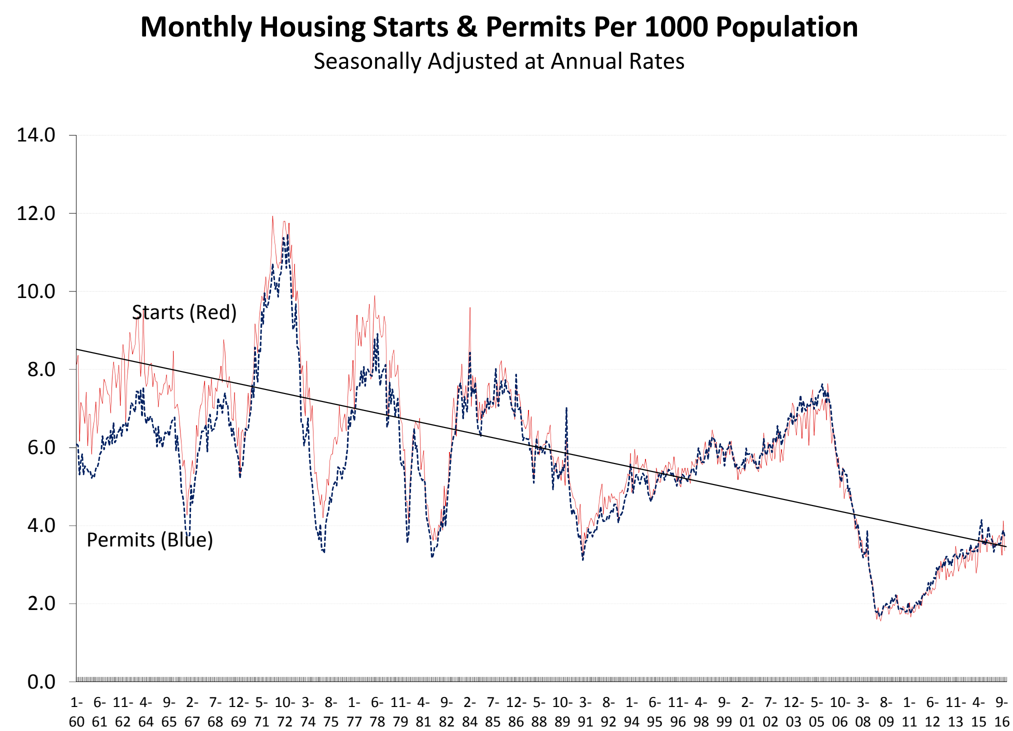


Exhibit 2

Prices contain lots of information, but one theme of this paper is that they are not a sufficient statistic for describing the housing market. Exhibit 2 presents monthly housing permits, adjusted for population, back to 1960. The large cycles of varying duration are familiar to most readers, but it is also interesting that this series has been trending down over more than half a century. It is possible that this is a cohort effect. Other data (annual data not shown here but available on request) confirm that in the 50s and several decades beyond mobilization of resources and new modes of production allowed the housing industry to build a large cohort of housing after decades of backlog during two world wars and the Great Depression, and a period of urban and suburban expansion. Now more of this housing may be reaching the end of its useful life, which could imply this trend will not continue indefinitely.

[1] Reliable house prices prior to the mid-1970s are difficult to find. Malpezzi and Mayo (2001) and Shiller (2015) present rough and ready longer time series, albeit of lesser quality.

Exhibit 2 also shows the close association between building permits, and later housing starts. Starts are cited most commonly when national data are examined, but are not available at the metropolitan level. Permits are available at metropolitan and other relatively small areas.

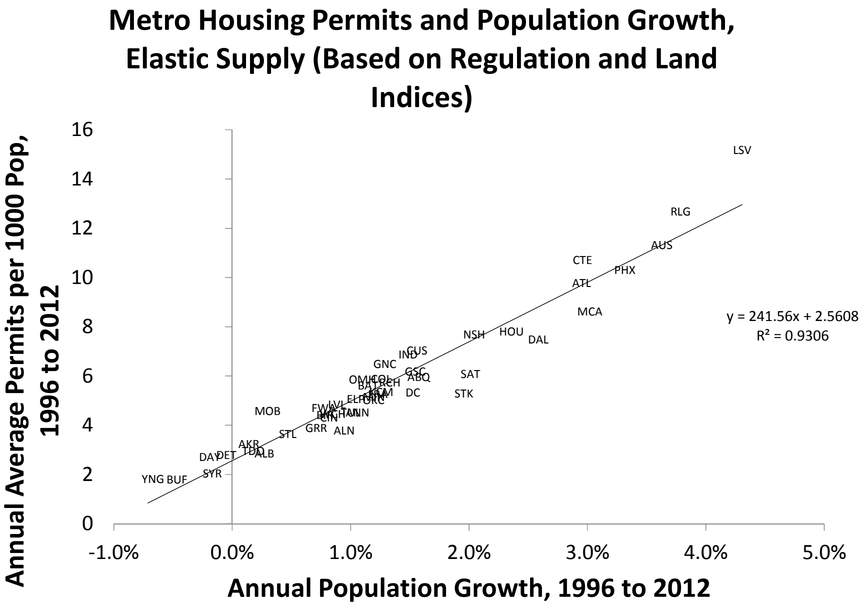


Exhibit 3

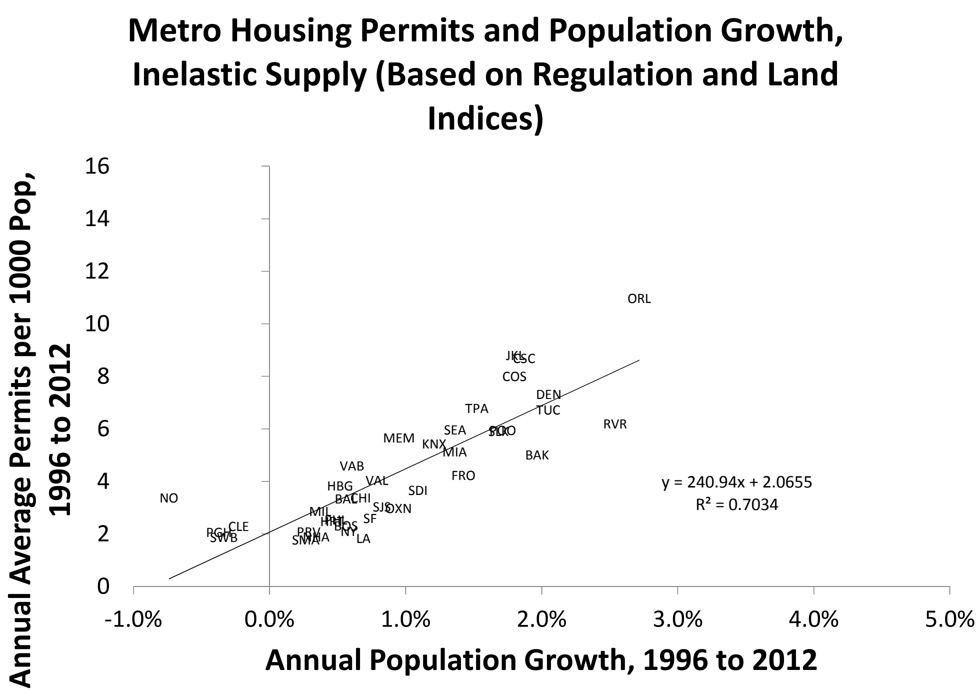


Exhibit 4

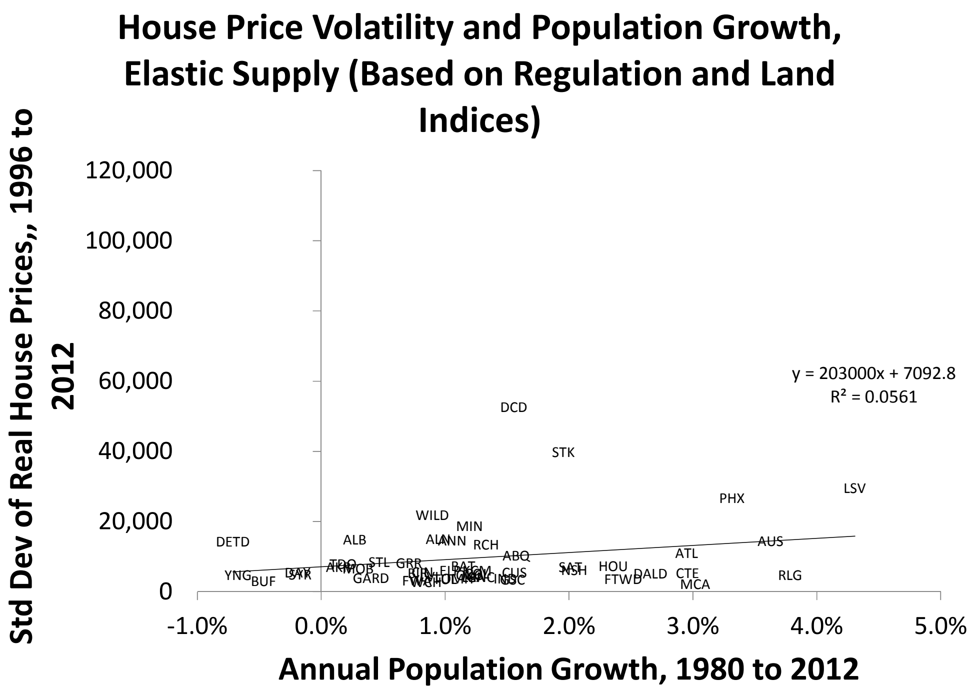


Exhibit 5

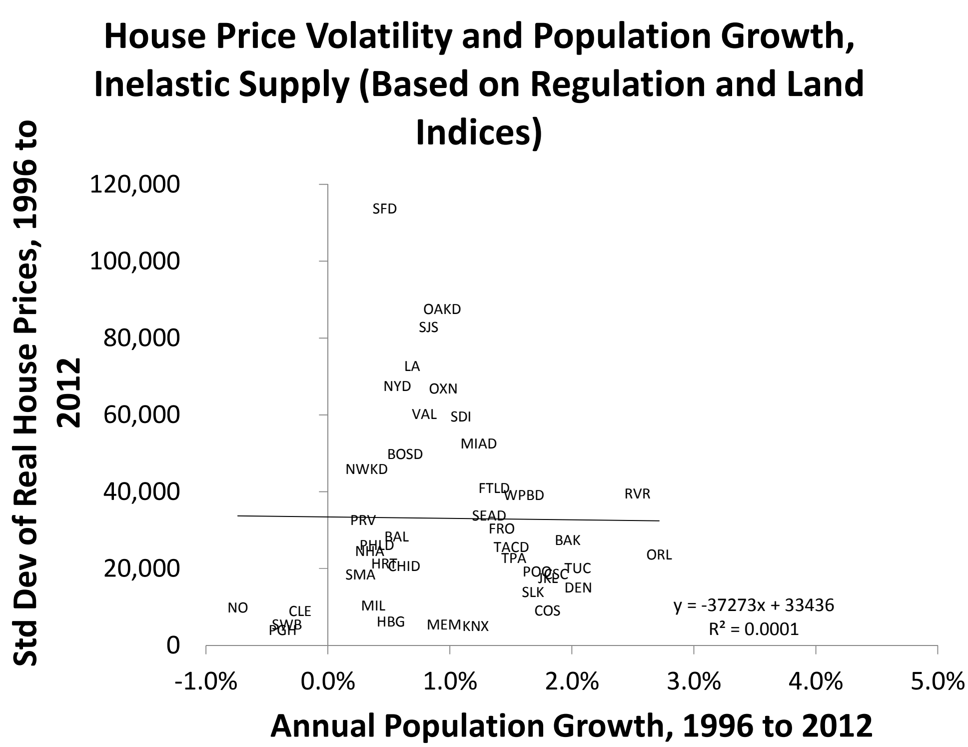


Exhibit 6

In the cross-section charts above, a subset of 104 MSAs are divided into 2 groups, using data on land availability and the stringency of land use and development regulation. Exhibits 3 and 4 show that house construction (building permits) are well correlated with population growth, but the correlation is stronger in elastic markets. Also notice there are no MSAs in the inelastic sample with population growth above 3%, while there are 6 MSAs in the elastic sample growing from 3-5%. Exhibits 5 and 6 are even more striking. While there are markets of high price volatility in both groups (hardly surprising given the 2000 era boom and bust) the volatility is much higher in the inelastic group.

Selections from a Large and Growing Literature

The literature on modeling housing prices is vast. We restrict ourselves here to a selection of recent papers that focus on the following questions: What are the determinants of the cyclical behavior of the housing prices? What is an appropriate functional form that models the effects of those determinants? What is the dynamic relationship between household income and housing price? These questions are the focus of our paper, and our goal is to develop a model that previous literature and our own work suggest will yield reliable answers.

Malpezzi and Wachter (2005) examine two possible sources of real estate price cycles: "speculation," a demand-side phenomenon, and inelasticity in the supply of housing. In their discussion of speculation, the authors state that real estate investors form their expectations based on past price trends. Since real estate markets are not efficient, informed investors cannot arbitrage easily and a "bubble" can form. Regarding inelasticity of Secondly, supply side factors, such as regulation as well as natural constraint, interact with adjusting expectations to increase both the first and second moments of housing price. By using a simulating model they confirm their view that supply conditions are very influential in forming a "bubble."

Capozza et al. (2004) include both short-term serial correlation and long-term mean reversion in a dynamic model, and explore the determinants of resulting cycles of housing price. They presents a difference equation with both serial correlation and mean reversion properties, and solve for the parameter values at which the dynamics will converge (a stable state) or diverge (bubbles) in response to shocks. Natural questions include: What are the empirically estimated values of the parameters on housing markets? What are the determinants of these parameters? The authors propose information costs, supply costs, and expectations as candidates that might determine the parameter values and then empirically estimate their values using a panel data set. According to their empirical results most MSAs in U.S.A. have convergent price processes. Their results also suggest that both demand side and supply side are important in the formation of housing price cycles.

Ortalo-Magné and Rady (2004) focus on the demand side to explain the cyclical behavior of the housing market. They develop a life-cycle model of the housing market with a property "ladder" and a credit constraint. The credit constraint is crucial in this model: On the one hand, it delays an individual's willingness to buy a house; on the other hand, the leverage effect helps a homeowner move up the property ladder. The capacity of young households to make a down payment is a powerful driver of the housing market. Housing price can overshoot in response to a permanent income increase. Their model rationalizes the possible overshooting of housing price with income change. Another empirical implication is that the income change of different demographic groups results in different impacts on the housing market.

Hwang and Quigley (2004) apply a three-equation model describing the movement of housing prices, housing supply, and vacancies in the market to specify the economic fundamentals influential in local housing price. Their results confirm the importance of several variables, such as change of income and employment, effects of lagged variable, and the vacancy rate.

In Malpezzi (1999), the housing price to income ratio is used as a basis for an error correction model. But Malpezzi offers no rigorous rationale for normalizing price by income, and recent studies call that previously maintained hypothesis into questions. For example, Ortalo-Magné and Rady (2004)'s model implies that it is the income of young households, rather than the overall average income level, which drives housing price changes. Empirically, Holly and Jones (1997) find that real price to income ratio is not stationary by a Phillips-Perron test. Gallin (2003) challenges the argument that housing price and households' income should move together based on some cointegration tests on a panel data set.

Gallin (2003) applies a variety of methods of cointegration tests on a panel data set. The strength of cointegration tests on a panel set is that by combining information from time series and cross-sectional dimension, more powerful tests for unit root or cointegration are possible. The main methods for unit root tests include the Levin-Lin test, the IPS (Im, Pesaran and Shin) test, and the Maddla-Wu test. The Levin, Lin and Chu (2002) test for unit root allows for fixed effects and unit-specific time trends, but does not allow for heterogeneous coefficients of lagged dependent variables. The IPS test allows for heterogeneous serial correlation. Maddala and Wu (1999) provide a method that is simpler and more robust to lag length and sample size. The main methods for direct cointegration tests (rather than a unit root test) include Pedroni (1999) which directly tests the null of no cointegration, and McCoskey and Kao's (1998) test which uses the null of cointegration rather than no cointegration. Applying these methods, Gallin remains uncertain about the cointegration of housing price and income. So an error correction specification for housing prices and incomes may or may not be warranted, according to the literature to date.

A recent paper by Zhou (2010) investigates whether tests of house price cointegration are driven by the assumption of a linear functional form. Zhou examines FHFA data from 1978 Q1 through 2007 Q4; hence his tests miss the downturn in 2008 and 2009. Zhou examines the national average reported by FHFA as well as the metropolitan indexes for 10 major cities. He does not take advantage of the panel nature of the data, but rather runs separate regressions for each metro area, using a simple model of house prices against per capita incomes, construction costs, and mortgage rates. His linear tests (AEG and Johansen tests) are able to reject the null for only one metro area, Cleveland, and only at the 10 percent level of significance. His nonlinear tests, taken at face value, reject the null (no cointegration) for the national index, and for six of the 9 or 10 cities. Notice that in Zhou's sample of 10 MSAs, it is no surprise that the cities with the biggest proportional booms -- Boston, Los Angeles, and New York -- are the ones that are not yet "tethered" back to fundamentals.

In the end, where do these tests leave us? If regression models find apparently significant and economically meaningful relationships between house prices and a reasonable list of fundamentals (income, population, interest rates, indexes of supply conditions), but the relevant tests are unable to confirm cointegrated relationships between house prices and those fundamentals, very broadly there are two possibilities. The first possibility is that house prices are indeed related to fundamentals, but that because of the low power of the test (or perhaps some critical mis-specification of the test), we are unable to reject the null that implies cointegration. Second, if the long run in housing markets is, well, long, our data series may be too short to reveal the true long run co-movements.

A Simple Analytic Framework

Malpezzi and Wachter (2005) present a simple supply and demand model that, like Wheaton's earlier dynamic model, demonstrates that more stringently regulated markets are also more volatile.

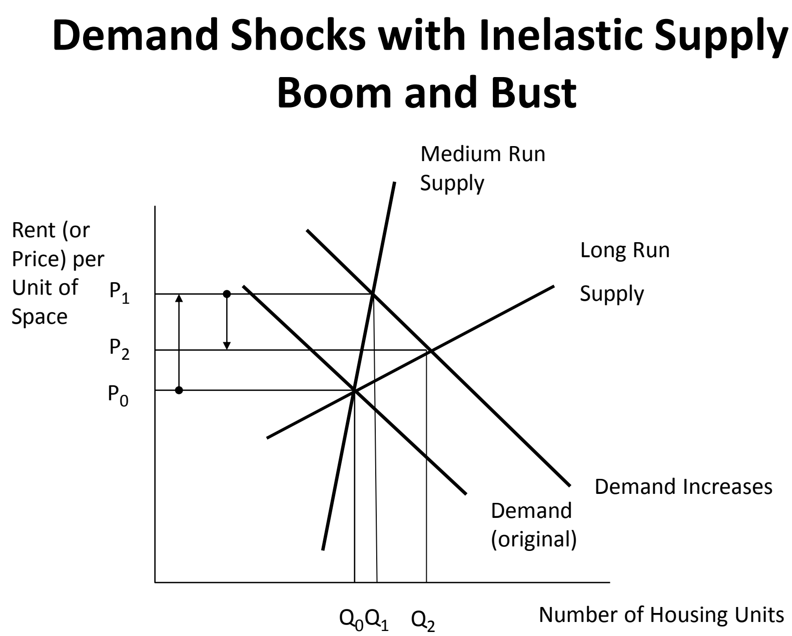


Exhibit 7

In Exhibit 7, a heavily regulated market with fairly inelastic medium-run supply has an initial demand shock characterized by the demand curve moving from D1 to D2. Given this demand shock in a very inelastic short and medium run supply, little supply response is observed and prices increase substantially from P0 to P1. But over the very long run, there is some elasticity even in the most convoluted markets. Eventually, markets and governments do respond to extraordinary price increases and supply shifts out. This results in a housing price crash from P1 to P2, as new housing is built to take the market from Q0 to Q1 and eventually to Q2.

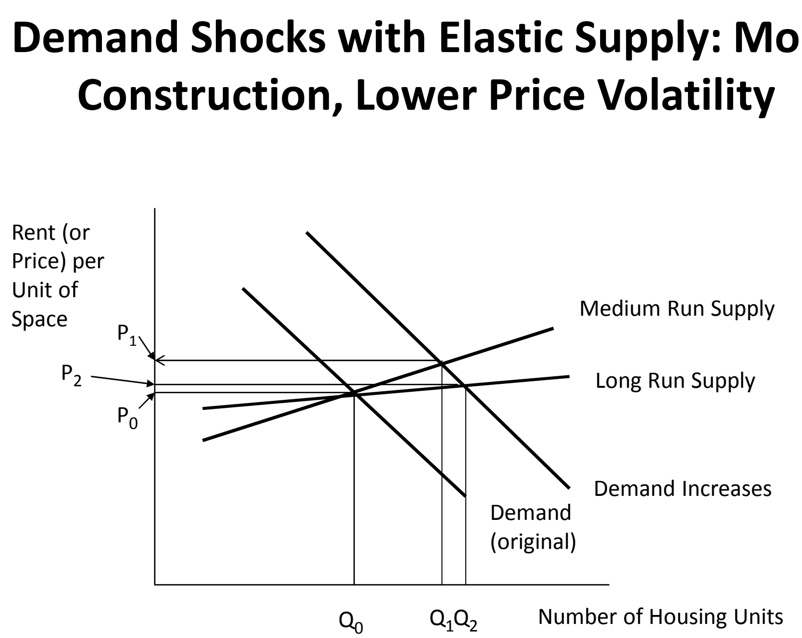


Exhibit 8

Contrast this with Exhibit 8, which is more or less the same except that the markets are more elastic. The initial increase does give rise to a price run up over the medium term, as one would expect, but the run up is much less. Therefore the boom and bust cycle is moderated. These are indicated by shifts from P0' to P1' and back down to P2'. Adjustment is much more on the quantity side, less on price.

Our empirical work will estimate simple reduced form models of P and Q (real house prices, and building permits), including both the "usual suspects" on the demand side (demographics, income, and mortgage rates) as well as the determinants of supply elasticity, both man-made (regulatory constraint) and natural (geographic constraint).

Data Sources

The data analyzed in this paper is based on the data set constructed by Malpezzi (1999) but extended for more years. In Malpezzi, the time horizon is from 1979 to 1996; in this paper the time span is from 1980 to 2014.[2] Housing price data are from the repeat sales price indexes provided by the Office of Federal Housing Enterprise Oversight ("OFHEO indexes") and Census-based hedonic price indexes from Malpezzi, Chun and Green (1998), hereafter MCG). Following Malpezzi, the MCG indexes are used to benchmark the metro area price level in the base year 1990. FHFA quarterly indexes are then collapsed into annual changes, and those data are used directly as our measure of price changes, and to calculate price levels pre- and post- 1990. As before, we deflated income and housing price by the GDP implicit price deflator using 2015 as the base year.

Data on the regulatory environment and the geographic constraints of metropolitan housing markets are taken from Malpezzi (1996) and MCG (1998). Regulation is stricter when the value of regulation index is higher. "Adjacent to water" is a dummy variable for a metropolitan area is located on a major coastline (ocean or Great Lake). "Adjacent to park" is a dummy variable for a metropolitan area located adjacent to a large national park, military reservation, or other major constraint on expansion. Income and population data are from the Bureau of Economic Analysis (BEA). Mortgage rates and inflation rates are from the Freddie Mac and BEA.

Appendixes 1, 2 and 3 present summary statistics on (1) our house price indexes, (2) annual percentage change of deflated housing price, and (3) building permits per thousand population, for each MSA respectively. They document what readers already know: metropolitan areas vary markedly in their price levels, rate of house price appreciation (or in some places and years, depreciation), and construction. This variation suggests that metropolitan area housing price data may be modeled more fruitfully than a national aggregate housing price index. We will find below that, consistent with simple supply and demand analysis, the interaction between price adjustment and quantity adjustment depends in large part on supply conditions.

As the preceding section makes clear, our framework is a simple one, albeit one that we believe will yield some interesting results. Another potential contribution comes from the fact that we are writing this paper in 2017 instead of 2007. Exhibit 9 shows the time span of data used for several representative panel studies of US housing prices. Nothing in, say, Malpezzi (1999) hinted at the boom to follow. Nothing in Gallin (2005) foretold the 2006 bust. The last decade of housing market behavior has been painful if not catastrophic for many individuals, and a disaster for the U.S. and global economies. Among

[2] In preliminary work we found some exceptionally noisy data in the 1980s; pending further review of that data, we are including it in our models. Actually, qualitative results are fairly robust to the inclusion of the early period. We will address this data issue more fully in the next edition of the paper.

the small groups of beneficiaries have been housing economists.[3] We have a lot of work to do and a lot of interesting data to do it with. Doubtless housing economists of 2027 will do even better.

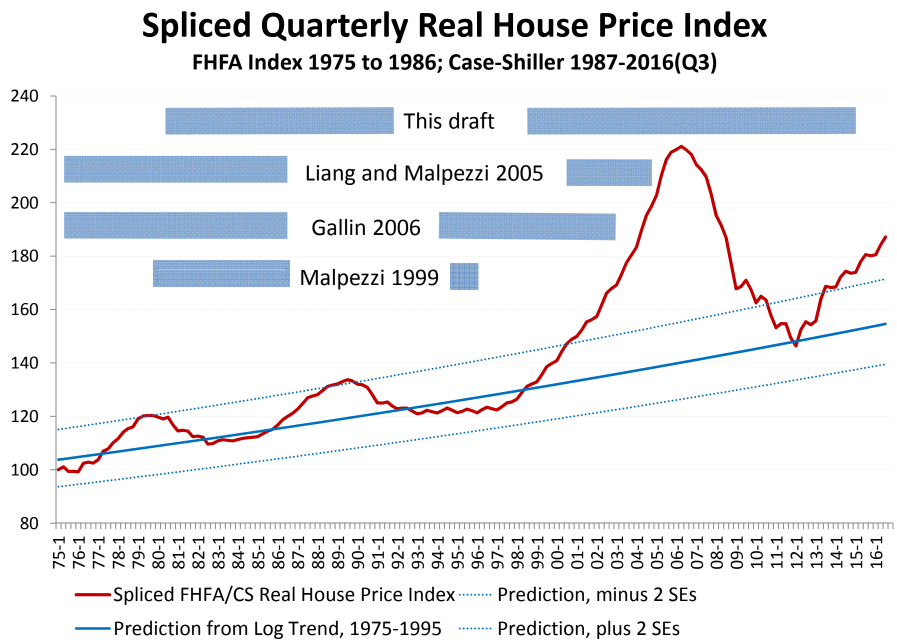


Exhibit 9

A Digression: Challenges in Constructing Metropolitan Panel Data

In this paper, and many others, we loosely state that metropolitan areas are our basic units of observation, over time. Most research papers using metro areas (including our own previous work) gloss over the complexities in matching up data from different sources. For the benefit of those not specializing in urban housing markets, we will briefly discuss these issues here.

The starting point for thinking about Metro areas is that the basic building block is the county. Only a small part of the country's area (about 4 percent) is urbanized.[4] But the entire country is covered by counties. Specifically, there are 3142 counties or county equivalents in the United States. (County equivalents include things like the parishes of Louisiana, and a few special places like a few large national parks.)

[3] Granted, some of the other "winners" found more pecuniary rewards than the typical housing economist. See Lewis (2011).

[4] Urbanized areas are defined by their population density; loosely, 500 persons per square mile, or more.

Metropolitan areas comprise one or more principal cities over 50,000 population, the county (or counties) that contain them; and very often additional contiguous counties which are economically linked to the central city. Since 2003, a similar concept, micropolitan areas, are defined in a similar manner, except that a micropolitan area is anchored by a principal city of somewhere between 10,000 and 50,000. Metropolitan areas and micropolitan areas together comprise Core Based Statistical Areas, or CBSAs.

Some CBSAs are combined into larger entities called (surprise!) Combined Statistical Areas (CSAs).

The larger metropolitan areas (New York, Los Angeles, etc.) also contain smaller units within, called metropolitan divisions. These are also large – they have a single core city, often 2 million or more.

To take perhaps the most complex example, New York City's 2010 population is about 8.2 million, of which all 8.2 million are urbanized (unsurprisingly – but this is not true of all cities!) The New York[5] CBSA, or metropolitan area, contained 25 counties, 21 more than the five familiar counties that comprise New York City (New York County, Manhattan; Kings County, Brooklyn; Queens County; Bronx County; and Richmond County, Staten Island). New York has four metropolitan divisions, New York (12 million), Nassau-Suffolk (3 million), Duchess-Putnam (400,000) and Newark (2 million). The 35 county New York CSA population was about 24 million in 2010.

So there are a lot of different units of observation labeled "New York." While most other cases are less complex, all give rise to data matching problems. Some basic sources, like BEA population and incomes, are available for both the large MSAs and their metro divisions. But some data only come for one or the other. Specifically, for our paper, Federal Housing Finance Agency housing price data are presented by Divisions, but not for the larger metro areas that contain divisions. That is, the Milwaukee data are for the Milwaukee metro area, because Milwaukee (and most metro areas) have no metro divisions. But LA, New York, Dallas etc. FHFA price data come for their divisions only, not for their metro areas.

Census data on building permits is available by metropolitan area, but not by metropolitan division. So research that needs to match up house prices and permits can't just download the data and match up by metro name or FIPS code.

Fortunately, building permits are available by county We are thus able to download county permits, obtain the county definitions of metropolitan divisions from the Office of Management and Budget, then sum permits by Division number. Now we have permits data that match our other data on housing prices, population, incomes, and so on.

[5] Long official Census place names are shortened here, and population figures are rounded, for readability. See more details on the definitions of city, urbanization, metropolitan areas, etc. at http://reudviewpoint.blogspot.com/. There is an excellent discussion of the New York definitions at https://en.wikipedia.org/wiki/New_York_metropolitan_area#Metropolitan_Statistical_Area.

A First Look at Prices

As we noted above, in this first draft we present very preliminary results based on single equation reduced forms, neglecting for the moment the joint determination of prices and housing construction. In this section we examine price. In the following section we will examine construction as proxied by building permits.

Exhibit 9 presents a simple OLS regression model explaining the logarithm of metropolitan house prices, between 1990 and 2014, as a function of basic demand and supply determinants as suggested above, and similar to the simpler reduced forms in previous literature:

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	9	922.1785	102.464	1818.26	<.0001
Error	6834	385.1155	0.05635		
Corrected Total	6843	1307.294			

Root MSE	0.2373	**R-Square**	0.7054
Dependent Mean	11.269	**Adj R-Sq**	0.7050
Coeff Var	2.1064		

Parameter Estimates					
Variable	**Label**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	Intercept	-4.16547	0.18542	-22.47	<.0001
lpop	Log Population	0.09013	0.00344	26.22	<.0001
dpop	Annual Change in Population	0.76818	0.14331	5.36	<.0001
lypc	Log Real Per Capita Income	1.19252	0.01884	63.28	<.0001
dypc	Annual Change in Real Y Per Capita	-0.16712	0.05923	-2.82	0.0048
pdot	Annual Change in GDP Deflator	5.56206	0.19639	28.32	<.0001
mortr	Real Mortgage Interest Rate	2.18652	0.18775	11.65	<.0001
REGHAT	IV for Regulation from MCG	0.07498	0.00138	54.48	<.0001
ADJWTR	Adjacent Large Body of Water	0.06870	0.00684	10.04	<.0001
ADJPARK	Adjacent Natl Park or Mil Base	0.05193	0.00752	6.90	<.0001

Exhibit 10

Taking these OLS results at face value, the model performs reasonably well, explaining most of the variation in prices; with all variables showing the expected signs, except for the annual change in real income per capita, and mortgage rates. As Schwab (1983) suggests, we decompose mortgage rates into real and inflationary components. Both elements yield positive coefficients in Exhibit 9. Other studies have often found that the effects of mortgage rates on prices are hard to pin down and often perverse, see for example Goodman (1995) and Pozdena (1990). Our measures of physical geography are dummies for, respectively, large bodies of water; and national parks, large military installations. The egulatory constraint is measured by an instrumental variable index of land use and development regulations, REGHAT from Malpezzi, Chun and Green. All perform as expected: more constraints raise housing prices.

To get a feel for how some of these model results play out in different contexts, we plotted out the actual values of our price index, and the model's predictions, for all metro areas that have the required data (about 200). Here we will examine 8. (Results for another 18 are presented in an appendix. Full results for all 200 are available on request.) In these Exhibits we present a few of the model's predictions (in blue) along with the actual values of the real price indices (in red). These results are preliminary and WILL change, we expect to improve our predictive ability as these charts present results from our simplest OLS model.

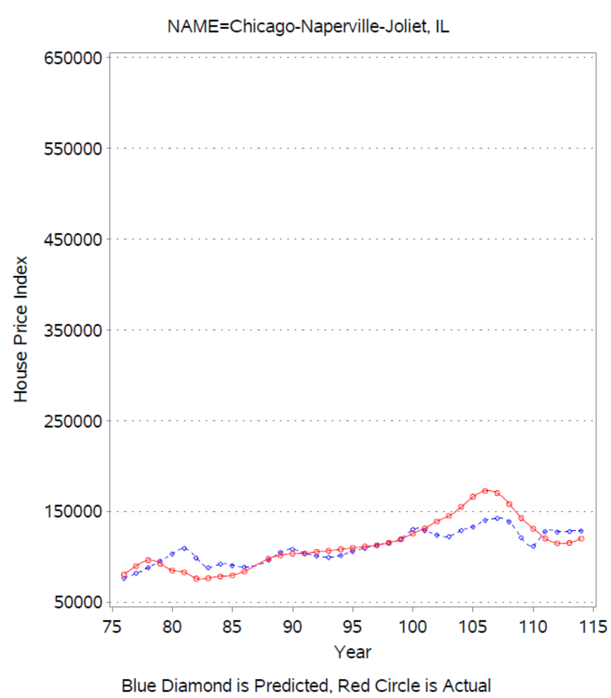


Exhibit 12

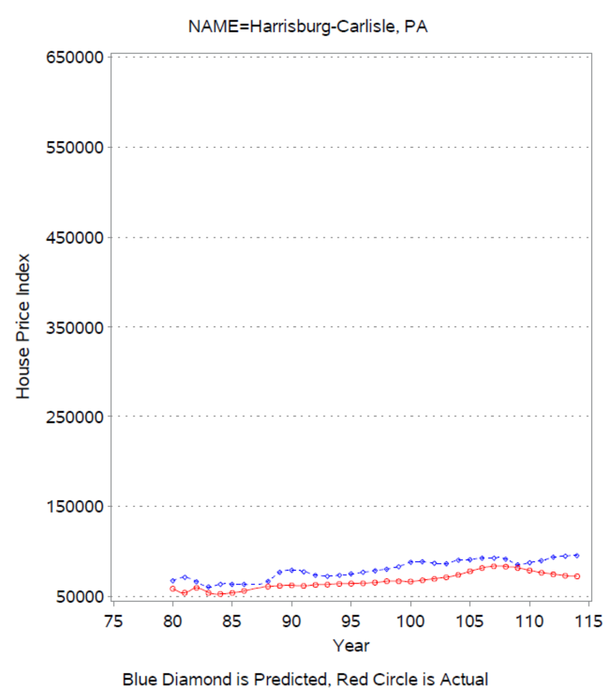


Exhibit 11

Exhibits 11 and 12, above, present two older, slower growth cities with fairly elastic supply conditions: Chicago, and Harrisburg. Both prices and model predictions of prices are fairly stable.

Chicago shows more of a boom and bust than Harrisburg (Malpezzi's original hometown if you wondered why it was chosen.) Dozens of slow growth markets without excessively stringent supply constraints look similar to Harrisburg or Chicago as perusal of the full results will confirm.

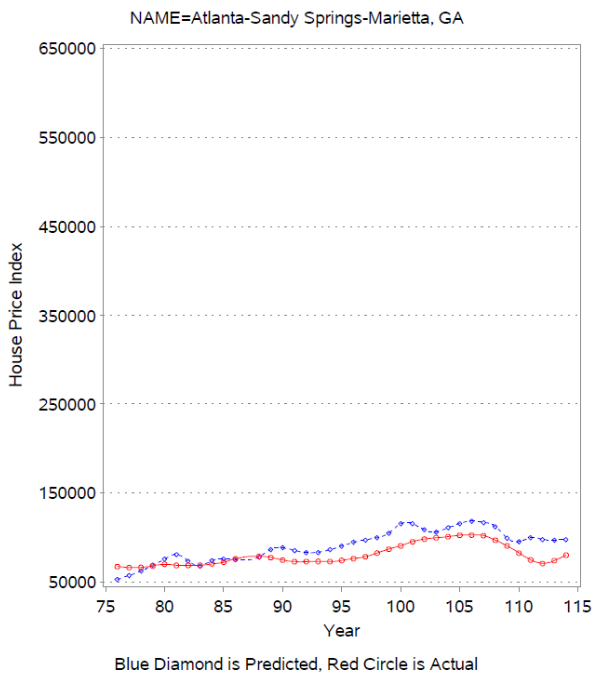


Exhibit 14

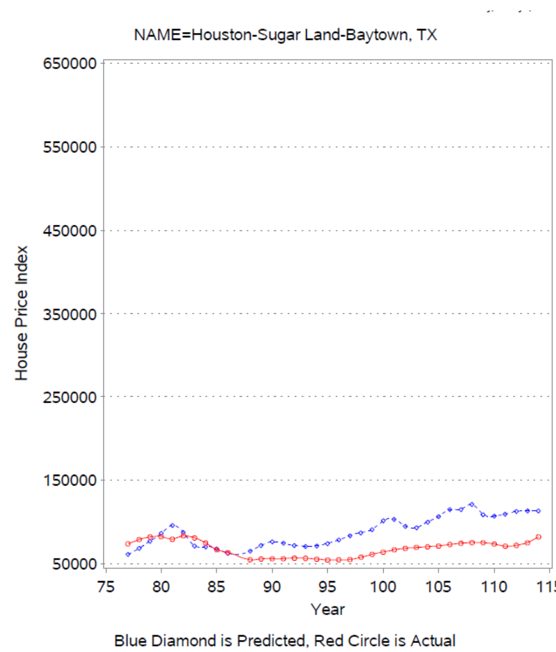


Exhibit 13

The next two Exhibits,13 and 14, Atlanta and Houston, represent faster growing, elastic metro areas. Prices and model predictions are still stable.

In recent papers, Davidoff (2013, 2014) has criticized some of the previous literature for failing to adequately address issues of endogeneity in regulatory measures (a fair criticism, that this paper has not yet fully addressed); and also pointed out that some of the metro areas with especially high rates of foreclosures and price declines were/are places like Las Vegas and Phoenix, which, according to the regulatory measures such as Malpezzi, Chun and Green, Gyourko Saiz and Summers, and others, usually count as "elastic." Exhibits 15 and 16 examine these two metro areas:

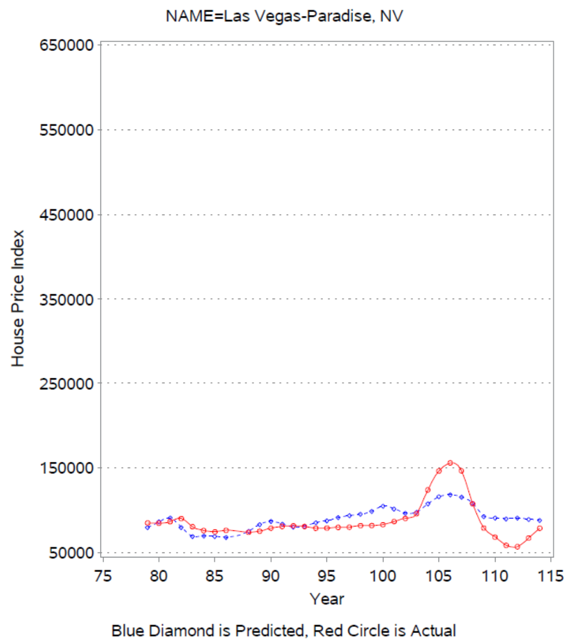


Exhibit 15

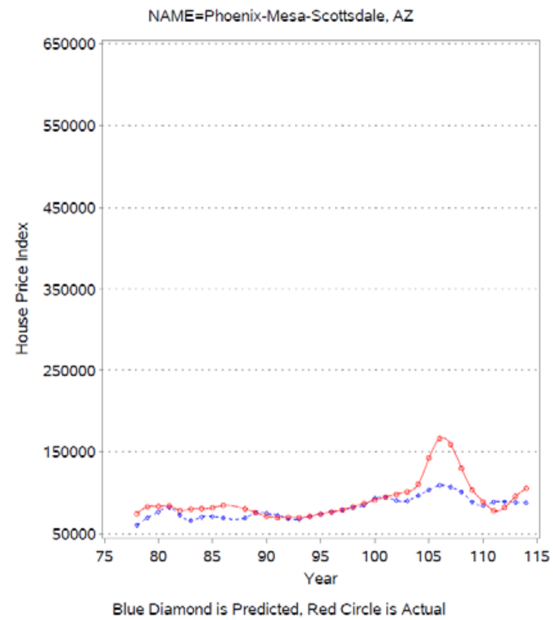


Exhibit 16

Here we see that, as Davidoff points out, there was a more pronounced boom and bust in the 2000s, in these two markets, after years of relative price stability. Hold that thought until the next section, when we look at construction in these two markets. And also hold it until the next page, you will see much bigger booms, and busts, in other markets.

Exhibit 17

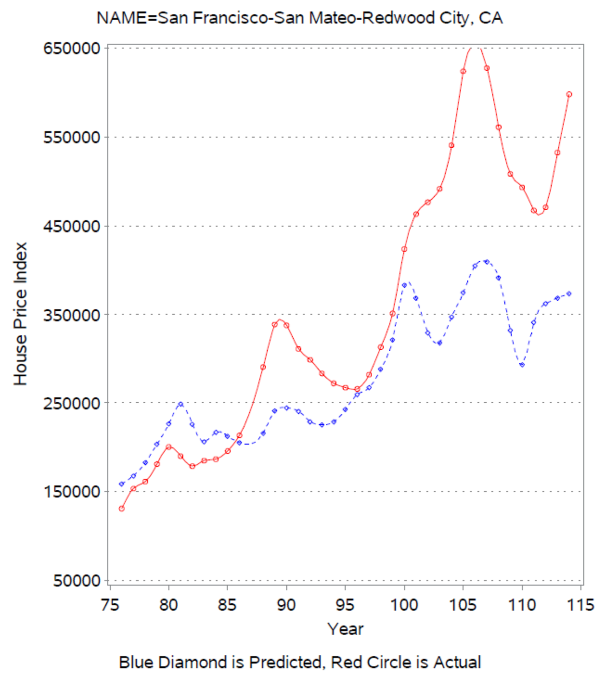


Exhibit 18

Of course, there are a number of markets that have had much more volatile prices than we observed in Exhibits 11 through 16. We chose New York and San Francisco to represent these markets; see Exhibits 17 and 18. Supply constraints and strong demand yield high and volatile model predictions (the blue lines) but the actual market outcomes (red lines) are even more volatile.

Sharp eyed readers familiar with San Francisco will notice that our 2014 "actual" house price is around $600,000, while median sales prices in 2014 were reported to be closer to $1 million. Our values are based on sales while our price index is benchmarked by all owner-occupied housing units in 1990. Even so our next draft will have more to say about alternative price index measures and how to place these results in context.

In the next version we will have more to say about current market conditions. Taking Exhibit 18 at face value, it appears that San Francisco is out of line with the predictions of the model. That may well be, but (1) we are not done yet with model construction and validation; and (2) Liang and Malpezzi (2005) showed what every reader already knows: it's extremely hard to pick turning points in the housing market.

New York and San Francisco are extreme cases, but not unique – a number of other California markets, Boston and Honolulu are qualitatively similar.

A First Look at Building Permits

In the preceding section we examined prices. Now let's focus on quantities. We normalize building permits, our dependent variable, by population; specifically, we calculate, on an annual basis for each metro area, the number of building permits issued, per thousand population. We then regress those adjusted permits on the same set of right hand side variables as used above. Again, these first estimates are OLS and do not address issues of the joint determination of prices and construction, which remains for the next edition.

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	9	30561	3395.6839	209.18	<.0001
Error	6635	107710	16.23362		
Corrected Total	6644	138271			

Root MSE	4.02910	**R-Square**	0.2210
Dependent Mean	5.69496	**Adj R-Sq**	0.2200
Coeff Var	70.7484		

Parameter Estimates					
Variable	**Label**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	Intercept	-0.92921	3.25835	-0.29	0.7755
lpop	Log Population	0.12770	0.06059	2.11	0.0351
dpop	Annual Change in Population	83.45910	2.44924	34.08	<.0001
lypc	Log Real Per Capita Income	0.17962	0.33464	0.54	0.5914
dypc	Annual Change in Real Y Per Capita	9.41027	1.01145	9.30	<.0001
pdot	Annual Change in GDP Deflator	21.72429	3.38938	6.41	<.0001
mortr	Real Mortgage Interest Rate	40.68846	3.37514	12.06	<.0001
REGHAT	IV for Regulation from MCG	-0.04421	0.02388	-1.85	0.0641
ADJWTR	Adjacent Large Body of Water	-0.36646	0.11795	-3.11	0.0019
ADJPARK	Adjacent Natl Park or Mil Base	1.24822	0.12963	9.63	<.0001

Exhibit 19

Exhibit 19 shows that while we can make some sense of construction, based on simple goodness of fit and variable performance, permits are harder to model well than prices. The R^2 of the permits equation is less than a third of the R^2 of the price equation; and several variables (income growth, and being adjacent to a large park or military base) have unexpected coefficients. On the other hand, as our exploratory work in the Introduction suggested, permits per thousand are very strongly driven by population growth, as expected; and the regulatory index and adjacency to large bodies of water have their expected negative effect.

How do these results play out at the metropolitan level? Once again we plot 200 metro areas and present 8 representative results here.

For both Chicago and Harrisburg, the model predicts about 5 units built per 1000 people each year, albeit with a little volatility and some slight decline over time. Harrisburg's actual performance hits the mark in most years (the early 1980s are an exception); Chicago under-builds compared to model estimates in most years.

Given the building construction results in Exhibit 19 (and many similar markets) the price results for Harrisburg in Exhibit 11, a lot above, are hardly surprising. In most years Chicago's actual housing construction permits lagged our model forecast; so some increase in prices is not at all surprising in fact perhaps we might have expected prices in Exhibit 12 to rise even faster than exhibited.

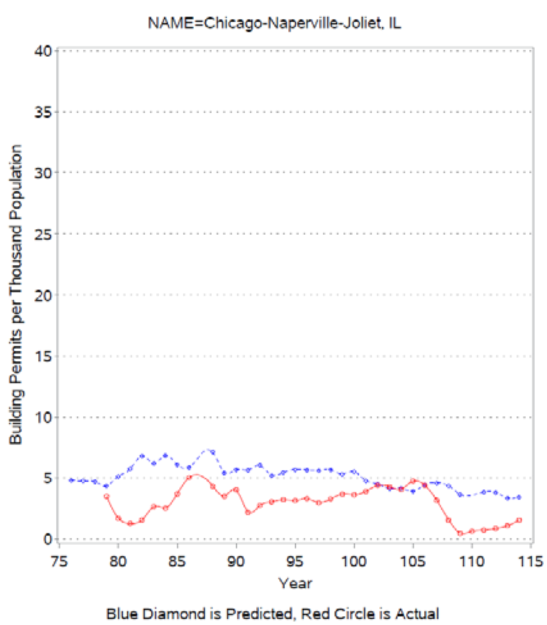


Exhibit 21

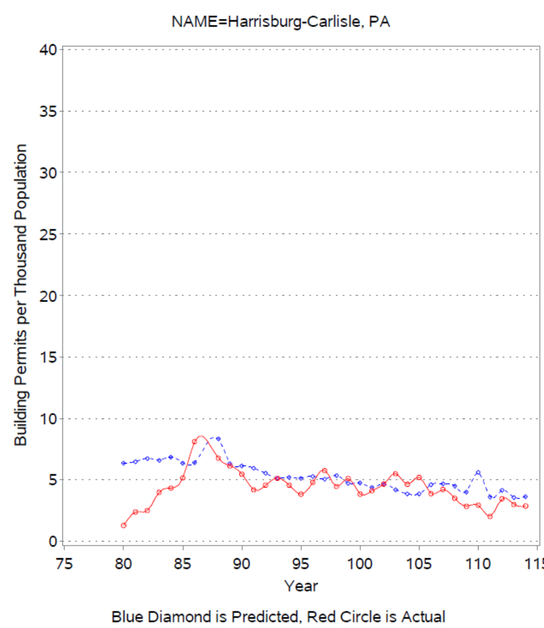
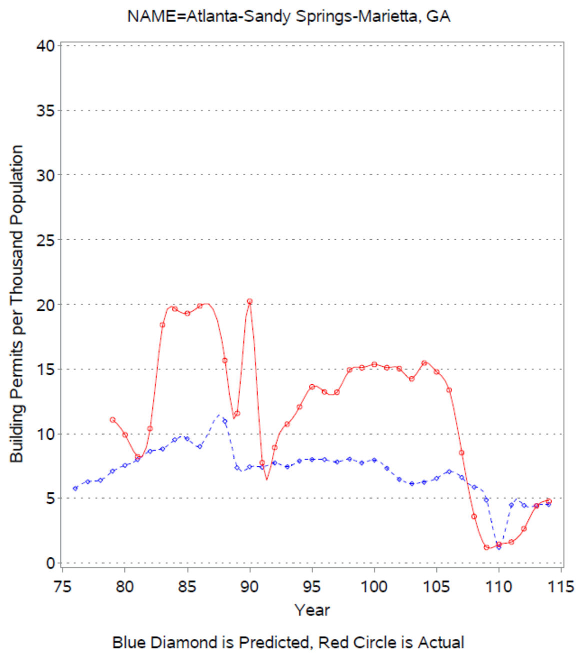
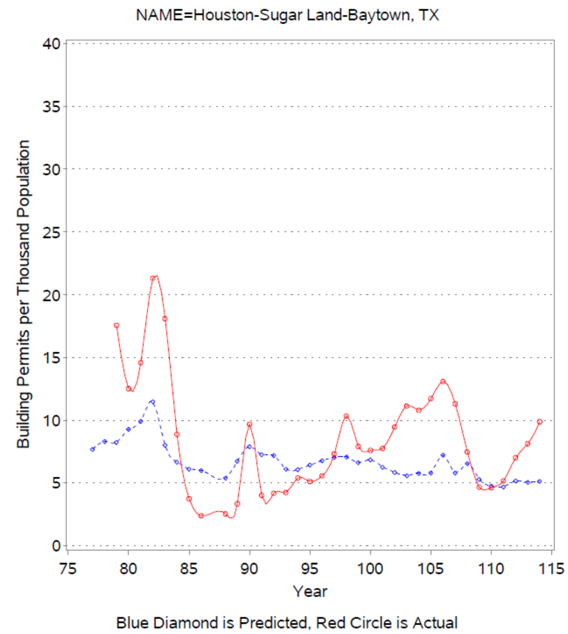


Exhibit 20





It's perhaps unsurprising that our two fast-growth representative metro areas are more volatile; the model predicts that Atlanta and Houston would build between 5 and 10 units per thousand in most years. But notice that the actual building is (1) much more volatile than model predictions here, and (2) in most years the actual is well above the model predictions.

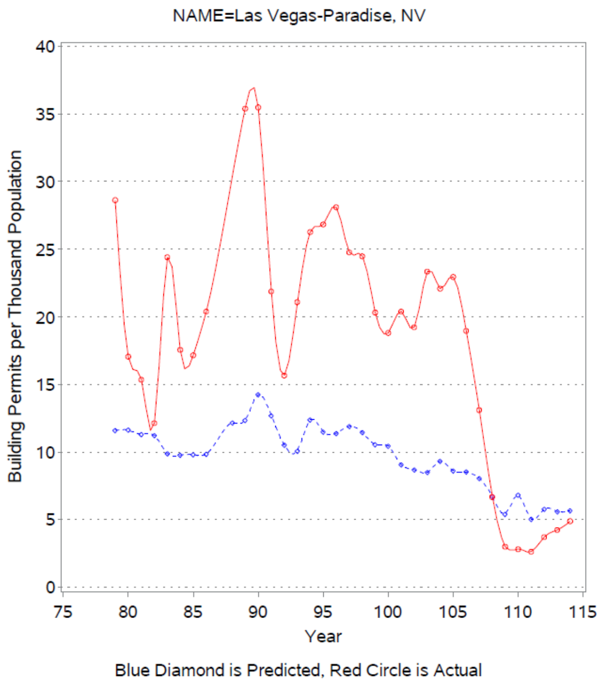


Exhibit 22

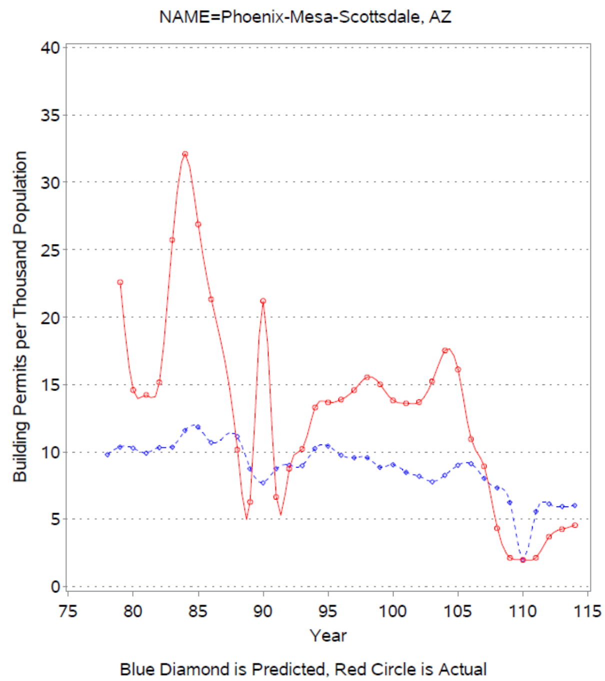


Exhibit 23

Exhibits 22 and 23 present our two "Sand State" price anomalies, i.e. representative of locations that have been flagged as being less elastic than formerly thought. Fast growing, the model predicts on the order of 10 or more permits per thousand, among the highest predictions. But prior to the 2005 construction bust, actual permits were often double or more this high prediction.

So what's going on here? If Las Vegas and Phoenix had problems, they weren't from lack of construction, if we take the model as a benchmark. (Remember, the permits model so far does not perform terribly well, so maybe that's part of the problem). But as Davidoff suggests, a simple supply-demand mismatch may not be behind the problems of markets like these two; it may have more to do with other issues, such as badly underwritten, highly leveraged loans, mortgage fraud, and other issues. We will discuss these in more detail in the next edition.

Other markets with high and volatile starts include Austin, Boise, Fort Myers, Charlotte, Daytona Beach, Fort Collins, Jacksonville, Orlando, Raleigh, and West Palm Beach.

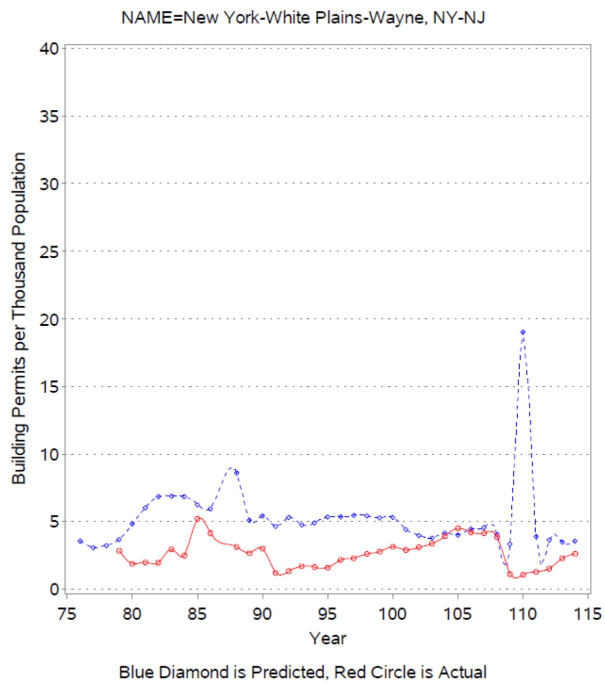


Exhibit 25

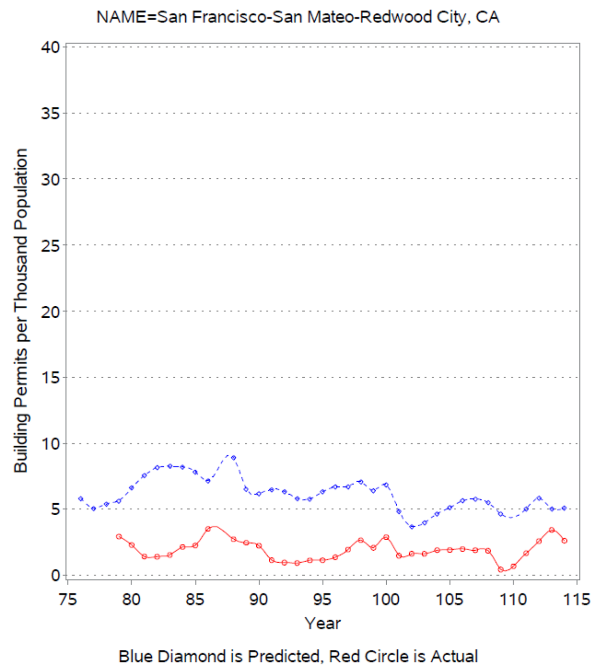


Exhibit 24

Finally, we look at our two representative inelastic markets, New York and San Francisco. The story is clear here, taking these first models at face value. Both New York and, especially San Francisco, seriously underbuild in most years (New York) or all years (San Francisco).[6]

Additional Results for Selected Metro Areas Can Be Found in Appendix 4

We have over 200 metropolitan areas analyzed and we only present 8 in the body of the paper. For convenience we present a number of additional metropolitan area charts in Appendix 4. First we present 9 Wisconsin metropolitan areas. Check the institutional affiliation on the title page for a hint why. All these Wisconsin markets are fairly elastic with levels of construction broadly in line with model predictions; prices are reasonably stable, with moderate boom and bust in some markets in the 2000s decade.

Then we include a pair charts from Minneapolis; along with Chicago, already discussed in the text, we naturally consider these as parts of "Greater Wisconsin." (Except of course during football Sundays.) Minneapolis, like Chicago, exhibits more price volatility than the Wisconsin metropolitan areas, but nothing like the California markets.

[6] The blip in New York's model prediction in the year 2010 is apparently a data error. Will check this and correct in the next edition.

Since Malpezzi has recently moved to Boston and Liang lives in Washington DC – and because these are two very interesting markets in their own right – the next page of Appendix 4 presents results for Boston and Washington. Both exhibit large booms and busts in prices. Washington's construction tracks model predictions better than Boston's, which consistently under-builds according to our benchmark.

West Palm Beach and Dallas are next, we present these because they have prices generally below model predictions and extremely volatile construction permits. West Palm Beach and Dallas's construction volatility is especially extreme in the 1980s. Notice that while West Palm Beach's actual prices are lower than the model forecast, the "actual" price index does show a substantial boom and bust during the 2000s decade. This reminds us that MSA averages, while a major improvement over national prices, still mask a lot. West Palm Beach has one of the most extreme distributions of income and housing quality within the United States; the statistician joke may apply here with particular force.[7]

Finally we present for more California markets: Los Angeles, San Diego, San Jose and Oakland. With the exception of 1980s San Diego, the results support the widely held notion the California consistently under builds and reaps the whirlwind of high in variable prices as a result. Course all these results are subject to change in future editions as we improve the model and incorporate more data. Qualitatively will be very surprised if our Midwest versus California story changes very much. There are lots of anomalies to study further, as David Davidoff has suggested.

Next Steps

Next steps include some additional data cleaning and checking; extending and improving our supply constraint measures; and implementing a switching regression model to test for regime switches based on regulatory regimes.

Please check the blog, "Real Estate and Urban Development Viewpoint," at http://reudviewpoint.blogspot.com for updates, or email me at stephen.malpezzi@wisc.com for updates. Comments are exceedingly welcome!

[7] Statistician joke: What's a statistician? Someone who puts her head in the oven, and feet in the freezer, and says, "on average, I'm comfortable." Then she computes a confidence interval and is clueless.

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Data Appendix

Appendix 1: Summary Statistics on Real House Prices ($2015) by Metro Area

Obs	NAME	NCases	Mean	Std	Max	Median	Min
1	Abilene, TX	27	49678.07	5303.55	58510	48534.0	40805
2	Akron, OH	37	63709.59	9000.08	78255	62852.0	49119
3	Albany-Schenectady-Troy, NY	34	80842.41	18636.43	109693	82684.0	47376
4	Albuquerque, NM	36	85424.36	12432.92	116423	85735.5	70042
5	Alexandria, LA	27	50715.93	7271.55	60522	52369.0	39958
6	Allentown-Bethlehem-Easton, PA-NJ	35	89954.57	17470.77	126224	90425.0	61785
7	Amarillo, TX	33	67730.09	7598.09	76511	70495.0	51625
8	Anchorage, AK	32	109223.19	19300.13	136276	110097.5	77413
9	Ann Arbor, MI	35	88330.03	18636.43	123461	82704.0	59097
10	Appleton, WI	28	64699.89	7196.81	75627	64733.0	53926
11	Asheville, NC	29	83722.79	20282.31	118328	83053.0	56319
12	Atlanta-Sandy Springs-Marietta, GA	38	80184.87	11924.06	102759	75381.5	66145
13	Atlantic City-Hammonton, NJ	30	113389.63	30287.25	181364	101576.5	74948
14	Augusta-Richmond County, GA-SC	34	55011.09	4688.72	66172	53470.0	49211
15	Austin-Round Rock, TX	36	99587.44	18986.26	140464	97927.0	68543
16	Bakersfield, CA	36	86360.92	20480.50	155926	81207.5	68578
17	Baltimore-Towson, MD	37	106129.03	30950.45	175732	95774.0	71429
18	Baton Rouge, LA	35	70805.63	10068.17	85809	72494.0	53425
19	Battle Creek, MI	27	52189.56	8343.86	65200	50657.0	39360
20	Beaumont-Port Arthur, TX	35	46888.40	5206.21	56896	47194.0	39175
21	Bellingham, WA	35	105624.29	35069.62	171241	99880.0	59889
22	Billings, MT	27	73065.22	15440.68	93840	69899.0	49408
23	Binghamton, NY	30	65286.60	6760.89	75930	66856.0	53279
24	Birmingham-Hoover, AL	36	61867.47	8733.54	77438	60941.0	48812
25	Bloomington-Normal, IL	27	67839.48	7307.42	76167	69257.0	54118
26	Boise City-Nampa, ID	34	73608.68	15153.12	114171	71553.0	54210
27	Boston-Quincy, MA	36	194069.36	70355.84	322022	182720.5	82277

Obs	NAME	NCases	Mean	Std	Max	Median	Min
28	Boulder, CO /1	35	131456.91	39699.89	184076	124327.0	83607
29	Bremerton-Silverdale, WA	34	104163.00	28934.01	170813	95191.5	66660
30	Bridgeport-Stamford-Norwalk, CT	37	161077.89	45540.59	252609	158223.0	88701
31	Brownsville-Harlingen, TX	26	45634.42	2904.30	49624	45502.5	40889
32	Buffalo-Niagara Falls, NY	36	63505.67	7586.24	71466	65699.0	47747
33	Burlington, NC	27	65846.81	5235.76	74106	65423.0	59582
34	Cambridge-Newton-Framingham, MA	37	208593.97	72881.81	335965	199808.0	87497
35	Camden, NJ	36	100468.75	24597.98	153551	97134.0	62095
36	Canton-Massillon, OH	36	59821.58	8152.81	73552	59249.5	48010
37	Cape Coral-Fort Myers, FL	31	81768.68	24351.17	160202	70951.0	64131
38	Cedar Rapids, IA	30	61223.77	7280.37	70007	63300.5	47924
39	Charleston-North Charleston-Summerville, SC	35	81724.86	22583.04	127901	70069.0	57095
40	Charlotte-Gastonia-Concord, NC-SC	36	67248.39	9750.26	84658	67233.5	52042
41	Chattanooga, TN-GA	31	61120.13	8553.46	74838	62274.0	48304
42	Chicago-Naperville-Joliet, IL	38	113890.74	27277.67	172676	110623.0	76087
43	Chico, CA	34	94495.50	26964.93	164783	82700.5	66311
44	Cincinnati-Middletown, OH-KY-IN	37	66740.68	7765.79	80512	65081.0	54257
45	Cleveland-Elyria-Mentor, OH	38	75247.71	9808.54	92291	73692.0	60426
46	Colorado Springs, CO	34	91713.74	16686.47	119163	92257.5	66735
47	Columbia, MO	28	55869.21	5606.60	64414	57070.5	46946
48	Columbia, SC	35	65604.74	7082.08	78908	62759.0	56261
49	Columbus, OH	37	65648.86	8533.28	80600	64988.0	53018
50	Corpus Christi, TX	34	60429.91	6978.08	72355	61940.0	49624
51	Dallas-Plano-Irving, TX	38	79892.82	7813.29	93703	81342.0	65007
52	Davenport-Moline-Rock Island, IA-IL	35	59188.74	8340.46	73879	62154.0	44278
53	Dayton, OH	36	57320.67	5994.31	66225	57163.5	45660
54	Decatur, AL	27	56678.81	3496.39	62737	56979.0	51641
55	Deltona-Daytona Beach-Ormond Beach, FL	35	75098.80	19929.93	138529	66564.0	56270
56	Denver-Aurora-Broomfield, CO /1	37	106791.68	25711.46	144725	96229.0	69918
57	Des Moines-West Des Moines, IA	36	64669.08	8184.45	77743	66564.5	53484

Obs	NAME	NCases	Mean	Std	Max	Median	Min
58	Detroit-Livonia-Dearborn, MI	37	56823.41	14024.59	83175	51569.0	38223
59	Duluth, MN-WI	27	64072.70	15834.49	86124	65959.0	40768
60	Eau Claire, WI	30	71675.57	14407.36	90816	76656.5	51854
61	El Paso, TX	32	55265.63	5280.75	66913	53129.5	49174
62	Elkhart-Goshen, IN	29	59052.83	5704.40	67144	58581.0	51260
63	Erie, PA	29	60593.69	6168.72	67160	62890.0	46826
64	Eugene-Springfield, OR	36	83619.42	24989.16	134426	86282.0	48279
65	Fayetteville, NC	27	57246.37	3540.60	63505	56819.0	51791
66	Fayetteville-Springdale-Rogers, AR-MO	31	60890.58	8597.68	79884	60216.0	50687
67	Flint, MI	36	51872.42	10106.43	70202	48157.0	38826
68	Florence, SC	27	54310.07	5421.06	61886	55110.0	46471
69	Fort Collins-Loveland, CO	36	93188.83	22293.27	124613	91639.5	64889
70	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	38	112946.55	35350.85	226444	95468.0	87322
71	Fort Wayne, IN	36	49696.44	3515.12	57901	49178.0	43996
72	Fort Worth-Arlington, TX	36	67946.53	6012.06	78019	68377.5	59018
73	Fresno, CA	36	91809.86	24348.78	170365	83921.0	74042
74	Gainesville, FL	29	65134.34	14738.28	100204	58906.0	51425
75	Gary, IN	35	64400.09	8265.64	77052	65766.0	48969
76	Grand Rapids-Wyoming, MI	35	65508.00	10666.45	84541	62557.0	49791
77	Greeley, CO /1	29	83159.97	16660.40	108170	83524.0	57730
78	Green Bay, WI	28	68502.79	9644.52	83016	68655.5	53942
79	Greensboro-High Point, NC	35	65740.60	6236.16	74575	64394.0	54533
80	Greenville-Mauldin-Easley, SC	34	57840.94	6876.97	68478	58440.5	48777
81	Hagerstown-Martinsburg, MD-WV	26	81157.88	17236.55	124360	74578.5	66075
82	Harrisburg-Carlisle, PA	34	67243.50	8945.23	83568	65994.0	52666
83	Hartford-West Hartford-East Hartford, CT	36	138768.06	27535.33	184691	139851.5	90630
84	Hickory-Lenoir-Morganton, NC	27	64145.41	7062.60	73495	64536.0	53287
85	Honolulu, HI	37	304054.49	102806.01	478869	300162.0	150122
86	Houma-Bayou Cane-Thibodaux, LA	28	62174.54	13099.07	80490	61217.0	44379
87	Houston-Sugar Land-Baytown, TX	37	68187.38	9716.15	83452	70322.0	54375

Obs	NAME	NCases	Mean	Std	Max	Median	Min
88	Huntington-Ashland, WV-KY-OH	27	52674.15	5140.42	59059	53744.0	43980
89	Indianapolis-Carmel, IN	37	58703.08	5827.07	68274	57617.0	49465
90	Jackson, MI	27	53338.81	10494.19	70525	51243.0	37867
91	Jackson, MS	33	58801.42	4255.09	66634	58837.0	51491
92	Jacksonville, FL	35	69670.43	16940.34	114669	61535.0	55355
93	Janesville, WI	29	56468.45	8991.21	69771	57220.0	42025
94	Joplin, MO	27	40338.59	3706.88	45284	41421.0	33983
95	Kalamazoo-Portage, MI	31	61976.23	9305.74	77111	61531.0	47861
96	Kansas City, MO-KS	38	61167.34	7160.50	74869	60176.5	51746
97	Killeen-Temple-Fort Hood, TX	27	55534.04	3610.53	61359	56281.0	48896
98	Knoxville, TN	30	55869.10	7384.02	68914	55080.5	45735
99	Lafayette, LA	33	71120.94	13059.02	91951	72489.0	47286
100	Lake County-Kenosha County, IL-WI	36	119402.86	24359.53	166686	116866.5	81485
101	Lakeland-Winter Haven, FL	31	63053.16	13557.58	102346	57635.0	52160
102	Lancaster, PA	34	79733.91	12307.81	102122	77696.0	59329
103	Lansing-East Lansing, MI	35	58620.91	9359.56	77748	55626.0	47372
104	Las Cruces, NM	29	68489.83	9010.22	89839	64536.0	58638
105	Las Vegas-Paradise, NV	35	87291.26	22742.95	156123	80917.0	57030
106	Lexington-Fayette, KY	34	68880.15	7489.44	81512	65344.0	59823
107	Lima, OH	30	50100.50	5046.25	58807	49602.5	42630
108	Lincoln, NE	31	64109.90	7690.34	75248	66825.0	53616
109	Little Rock-North Little Rock-Conway, AR	36	64652.67	5552.77	74497	64246.5	55041
110	Longview, TX	30	53594.80	6462.34	64122	52955.5	44894
111	Los Angeles-Long Beach-Santa Ana, CA	38	192943.63	74846.72	385147	173038.5	85359
112	Louisville/Jefferson County, KY-IN	37	60793.59	10055.99	75425	60679.0	45875
113	Lubbock, TX	34	53755.38	4167.70	61918	55510.5	45917
114	Macon, GA	33	54761.67	4657.89	63037	53433.0	47988
115	Madison, WI	37	83100.46	18225.79	113316	82255.0	59831
116	Manchester-Nashua, NH	31	125177.26	28186.92	179645	126861.0	81342
117	Mansfield, OH	29	52338.90	7569.76	64483	50659.0	43058

Obs	NAME	NCases	Mean	Std	Max	Median	Min
118	McAllen-Edinburg-Mission, TX	27	45994.00	2351.57	50633	45437.0	42210
119	Medford, OR	30	106175.33	35780.13	188625	101758.5	60075
120	Memphis, TN-MS-AR	36	68764.06	5599.34	78638	67463.5	58841
121	Merced, CA	34	82456.71	28828.46	174253	70557.5	57938
122	Miami-Miami Beach-Kendall, FL	38	135354.92	50262.38	282548	112192.0	89296
123	Midland, TX	32	57016.59	14745.15	88152	48547.0	43337
124	Milwaukee-Waukesha-West Allis, WI	36	82237.75	15903.19	112264	79872.5	60005
125	Minneapolis-St. Paul-Bloomington, MN-WI	37	91953.49	22235.37	139344	80178.0	67288
126	Mobile, AL	30	58970.60	7928.32	75780	57759.5	48217
127	Modesto, CA	36	99595.86	32856.41	202463	87146.0	70978
128	Monroe, LA	28	60326.96	8092.28	69062	62136.5	47799
129	Montgomery, AL	27	58094.19	3444.21	65586	57571.0	53221
130	Nashville-Davidson--Murfreesboro--Franklin, TN	34	72143.24	11987.99	92182	73683.0	55331
131	Nassau-Suffolk, NY	38	219056.87	93993.06	401546	195687.0	88378
132	New Haven-Milford, CT	31	131915.58	26068.27	182508	128779.0	81125
133	New Orleans-Metairie-Kenner, LA	36	77303.75	12337.67	100762	77280.5	56436
134	New York-White Plains-Wayne, NY-NJ	38	234225.95	87144.23	406801	212717.0	112027
135	Newark-Union, NJ-PA	37	188991.03	60046.21	307841	176242.0	93536
136	Niles-Benton Harbor, MI	29	65945.52	12173.63	83517	67240.0	41522
137	Norwich-New London, CT	28	135796.86	23955.49	184115	131089.0	106932
138	Oakland-Fremont-Hayward, CA	38	253277.13	100744.62	498520	228376.5	108921
139	Ocala, FL	27	62426.04	14661.78	101977	55742.0	50899
140	Odessa, TX	31	48397.94	10665.44	69438	41752.0	38193
141	Oklahoma City, OK	36	61217.42	8772.74	77628	63104.0	47757
142	Olympia, WA	32	97879.19	27603.99	153390	96382.5	60677
143	Omaha-Council Bluffs, NE-IA	35	59771.43	7007.06	71324	60044.0	49719
144	Orlando-Kissimmee, FL	35	81127.57	19974.09	143464	72404.0	66573
145	Oxnard-Thousand Oaks-Ventura, CA	37	191975.24	69542.77	372158	175223.0	99160
146	Palm Bay-Melbourne-Titusville, FL	33	71685.42	18018.94	129603	64552.0	58722
147	Pensacola-Ferry Pass-Brent, FL	30	58649.80	11184.17	88295	56535.5	46383

Obs	NAME	NCases	Mean	Std	Max	Median	Min
148	Peoria, IL	34	55894.68	8334.69	65684	59394.0	40586
149	Philadelphia, PA	37	106348.86	30496.00	162627	100923.0	65610
150	Phoenix-Mesa-Scottsdale, AZ	36	91602.75	23779.82	166624	83389.0	69972
151	Pittsburgh, PA	37	59218.78	7455.27	69174	59385.0	46816
152	Portland-Vancouver-Beaverton, OR-WA	37	97849.92	31384.48	162853	96704.0	57697
153	Providence-New Bedford-Fall River, RI-MA	37	118395.30	39674.35	200159	113509.0	61726
154	Provo-Orem, UT	31	84525.16	19128.40	122405	91223.0	56157
155	Pueblo, CO	35	61536.71	9738.98	76194	62056.0	47637
156	Racine, WI	31	77355.35	13771.81	103092	75632.0	58279
157	Raleigh-Cary, NC	36	80455.36	10987.24	98494	81477.5	62760
158	Reading, PA	33	74574.73	10246.60	95371	75095.0	57493
159	Redding, CA	33	90857.82	24808.53	158244	83510.0	65021
160	Reno-Sparks, NV	35	110571.54	27629.26	194229	101745.0	83550
161	Richmond, VA	37	73748.59	14498.72	108058	67057.0	57811
162	Riverside-San Bernardino-Ontario, CA	37	104214.11	33120.00	207311	95252.0	69433
163	Roanoke, VA	33	68499.21	12833.21	91111	67512.0	44299
164	Rochester, MN	30	65907.67	9500.77	81837	66556.0	54960
165	Rochester, NY	35	66286.11	4724.95	74583	66107.0	55057
166	Rockford, IL	35	57879.66	5984.47	68151	58758.0	47363
167	Rockingham County-Strafford County, NH	30	143528.73	32629.69	205342	146810.5	94344
168	Sacramento--Arden-Arcade--Roseville, CA	37	118914.59	38015.63	223908	109306.0	71089
169	Saginaw-Saginaw Township North, MI	33	50279.52	7645.15	63706	47701.0	40848
170	Salem, OR	31	80514.32	20736.70	120505	85308.0	50039
171	Salinas, CA	36	209338.50	88887.94	456311	183607.5	117794
172	Salt Lake City, UT	37	102041.51	26369.44	157288	106140.0	66168
173	San Antonio, TX	34	73670.12	8974.48	87773	75013.5	59114
174	San Diego-Carlsbad-San Marcos, CA	38	164566.97	63526.60	317287	145342.0	79261
175	San Francisco-San Mateo-Redwood City, CA	38	355904.61	156764.29	651500	312165.5	131018
176	San Jose-Sunnyvale-Santa Clara, CA	38	275766.87	118992.28	510656	244822.0	98958
177	Santa Cruz-Watsonville, CA	36	253560.00	101987.19	473394	221468.5	120868

Obs	NAME	NCases	Mean	Std	Max	Median	Min
178	Santa Fe, NM	29	138935.07	30986.18	197435	134893.0	93220
179	Santa Rosa-Petaluma, CA	37	181932.62	69565.33	345493	164144.0	89882
180	Savannah, GA	29	84903.31	18312.61	120907	83103.0	63275
181	Scranton--Wilkes-Barre, PA	29	64957.00	8736.48	78746	64148.0	41278
182	Seattle-Bellevue-Everett, WA	38	138944.50	50413.85	245105	123117.5	63432
183	Sheboygan, WI	27	72501.48	11139.78	88462	73927.0	53910
184	Shreveport-Bossier City, LA	29	62383.48	7595.94	72082	62478.0	50640
185	South Bend-Mishawaka, IN-MI	31	52212.13	5907.17	61099	51390.0	42127
186	Spokane, WA	36	74073.69	15835.32	109325	74344.0	52513
187	Springfield, IL	29	58538.03	2515.24	61643	59451.0	52272
188	Springfield, MA	34	105504.24	25036.24	147017	106262.5	56755
189	Springfield, MO	29	56654.17	4773.72	65476	56589.0	48887
190	St. Cloud, MN	26	62404.92	12031.13	82920	62535.5	46401
191	St. Louis, MO-IL	38	73051.05	10583.16	94652	69182.0	58034
192	State College, PA	25	69437.80	9095.86	81038	68223.0	56321
193	Stockton, CA	36	99381.19	33166.04	201396	88165.0	70758
194	Syracuse, NY	35	60944.29	6038.31	68909	62507.0	49065
195	Tacoma, WA	36	110283.42	32264.43	186373	102828.5	73381
196	Tampa-St. Petersburg-Clearwater, FL	37	78437.59	20572.88	141366	68272.0	59195
197	Toledo, OH	35	60389.34	7667.74	73989	58445.0	50582
198	Trenton-Ewing, NJ	34	136041.91	34794.84	207188	131214.5	80233
199	Tucson, AZ	36	86202.14	20008.52	143040	79587.5	66857
200	Tulsa, OK	36	59060.81	6653.57	69733	60179.0	48067
201	Tuscaloosa, AL	24	62684.13	6721.97	71810	64442.0	49855
202	Tyler, TX	28	56069.79	5631.54	63679	56582.0	47163
203	Utica-Rome, NY	27	58153.33	5519.71	65872	60036.0	48487
204	Vallejo-Fairfield, CA	36	151057.56	53171.53	302746	132868.5	98701
205	Vineland-Millville-Bridgeton, NJ	27	75514.04	13028.38	106534	70220.0	63862
206	Visalia-Porterville, CA	35	80549.83	18082.18	141308	73803.0	67067
207	Waco, TX	27	46969.81	4362.90	52614	47226.0	40091

Obs	NAME	NCases	Mean	Std	Max	Median	Min
208	Washington-Arlington-Alexandria, DC-VA-MD-WV	38	169226.61	56953.56	307711	151953.5	102639
209	Waterloo-Cedar Falls, IA	30	56900.90	11847.35	70418	59425.0	37400
210	Wausau, WI	27	62926.70	8667.50	75213	64459.0	48223
211	West Palm Beach-Boca Raton-Boynton Beach, FL	36	114182.44	33157.37	221141	99863.0	90061
212	Wichita Falls, TX	27	49681.30	3873.35	55348	49939.0	42934
213	Wichita, KS	37	60504.03	4888.77	71210	60678.0	51598
214	Williamsport, PA	24	60273.67	5546.25	68889	58995.0	51690
215	Wilmington, DE-MD-NJ	34	113169.35	26202.24	166151	109067.5	72862
216	Wilmington, NC	29	82378.28	18360.98	121464	82381.0	57767
217	Worcester, MA	34	126708.06	34388.12	193449	126436.0	68370
218	Yakima, WA	27	72510.15	11820.59	88332	75823.0	48001
219	York-Hanover, PA	30	71123.97	10058.69	93083	68125.5	52666
220	Youngstown-Warren-Boardman, OH-PA	28	54441.79	5855.22	62989	54252.5	44952
221	Yuba City, CA	27	83051.74	24168.03	147118	74395.0	61935
222	Yuma, AZ	26	70518.00	15197.76	111038	63638.5	58964

Appendix 2: Summary Statistics on Annual Real House Price Changes by Metro Area

Obs	NAME	NCases	Mean	Std	Max	Median	Min
1	Abilene, TX	26	0.001929	0.04195	0.05327	0.009539	-0.15418
2	Akron, OH	35	-0.000904	0.03820	0.08588	0.009672	-0.08188
3	Albany-Schenectady-Troy, NY	32	0.016519	0.05570	0.17666	-0.007129	-0.04964
4	Albuquerque, NM	34	0.006835	0.04322	0.12104	0.007756	-0.06822
5	Alexandria, LA	26	0.008293	0.02796	0.05041	0.010962	-0.05535
6	Allentown-Bethlehem-Easton, PA-NJ	33	0.005344	0.05466	0.14754	-0.001388	-0.06304
7	Amarillo, TX	31	0.002838	0.03398	0.07767	0.007752	-0.09957
8	Anchorage, AK	30	0.008655	0.05082	0.10722	0.009560	-0.16682
9	Ann Arbor, MI	33	0.003092	0.05489	0.08790	0.010984	-0.11997
10	Appleton, WI	26	0.005335	0.02224	0.04844	0.013577	-0.04201
11	Asheville, NC	27	0.019332	0.03667	0.07855	0.029072	-0.06338
12	Atlanta-Sandy Springs-Marietta, GA	36	0.004733	0.04015	0.08369	0.008519	-0.09419
13	Atlantic City-Hammonton, NJ	28	0.016145	0.06936	0.16561	0.003780	-0.09163
14	Augusta-Richmond County, GA-SC	32	-0.000776	0.03027	0.05071	-0.000065	-0.06791
15	Austin-Round Rock, TX	34	0.020638	0.05297	0.10276	0.017477	-0.12259
16	Bakersfield, CA	34	0.007431	0.10147	0.27655	-0.011350	-0.26249
17	Baltimore-Towson, MD	35	0.016228	0.05577	0.16985	0.010138	-0.08680
18	Baton Rouge, LA	33	0.002302	0.03443	0.08477	0.006814	-0.08694
19	Battle Creek, MI	26	0.006691	0.03980	0.06491	0.013589	-0.06560
20	Beaumont-Port Arthur, TX	33	-0.002877	0.02901	0.05186	0.001036	-0.07585
21	Bellingham, WA	33	0.021618	0.06805	0.22156	0.011269	-0.06736
22	Billings, MT	26	0.020505	0.02845	0.06975	0.021366	-0.04241
23	Binghamton, NY	28	0.001776	0.04480	0.09808	-0.002540	-0.08435
24	Birmingham-Hoover, AL	34	0.001619	0.03352	0.04180	0.008809	-0.08990
25	Bloomington-Normal, IL	26	0.012054	0.01827	0.04852	0.010671	-0.02786
26	Boise City-Nampa, ID	32	0.008873	0.07559	0.20622	0.019073	-0.14899
27	Boston-Quincy, MA	34	0.033927	0.07876	0.22777	0.024781	-0.08884

Obs	NAME	NCases	Mean	Std	Max	Median	Min
28	Boulder, CO /1	33	0.020871	0.04879	0.12740	0.007837	-0.06667
29	Bremerton-Silverdale, WA	32	0.013290	0.06274	0.14840	0.007129	-0.09702
30	Bridgeport-Stamford-Norwalk, CT	35	0.019251	0.07880	0.26157	0.005124	-0.08810
31	Brownsville-Harlingen, TX	24	0.002929	0.01866	0.04343	0.005020	-0.03342
32	Buffalo-Niagara Falls, NY	34	0.006248	0.03404	0.09885	0.003029	-0.06081
33	Burlington, NC	26	0.001503	0.02587	0.06531	-0.003949	-0.04511
34	Cambridge-Newton-Framingham, MA	35	0.033916	0.07640	0.22445	0.024240	-0.08638
35	Camden, NJ	34	0.014330	0.05856	0.12359	-0.002376	-0.07521
36	Canton-Massillon, OH	34	-0.002509	0.03547	0.04749	0.006189	-0.09356
37	Cape Coral-Fort Myers, FL	29	0.013000	0.10796	0.28386	0.012531	-0.29799
38	Cedar Rapids, IA	28	0.008245	0.01833	0.06022	0.009068	-0.02691
39	Charleston-North Charleston-Summerville, SC	33	0.017755	0.06150	0.17997	0.010676	-0.11824
40	Charlotte-Gastonia-Concord, NC-SC	34	0.006909	0.03047	0.04357	0.010278	-0.07249
41	Chattanooga, TN-GA	29	0.008274	0.02310	0.04119	0.018582	-0.04540
42	Chicago-Naperville-Joliet, IL	36	0.009583	0.05269	0.11312	0.015657	-0.09715
43	Chico, CA	32	0.013388	0.08066	0.16702	0.003302	-0.12910
44	Cincinnati-Middletown, OH-KY-IN	35	0.000374	0.03092	0.05772	0.008989	-0.07268
45	Cleveland-Elyria-Mentor, OH	36	-0.001802	0.03898	0.08220	0.013255	-0.09039
46	Colorado Springs, CO	32	0.008884	0.04038	0.08511	0.017352	-0.06941
47	Columbia, MO	26	0.006424	0.02522	0.08729	0.007929	-0.02948
48	Columbia, SC	33	0.001883	0.02477	0.03842	0.002601	-0.05619
49	Columbus, OH	35	0.004386	0.02782	0.05937	0.010283	-0.04572
50	Corpus Christi, TX	32	0.001346	0.03821	0.08157	0.005827	-0.10252
51	Dallas-Plano-Irving, TX	36	0.010997	0.04024	0.10331	0.005158	-0.09225
52	Davenport-Moline-Rock Island, IA-IL	33	-0.002924	0.03907	0.04002	0.000577	-0.10769
53	Dayton, OH	34	-0.004501	0.03622	0.06346	0.003447	-0.10092
54	Decatur, AL	25	-0.000217	0.02159	0.05385	0.004654	-0.03917
55	Deltona-Daytona Beach-Ormond Beach, FL	33	0.006761	0.08972	0.22980	0.004747	-0.19693
56	Denver-Aurora-Broomfield, CO /1	35	0.022085	0.05394	0.17934	0.004240	-0.05981
57	Des Moines-West Des Moines, IA	34	0.000363	0.03664	0.05085	0.012619	-0.11766

Obs	NAME	NCases	Mean	Std	Max	Median	Min
58	Detroit-Livonia-Dearborn, MI	35	0.003653	0.07060	0.13027	0.011793	-0.15335
59	Duluth, MN-WI	26	0.023612	0.03502	0.07271	0.028474	-0.04275
60	Eau Claire, WI	28	0.014960	0.02884	0.07951	0.018326	-0.03037
61	El Paso, TX	30	0.001413	0.03553	0.11798	-0.008333	-0.05773
62	Elkhart-Goshen, IN	27	0.003068	0.02738	0.05802	0.006844	-0.05801
63	Erie, PA	27	0.008998	0.01600	0.03357	0.008255	-0.02085
64	Eugene-Springfield, OR	34	0.009726	0.06858	0.13887	0.024287	-0.14891
65	Fayetteville, NC	25	0.002030	0.01920	0.03654	0.004560	-0.03948
66	Fayetteville-Springdale-Rogers, AR-MO	29	0.007905	0.03720	0.07053	0.013762	-0.07057
67	Flint, MI	34	-0.002927	0.05790	0.09647	0.009344	-0.12238
68	Florence, SC	26	0.006450	0.01975	0.04424	0.009923	-0.04603
69	Fort Collins-Loveland, CO	34	0.015379	0.04442	0.14205	0.004774	-0.06233
70	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	36	0.012231	0.09078	0.23959	0.001666	-0.23907
71	Fort Wayne, IN	34	-0.005586	0.03464	0.08275	-0.004532	-0.11310
72	Fort Worth-Arlington, TX	34	0.002871	0.03344	0.09774	0.001821	-0.09129
73	Fresno, CA	34	0.007784	0.09541	0.22189	-0.009657	-0.22959
74	Gainesville, FL	27	0.008974	0.06350	0.14459	0.014361	-0.09497
75	Gary, IN	33	-0.000980	0.03401	0.05327	0.009873	-0.09279
76	Grand Rapids-Wyoming, MI	33	0.003859	0.03646	0.05865	0.012000	-0.06803
77	Greeley, CO /1	27	0.013358	0.05150	0.11567	0.009011	-0.08311
78	Green Bay, WI	26	0.006535	0.02963	0.08065	0.009233	-0.04232
79	Greensboro-High Point, NC	33	0.000058	0.02557	0.04471	-0.000993	-0.05072
80	Greenville-Mauldin-Easley, SC	32	0.005728	0.02302	0.04323	0.009389	-0.05653
81	Hagerstown-Martinsburg, MD-WV	24	0.008576	0.07355	0.18919	0.006640	-0.13254
82	Harrisburg-Carlisle, PA	32	0.005110	0.03667	0.10149	0.007503	-0.09513
83	Hartford-West Hartford-East Hartford, CT	34	0.010065	0.06543	0.18387	-0.013194	-0.08079
84	Hickory-Lenoir-Morganton, NC	26	0.006233	0.02490	0.04725	0.011161	-0.05998
85	Honolulu, HI	35	0.034874	0.09288	0.20901	0.018436	-0.23318
86	Houma-Bayou Cane-Thibodaux, LA	26	0.016061	0.03794	0.06193	0.022091	-0.12650
87	Houston-Sugar Land-Baytown, TX	35	0.006517	0.04100	0.09477	0.009706	-0.10667

Obs	NAME	NCases	Mean	Std	Max	Median	Min
88	Huntington-Ashland, WV-KY-OH	26	0.005940	0.01731	0.03798	0.006009	-0.02384
89	Indianapolis-Carmel, IN	35	0.002989	0.02784	0.07233	0.004724	-0.08033
90	Jackson, MI	26	0.009821	0.05120	0.06623	0.025211	-0.08504
91	Jackson, MS	31	0.000448	0.02207	0.03447	0.003712	-0.04484
92	Jacksonville, FL	33	0.009839	0.06257	0.14738	0.015426	-0.12095
93	Janesville, WI	27	0.007630	0.03477	0.09525	0.013901	-0.06503
94	Joplin, MO	25	0.005241	0.02251	0.04228	0.007722	-0.03698
95	Kalamazoo-Portage, MI	29	0.006726	0.03076	0.04728	0.011300	-0.05306
96	Kansas City, MO-KS	36	0.003021	0.03505	0.08310	0.003035	-0.07870
97	Killeen-Temple-Fort Hood, TX	26	-0.002386	0.02965	0.03290	0.002525	-0.09155
98	Knoxville, TN	28	0.008455	0.02268	0.04790	0.012224	-0.04025
99	Lafayette, LA	31	0.003418	0.05028	0.06071	0.022081	-0.14424
100	Lake County-Kenosha County, IL-WI	34	0.001367	0.04807	0.07006	0.011654	-0.11321
101	Lakeland-Winter Haven, FL	29	0.001060	0.08217	0.20223	0.001181	-0.15519
102	Lancaster, PA	32	0.006187	0.03564	0.07306	0.001825	-0.08421
103	Lansing-East Lansing, MI	33	-0.003343	0.04662	0.04719	0.011195	-0.13683
104	Las Cruces, NM	27	0.001482	0.04125	0.10147	0.003391	-0.07664
105	Las Vegas-Paradise, NV	33	0.004205	0.11164	0.29270	0.008627	-0.26630
106	Lexington-Fayette, KY	32	0.004622	0.02494	0.05831	0.004842	-0.05376
107	Lima, OH	28	0.002888	0.02164	0.04325	0.005235	-0.03642
108	Lincoln, NE	29	0.006478	0.02116	0.05164	0.007465	-0.02398
109	Little Rock-North Little Rock-Conway, AR	34	0.004241	0.03052	0.09811	0.007098	-0.06273
110	Longview, TX	28	0.004925	0.02963	0.06157	0.009636	-0.09997
111	Los Angeles-Long Beach-Santa Ana, CA	36	0.036227	0.09790	0.22525	0.039000	-0.19694
112	Louisville/Jefferson County, KY-IN	35	0.007258	0.02842	0.05762	0.015179	-0.06862
113	Lubbock, TX	32	-0.001688	0.02230	0.03550	0.003034	-0.05784
114	Macon, GA	31	-0.001173	0.02797	0.04910	0.003420	-0.07815
115	Madison, WI	35	0.011098	0.03587	0.10436	0.013509	-0.06493
116	Manchester-Nashua, NH	29	0.017529	0.07880	0.19165	0.006401	-0.11679
117	Mansfield, OH	27	0.000976	0.03624	0.05355	0.004187	-0.07144

Obs	NAME	NCases	Mean	Std	Max	Median	Min
118	McAllen-Edinburg-Mission, TX	25	0.000635	0.02421	0.03504	0.006444	-0.07102
119	Medford, OR	28	0.026820	0.08080	0.20686	0.039395	-0.13152
120	Memphis, TN-MS-AR	34	-0.001730	0.03371	0.09471	0.001425	-0.06541
121	Merced, CA	32	0.014922	0.12909	0.26704	0.011999	-0.39589
122	Miami-Miami Beach-Kendall, FL	36	0.022705	0.09092	0.21326	0.018460	-0.23911
123	Midland, TX	30	0.006505	0.06272	0.15742	0.008841	-0.11580
124	Milwaukee-Waukesha-West Allis, WI	34	0.002534	0.04102	0.06641	0.014995	-0.09867
125	Minneapolis-St. Paul-Bloomington, MN-WI	35	0.012691	0.05212	0.11106	0.009307	-0.08174
126	Mobile, AL	28	0.002075	0.04237	0.11225	0.005760	-0.07969
127	Modesto, CA	34	0.016190	0.11881	0.23823	0.006044	-0.33602
128	Monroe, LA	26	0.008238	0.02758	0.05008	0.009110	-0.07553
129	Montgomery, AL	26	-0.004184	0.02380	0.03858	0.000582	-0.04895
130	Nashville-Davidson--Murfreesboro--Franklin, TN	32	0.012017	0.03266	0.06284	0.014817	-0.04385
131	Nassau-Suffolk, NY	36	0.030318	0.07964	0.19632	0.013393	-0.07799
132	New Haven-Milford, CT	29	0.012061	0.07593	0.24082	-0.011362	-0.08336
133	New Orleans-Metairie-Kenner, LA	34	0.007088	0.04564	0.14476	0.005949	-0.08360
134	New York-White Plains-Wayne, NY-NJ	36	0.025626	0.07134	0.21948	0.012579	-0.07654
135	Newark-Union, NJ-PA	35	0.022900	0.06893	0.19978	0.020198	-0.08166
136	Niles-Benton Harbor, MI	27	0.015556	0.03327	0.06079	0.024146	-0.05623
137	Norwich-New London, CT	26	0.002008	0.06287	0.13970	-0.011017	-0.08377
138	Oakland-Fremont-Hayward, CA	36	0.037132	0.09226	0.19045	0.044344	-0.19433
139	Ocala, FL	26	0.000849	0.08710	0.20913	0.001164	-0.15404
140	Odessa, TX	29	0.004587	0.06109	0.15227	-0.000131	-0.10792
141	Oklahoma City, OK	34	0.003790	0.03887	0.10164	0.011918	-0.12389
142	Olympia, WA	30	0.019992	0.05577	0.14600	0.016635	-0.09482
143	Omaha-Council Bluffs, NE-IA	33	0.002307	0.02463	0.04443	-0.000180	-0.06021
144	Orlando-Kissimmee, FL	33	0.009983	0.08359	0.23093	0.002372	-0.17590
145	Oxnard-Thousand Oaks-Ventura, CA	35	0.030321	0.09517	0.22462	0.025233	-0.20027
146	Palm Bay-Melbourne-Titusville, FL	31	0.002801	0.09598	0.27065	-0.002248	-0.22034
147	Pensacola-Ferry Pass-Brent, FL	28	0.007348	0.06369	0.22661	0.011560	-0.10913

Obs	NAME	NCases	Mean	Std	Max	Median	Min
148	Peoria, IL	32	-0.000977	0.04228	0.06076	0.008410	-0.14913
149	Philadelphia, PA	35	0.016123	0.05048	0.12910	-0.001566	-0.05138
150	Phoenix-Mesa-Scottsdale, AZ	34	0.015047	0.09663	0.29046	0.026101	-0.20120
151	Pittsburgh, PA	35	0.004494	0.03191	0.06373	0.010535	-0.11449
152	Portland-Vancouver-Beaverton, OR-WA	35	0.021094	0.06535	0.13535	0.029962	-0.12575
153	Providence-New Bedford-Fall River, RI-MA	35	0.018781	0.07566	0.20537	0.001541	-0.10525
154	Provo-Orem, UT	29	0.016366	0.06245	0.13406	0.002222	-0.11514
155	Pueblo, CO	33	-0.000060	0.04353	0.08216	0.003133	-0.11089
156	Racine, WI	29	0.005973	0.03736	0.07092	0.016832	-0.07302
157	Raleigh-Cary, NC	34	0.010181	0.03111	0.07393	0.009219	-0.04464
158	Reading, PA	31	0.006581	0.03903	0.08991	-0.005517	-0.05655
159	Redding, CA	31	0.010658	0.08743	0.18562	-0.003773	-0.14375
160	Reno-Sparks, NV	33	0.005351	0.09523	0.23416	0.009243	-0.18840
161	Richmond, VA	35	0.007880	0.04110	0.11467	0.006431	-0.07477
162	Riverside-San Bernardino-Ontario, CA	35	0.023191	0.11028	0.25456	0.020941	-0.29386
163	Roanoke, VA	31	0.014873	0.03867	0.13192	0.013894	-0.05366
164	Rochester, MN	28	0.007192	0.03110	0.07269	0.008235	-0.05007
165	Rochester, NY	33	0.001566	0.02784	0.08330	-0.006143	-0.03593
166	Rockford, IL	33	-0.010707	0.03592	0.03305	0.001114	-0.10492
167	Rockingham County-Strafford County, NH	28	0.018024	0.07879	0.21388	-0.003347	-0.11055
168	Sacramento--Arden-Arcade--Roseville, CA	35	0.024389	0.09779	0.18725	0.024714	-0.21198
169	Saginaw-Saginaw Township North, MI	31	-0.005663	0.04121	0.05394	0.007340	-0.10013
170	Salem, OR	29	0.016428	0.05563	0.12291	0.020126	-0.10361
171	Salinas, CA	34	0.025159	0.10734	0.22218	0.034002	-0.28782
172	Salt Lake City, UT	35	0.018442	0.06177	0.15573	0.004231	-0.09253
173	San Antonio, TX	32	0.003812	0.03946	0.05284	0.011862	-0.12254
174	San Diego-Carlsbad-San Marcos, CA	36	0.033347	0.09149	0.21671	0.013971	-0.18584
175	San Francisco-San Mateo-Redwood City, CA	36	0.043849	0.08605	0.20696	0.038798	-0.10622
176	San Jose-Sunnyvale-Santa Clara, CA	36	0.046060	0.09350	0.25358	0.033572	-0.12944
177	Santa Cruz-Watsonville, CA	34	0.033111	0.08473	0.20818	0.032856	-0.13269

Obs	NAME	NCases	Mean	Std	Max	Median	Min
178	Santa Fe, NM	27	0.014362	0.04569	0.08320	0.021154	-0.07854
179	Santa Rosa-Petaluma, CA	35	0.032223	0.09300	0.20668	0.017714	-0.18252
180	Savannah, GA	27	0.012081	0.04616	0.08478	0.027099	-0.09099
181	Scranton--Wilkes-Barre, PA	27	0.013845	0.03572	0.09387	0.013719	-0.03981
182	Seattle-Bellevue-Everett, WA	36	0.034038	0.07579	0.22559	0.026962	-0.10866
183	Sheboygan, WI	26	0.008998	0.03336	0.08458	0.012447	-0.05595
184	Shreveport-Bossier City, LA	27	0.003373	0.03037	0.04051	0.007602	-0.09688
185	South Bend-Mishawaka, IN-MI	29	0.004876	0.02332	0.04947	0.010642	-0.04868
186	Spokane, WA	34	0.007430	0.05689	0.12634	0.008434	-0.11488
187	Springfield, IL	27	0.002309	0.01023	0.02164	0.000199	-0.01434
188	Springfield, MA	32	0.017920	0.06302	0.17364	-0.002861	-0.06243
189	Springfield, MO	27	0.001835	0.02768	0.07102	0.003633	-0.05732
190	St. Cloud, MN	24	0.013068	0.04033	0.06693	0.021411	-0.05692
191	St. Louis, MO-IL	36	0.006297	0.03921	0.07441	0.014804	-0.11337
192	State College, PA	23	0.014036	0.01762	0.05699	0.015201	-0.01619
193	Stockton, CA	34	0.017900	0.11657	0.24302	0.018024	-0.35481
194	Syracuse, NY	33	0.003401	0.03471	0.08845	-0.002627	-0.05179
195	Tacoma, WA	34	0.016841	0.06057	0.14039	0.018135	-0.10835
196	Tampa-St. Petersburg-Clearwater, FL	35	0.013738	0.07602	0.18964	0.005368	-0.17739
197	Toledo, OH	33	-0.008985	0.03781	0.04047	0.001970	-0.08391
198	Trenton-Ewing, NJ	32	0.012226	0.06744	0.18420	-0.009643	-0.07158
199	Tucson, AZ	34	0.011034	0.07630	0.20030	0.019010	-0.13268
200	Tulsa, OK	34	0.000295	0.03291	0.07367	0.002361	-0.07625
201	Tuscaloosa, AL	22	0.011531	0.02490	0.05884	0.009466	-0.04844
202	Tyler, TX	26	0.000639	0.03379	0.03976	0.008936	-0.10631
203	Utica-Rome, NY	26	0.002280	0.03315	0.06295	0.004075	-0.07727
204	Vallejo-Fairfield, CA	34	0.022041	0.10885	0.18752	0.025288	-0.28729
205	Vineland-Millville-Bridgeton, NJ	26	0.009694	0.06080	0.15184	-0.007434	-0.09082
206	Visalia-Porterville, CA	33	0.004404	0.09191	0.26812	-0.010575	-0.21280
207	Waco, TX	26	0.001402	0.02768	0.03670	0.007062	-0.09613

Obs	NAME	NCases	Mean	Std	Max	Median	Min
208	Washington-Arlington-Alexandria, DC-VA-MD-WV	36	0.022417	0.06804	0.20529	0.020078	-0.14191
209	Waterloo-Cedar Falls, IA	28	0.016784	0.03329	0.06636	0.021947	-0.09149
210	Wausau, WI	26	0.009193	0.02654	0.05567	0.019464	-0.04008
211	West Palm Beach-Boca Raton-Boynton Beach, FL	34	0.013981	0.09167	0.24245	0.003254	-0.22432
212	Wichita Falls, TX	26	0.001083	0.02625	0.05304	0.007902	-0.07901
213	Wichita, KS	35	-0.002762	0.02655	0.04696	-0.002240	-0.07193
214	Williamsport, PA	22	0.011505	0.01388	0.03299	0.009182	-0.01153
215	Wilmington, DE-MD-NJ	32	0.012774	0.05084	0.11639	0.004989	-0.07201
216	Wilmington, NC	27	0.015314	0.05563	0.15478	0.009993	-0.08715
217	Worcester, MA	32	0.022018	0.07927	0.22058	0.002535	-0.08500
218	Yakima, WA	26	0.013815	0.03865	0.10924	0.008061	-0.05659
219	York-Hanover, PA	28	0.007837	0.04017	0.10464	0.001922	-0.06531
220	Youngstown-Warren-Boardman, OH-PA	26	0.003088	0.02716	0.04561	0.005440	-0.04525
221	Yuba City, CA	26	0.018846	0.11441	0.22675	0.012910	-0.24488
222	Yuma, AZ	24	0.006271	0.08593	0.28084	0.000812	-0.12198

Appendix 3: Annual Building Permits per Thousand Population, by Metro Area

Obs	NAME	NCases	Mean	Std	Max	Median	Min
1	Abilene, TX	27	1.8375	0.7154	3.7273	1.8269	0.72326
2	Akron, OH	35	3.5147	1.6508	5.8072	3.8738	0.87665
3	Albany-Schenectady-Troy, NY	34	3.2979	1.2966	6.6978	3.3097	1.07408
4	Albuquerque, NM	35	6.7712	3.6014	16.6434	6.9053	0.00000
5	Alexandria, LA	27	2.7854	1.3781	6.2497	2.8164	0.32876
6	Allentown-Bethlehem-Easton, PA-NJ	35	3.9714	1.6750	7.4515	4.0287	1.29276
7	Amarillo, TX	33	4.0896	3.1440	18.8099	3.5467	0.73481
8	Anchorage, AK	32	6.0769	8.0700	37.8241	4.0727	0.75012
9	Ann Arbor, MI	35	4.6970	2.9151	9.2834	4.9532	0.72793
10	Appleton, WI	28	6.5945	2.5613	10.6068	7.1312	2.32994
11	Asheville, NC	29	7.1863	2.3908	10.8455	7.2927	2.33600
12	Atlanta-Sandy Springs-Marietta, GA	35	11.5873	5.5293	20.2531	13.2110	1.19941
13	Atlantic City-Hammonton, NJ	30	5.6164	4.2918	16.7488	4.2650	0.00000
14	Augusta-Richmond County, GA-SC	34	6.3000	2.3607	13.3409	5.7303	3.41139
15	Austin-Round Rock, TX	35	13.4432	7.7167	39.4537	12.7345	2.32134
16	Bakersfield, CA	35	6.5600	3.3552	13.5391	5.6739	1.14072
17	Baltimore-Towson, MD	35	4.5985	1.9315	8.6606	4.2750	1.90086
18	Baton Rouge, LA	35	5.6390	2.5841	11.8476	5.2410	1.56247
19	Battle Creek, MI	27	2.4297	1.3972	4.3547	2.8770	0.24263
20	Beaumont-Port Arthur, TX	35	2.8002	1.6042	6.5982	2.4647	0.81293
21	Bellingham, WA	35	8.2987	3.7958	15.0414	8.4321	2.27242
22	Billings, MT	27	4.1440	2.2041	12.7116	3.9010	0.68120
23	Binghamton, NY	30	1.4265	1.0424	4.5553	1.1659	0.34443
24	Birmingham-Hoover, AL	35	4.3952	1.6839	7.2108	4.7569	1.38415
25	Bloomington-Normal, IL	0	.	.	.	.	.
26	Boise City-Nampa, ID	34	10.2476	5.5863	21.2897	9.1391	0.12591
27	Boston-Quincy, MA	35	2.5430	1.0865	6.1582	2.3333	0.78917
28	Boulder, CO /1	35	8.4301	5.0850	21.1006	8.2384	1.13681

Obs	NAME	NCases	Mean	Std	Max	Median	Min
29	Bremerton-Silverdale, WA	34	5.9294	3.1809	12.8935	5.5111	0.00000
30	Bridgeport-Stamford-Norwalk, CT	35	2.8845	1.2867	6.3858	2.5757	1.00722
31	Brownsville-Harlingen, TX	26	6.1807	2.9621	11.2060	6.3948	2.36246
32	Buffalo-Niagara Falls, NY	35	2.0296	0.7617	3.9201	2.1851	0.24273
33	Burlington, NC	27	7.1193	3.0081	14.0523	6.8975	2.32964
34	Cambridge-Newton-Framingham, MA	35	3.2135	1.8290	8.5741	3.5260	0.00000
35	Camden, NJ	35	3.7276	1.4254	7.3790	3.9233	1.48263
36	Canton-Massillon, OH	35	2.6737	1.0512	5.4060	2.8092	0.63463
37	Cape Coral-Fort Myers, FL	31	18.8955	12.9468	54.1602	19.0690	1.60843
38	Cedar Rapids, IA	30	5.1868	1.9791	8.5985	5.2622	1.32712
39	Charleston-North Charleston-Summerville, SC	35	9.1343	4.1332	18.3748	8.4020	3.69913
40	Charlotte-Gastonia-Concord, NC-SC	35	13.1112	5.3214	26.0819	13.9539	2.74416
41	Chattanooga, TN-GA	31	5.1545	1.7209	9.0193	5.3767	2.05251
42	Chicago-Naperville-Joliet, IL	35	2.8677	1.2875	5.0307	3.1500	0.45810
43	Chico, CA	34	5.5743	2.6983	11.1295	5.4284	1.09134
44	Cincinnati-Middletown, OH-KY-IN	35	4.7197	2.0139	8.3829	5.8274	1.50188
45	Cleveland-Elyria-Mentor, OH	35	2.5139	1.0177	3.9883	3.0393	0.53657
46	Colorado Springs, CO	34	9.8156	6.3663	31.1751	9.2848	2.18611
47	Columbia, MO	28	9.1550	3.0603	15.2005	8.5781	3.30731
48	Columbia, SC	35	7.3985	2.3215	11.8217	7.3054	3.73035
49	Columbus, OH	35	6.4200	2.7535	11.6805	7.0220	2.29154
50	Corpus Christi, TX	34	4.9736	3.1996	16.7177	3.9821	0.96670
51	Dallas-Plano-Irving, TX	35	9.9915	5.9217	32.8516	9.2720	3.09566
52	Davenport-Moline-Rock Island, IA-IL	35	2.5928	1.0420	6.0109	2.4078	1.05253
53	Dayton, OH	35	2.8395	1.2093	4.8542	2.9584	0.90539
54	Decatur, AL	27	2.7525	1.3418	5.1466	2.8006	0.61427
55	Deltona-Daytona Beach-Ormond Beach, FL	35	13.1052	8.2139	27.7010	11.3063	1.68106
56	Denver-Aurora-Broomfield, CO /1	35	8.3781	3.9011	16.8849	9.2695	1.54847
57	Des Moines-West Des Moines, IA	35	6.9304	2.2777	12.0514	7.0741	2.51549
58	Detroit-Livonia-Dearborn, MI	35	1.4214	0.7939	3.1011	1.6315	0.00000

Obs	NAME	NCases	Mean	Std	Max	Median	Min
59	Duluth, MN-WI	27	3.4151	1.1774	6.2372	3.6548	1.58630
60	Eau Claire, WI	30	5.2186	2.1982	9.4988	4.8218	2.21203
61	El Paso, TX	32	5.6375	1.9629	12.4118	5.3106	2.90786
62	Elkhart-Goshen, IN	29	5.1956	2.6470	11.1081	5.9340	0.73542
63	Erie, PA	29	2.5394	0.6735	3.6699	2.6547	1.10707
64	Eugene-Springfield, OR	35	4.3600	2.3702	10.8466	4.2638	1.08258
65	Fayetteville, NC	27	7.1763	2.4608	12.5417	6.6348	2.85890
66	Fayetteville-Springdale-Rogers, AR-MO	31	8.9136	4.1973	18.3505	8.1645	2.54400
67	Flint, MI	35	3.0405	2.1085	7.8853	2.8396	0.15649
68	Florence, SC	27	3.5787	1.4129	5.2823	4.2119	1.19712
69	Fort Collins-Loveland, CO	35	10.8034	5.1214	27.1389	11.1952	1.51149
70	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	35	7.4429	4.6428	16.7008	7.3358	0.59384
71	Fort Wayne, IN	35	5.0901	2.3802	10.6725	5.6008	1.22709
72	Fort Worth-Arlington, TX	35	9.1128	6.9794	34.4231	7.2581	2.79638
73	Fresno, CA	35	5.8143	3.0365	12.7074	5.4114	1.72375
74	Gainesville, FL	29	7.4562	3.3469	14.5162	7.8872	1.74021
75	Gary, IN	35	3.8073	1.8756	6.7151	4.6643	0.77027
76	Grand Rapids-Wyoming, MI	35	6.1321	3.1290	10.1568	7.3054	0.32510
77	Greeley, CO /1	29	11.0210	7.7254	26.9141	7.9007	2.07259
78	Green Bay, WI	28	7.2688	2.6645	10.6918	7.8198	2.74622
79	Greensboro-High Point, NC	35	6.7823	2.7036	11.4327	7.2846	2.56322
80	Greenville-Mauldin-Easley, SC	34	8.4842	2.9505	13.5334	9.5182	2.37583
81	Hagerstown-Martinsburg, MD-WV	26	6.3709	3.6176	15.5476	6.3005	1.93293
82	Harrisburg-Carlisle, PA	34	4.2619	1.3854	8.1016	4.2641	1.27920
83	Hartford-West Hartford-East Hartford, CT	35	3.2813	1.9874	9.8860	3.0053	0.92346
84	Hickory-Lenoir-Morganton, NC	27	4.4899	2.0151	7.3563	4.7985	0.92102
85	Honolulu, HI	35	3.4725	1.4809	6.7465	3.4094	1.14150
86	Houma-Bayou Cane-Thibodaux, LA	28	3.5589	1.0649	5.7393	3.6613	1.54962
87	Houston-Sugar Land-Baytown, TX	35	8.5262	4.5636	21.3304	7.7521	2.37649
88	Huntington-Ashland, WV-KY-OH	27	1.9478	0.6759	3.2123	1.9871	0.95738

Obs	NAME	NCases	Mean	Std	Max	Median	Min
89	Indianapolis-Carmel, IN	35	7.2723	2.9027	12.6393	7.3315	2.62388
90	Jackson, MI	27	3.5734	2.0200	6.7076	4.0778	0.35681
91	Jackson, MS	33	5.3416	2.1531	9.3596	5.6993	1.51165
92	Jacksonville, FL	35	9.7117	4.2222	20.0941	8.7013	2.67290
93	Janesville, WI	29	4.2680	2.3037	7.5557	4.8400	0.61865
94	Joplin, MO	27	3.1505	1.1890	5.0560	3.1776	1.14832
95	Kalamazoo-Portage, MI	31	4.1783	1.8553	7.6676	4.8880	1.06874
96	Kansas City, MO-KS	35	5.8945	2.5982	11.6942	6.4904	1.33139
97	Killeen-Temple-Fort Hood, TX	27	6.4209	2.4770	12.7543	5.8104	1.70897
98	Knoxville, TN	30	5.8574	2.0956	9.8789	6.1323	1.57307
99	Lafayette, LA	33	6.8535	3.4554	16.8342	6.4279	2.12132
100	Lake County-Kenosha County, IL-WI	35	5.4377	2.9481	9.4844	6.4615	0.78820
101	Lakeland-Winter Haven, FL	31	8.1839	5.0037	24.4673	7.3620	1.89431
102	Lancaster, PA	34	4.6094	1.9356	8.9718	4.6743	0.00000
103	Lansing-East Lansing, MI	35	3.8006	1.8705	9.1913	4.1996	0.55335
104	Las Cruces, NM	29	6.4582	2.4623	13.2671	5.9526	2.89714
105	Las Vegas-Paradise, NV	35	18.8815	9.6596	40.8366	20.3261	2.61723
106	Lexington-Fayette, KY	34	7.8212	2.8484	13.1746	8.2268	2.87473
107	Lima, OH	30	1.9495	1.0046	4.6267	2.1115	0.00000
108	Lincoln, NE	31	6.4231	1.9442	9.6380	6.6093	2.44285
109	Little Rock-North Little Rock-Conway, AR	35	5.2284	1.6659	8.9023	4.8885	2.35913
110	Longview, TX	30	1.8679	0.7791	3.6438	1.8436	0.72501
111	Los Angeles-Long Beach-Santa Ana, CA	35	2.8251	1.9882	8.9562	2.1463	0.56552
112	Louisville/Jefferson County, KY-IN	35	4.7271	1.8277	8.1829	4.6289	1.31673
113	Lubbock, TX	34	5.5674	3.4019	18.3043	4.9540	1.74133
114	Macon, GA	33	4.6375	1.9524	8.2892	4.6339	0.94834
115	Madison, WI	35	7.1876	2.7253	12.2146	7.5697	2.06458
116	Manchester-Nashua, NH	31	5.0904	4.8430	23.2690	4.5171	0.00000
117	Mansfield, OH	29	2.4984	1.3696	4.6834	2.8018	0.34120
118	McAllen-Edinburg-Mission, TX	27	8.2404	3.9172	14.7211	9.2495	3.18407

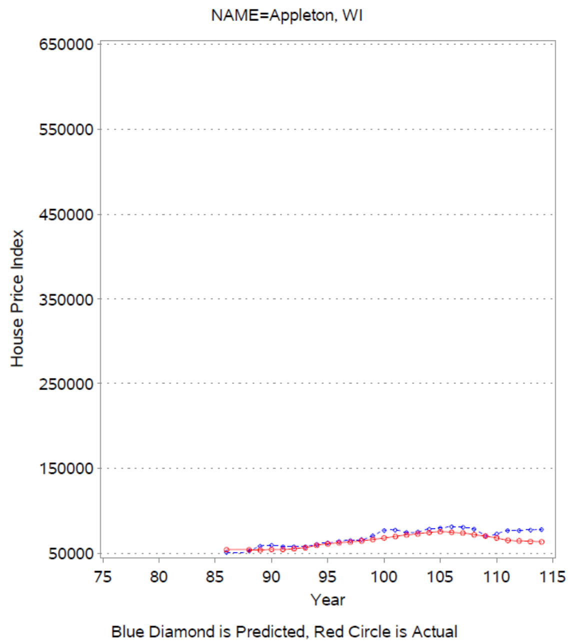
Obs	NAME	NCases	Mean	Std	Max	Median	Min
119	Medford, OR	30	6.7345	3.1945	11.9206	7.4529	1.59475
120	Memphis, TN-MS-AR	35	6.1351	2.7137	10.3235	6.8209	1.55871
121	Merced, CA	34	5.6640	3.6497	15.4056	5.4202	0.40355
122	Miami-Miami Beach-Kendall, FL	0	.	.	.	.	.
123	Midland, TX	32	4.6394	7.0349	39.4007	2.4540	1.08824
124	Milwaukee-Waukesha-West Allis, WI	35	3.3012	1.4600	6.0361	3.8476	0.92520
125	Minneapolis-St. Paul-Bloomington, MN-WI	35	6.4199	2.6030	11.9268	7.1428	1.45146
126	Mobile, AL	30	4.0343	1.7571	6.9045	4.2864	1.20838
127	Modesto, CA	35	6.1067	4.7652	18.7624	4.9771	0.31669
128	Monroe, LA	28	3.1797	1.0671	6.4029	3.2178	1.54168
129	Montgomery, AL	27	4.4824	1.6106	7.9047	4.5123	1.27456
130	Nashville-Davidson--Murfreesboro--Franklin, TN	34	9.2426	4.0068	18.2108	9.6266	2.45940
131	Nassau-Suffolk, NY	35	1.8076	0.8783	4.3836	1.7006	0.47568
132	New Haven-Milford, CT	31	2.7883	1.9555	9.2777	2.3988	0.60023
133	New Orleans-Metairie-Kenner, LA	35	3.9595	1.9141	10.0015	3.3994	1.84904
134	New York-White Plains-Wayne, NY-NJ	35	2.6375	1.0650	5.2027	2.6066	1.06101
135	Newark-Union, NJ-PA	35	3.3886	1.2942	7.2361	3.4147	1.14246
136	Niles-Benton Harbor, MI	29	2.9191	1.2565	5.0901	3.3217	0.74779
137	Norwich-New London, CT	28	3.3211	1.7110	8.3632	3.1943	0.76268
138	Oakland-Fremont-Hayward, CA	35	4.2447	2.3739	11.8560	3.9342	1.01392
139	Ocala, FL	27	11.1162	7.3192	24.7022	10.3658	1.08543
140	Odessa, TX	31	2.0145	2.1458	8.6358	1.0349	0.00000
141	Oklahoma City, OK	35	6.1237	3.8984	22.0964	5.2676	2.13985
142	Olympia, WA	32	8.6806	2.9688	13.7313	8.8114	3.76817
143	Omaha-Council Bluffs, NE-IA	35	5.6622	1.6363	8.1814	5.2104	2.16101
144	Orlando-Kissimmee, FL	35	14.0115	6.5030	27.7403	14.0717	2.15470
145	Oxnard-Thousand Oaks-Ventura, CA	35	4.4061	3.0861	12.2079	3.3221	0.43837
146	Palm Bay-Melbourne-Titusville, FL	33	10.4660	7.6819	30.6494	9.0208	0.00000
147	Pensacola-Ferry Pass-Brent, FL	30	7.4945	3.3362	16.8561	7.4951	2.28960
148	Peoria, IL	34	2.7182	1.4405	5.2731	2.6244	0.18074

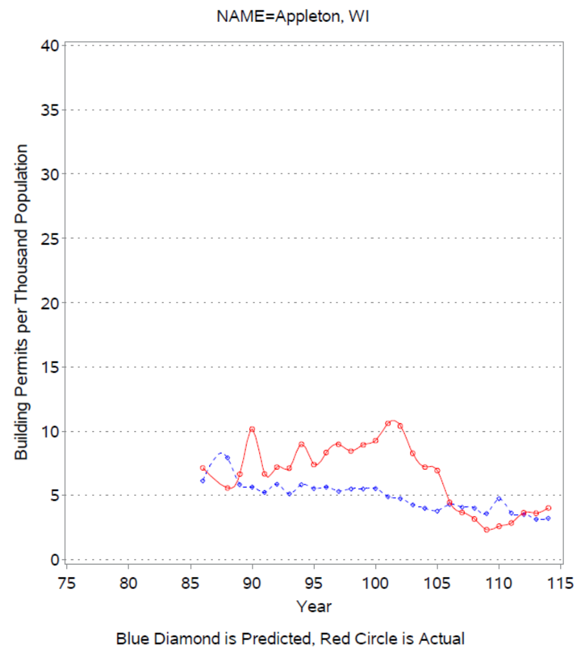
Obs	NAME	NCases	Mean	Std	Max	Median	Min
149	Philadelphia, PA	35	0.6731	0.3599	2.0783	0.6047	0.24348
150	Phoenix-Mesa-Scottsdale, AZ	35	12.9978	7.3140	32.1308	13.6973	1.97207
151	Pittsburgh, PA	35	2.2014	0.6297	3.2343	2.3413	0.31991
152	Portland-Vancouver-Beaverton, OR-WA	35	6.8578	2.7860	11.8591	7.1509	1.79317
153	Providence-New Bedford-Fall River, RI-MA	35	2.6741	1.5212	8.0357	2.6759	0.73643
154	Provo-Orem, UT	31	8.1828	3.7562	15.5663	9.2165	2.45482
155	Pueblo, CO	35	4.8134	3.5864	11.6702	3.1032	0.00000
156	Racine, WI	31	3.6423	1.9132	6.5575	4.2000	0.00000
157	Raleigh-Cary, NC	35	14.3638	5.9750	29.6240	14.2357	4.34703
158	Reading, PA	33	3.6423	1.8189	6.6590	4.1862	0.00000
159	Redding, CA	33	5.3345	3.2295	11.4612	5.4103	0.00000
160	Reno-Sparks, NV	35	9.3262	5.6553	21.9881	10.5829	0.00000
161	Richmond, VA	35	6.8286	2.6198	12.4443	6.8689	2.10139
162	Riverside-San Bernardino-Ontario, CA	35	8.8779	7.1847	28.8953	6.5585	1.10159
163	Roanoke, VA	33	4.4307	1.6510	7.1498	5.1847	1.37875
164	Rochester, MN	30	7.3294	3.3984	13.0251	6.9448	1.84220
165	Rochester, NY	35	2.9602	1.0780	5.6290	2.9465	1.25083
166	Rockford, IL	35	4.3727	2.5849	7.9255	5.4855	0.18410
167	Rockingham County-Strafford County, NH	30	5.4217	4.1259	18.9325	4.5929	0.00000
168	Sacramento--Arden-Arcade--Roseville, CA	35	7.8064	4.7431	19.0588	6.4023	1.14516
169	Saginaw-Saginaw Township North, MI	33	2.0617	1.1724	4.6301	2.3166	0.00000
170	Salem, OR	31	5.0348	2.4505	10.3958	5.4599	1.09428
171	Salinas, CA	35	3.4658	2.1021	8.3937	3.0967	0.37024
172	Salt Lake City, UT	35	6.3961	2.8920	16.0074	6.4078	2.51591
173	San Antonio, TX	34	6.4574	3.3669	14.6605	6.2897	1.25742
174	San Diego-Carlsbad-San Marcos, CA	35	5.5993	4.7148	20.0880	4.3450	0.96470
175	San Francisco-San Mateo-Redwood City, CA	35	1.9006	0.7380	3.5010	1.8923	0.42127
176	San Jose-Sunnyvale-Santa Clara, CA	35	3.7464	1.5066	6.9259	3.5242	0.59466
177	Santa Cruz-Watsonville, CA	35	3.1711	2.0711	8.7535	2.3965	0.58154
178	Santa Fe, NM	29	3.7027	2.3174	8.6426	3.7819	0.64645

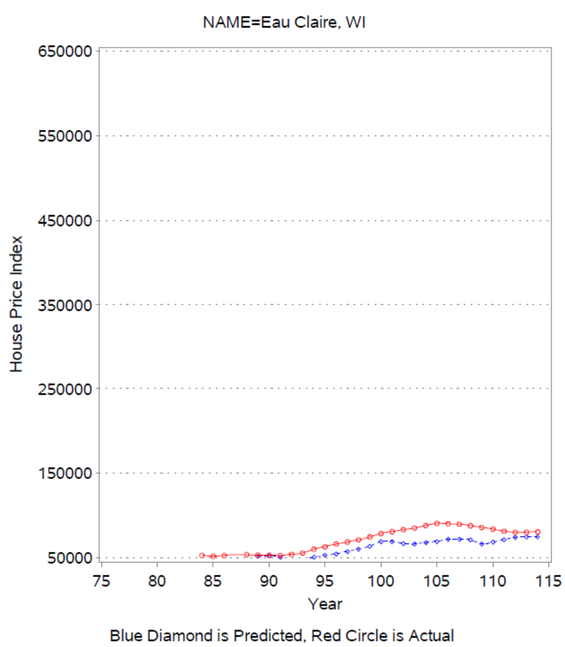
Obs	NAME	NCases	Mean	Std	Max	Median	Min
179	Santa Rosa-Petaluma, CA	35	6.1681	4.3535	17.3219	4.8772	0.93624
180	Savannah, GA	29	8.0795	2.8558	15.1203	8.2829	3.72928
181	Scranton--Wilkes-Barre, PA	29	2.2713	0.8173	4.1087	2.2797	0.77864
182	Seattle-Bellevue-Everett, WA	35	7.5469	2.9594	14.6683	6.8483	2.05744
183	Sheboygan, WI	27	4.2524	2.1613	6.6836	5.0656	0.54795
184	Shreveport-Bossier City, LA	29	3.4206	1.3922	6.8083	3.1953	1.13883
185	South Bend-Mishawaka, IN-MI	31	3.7146	1.6791	6.2686	4.3279	0.00000
186	Spokane, WA	35	6.1681	2.4263	13.0258	5.7525	2.74164
187	Springfield, IL	29	4.5081	1.7626	7.7014	4.7243	1.47660
188	Springfield, MA	34	1.9834	1.1986	5.9267	1.8473	0.72426
189	Springfield, MO	29	7.2885	2.7439	12.7756	7.0962	2.77559
190	St. Cloud, MN	26	6.5165	2.8115	11.3204	7.2872	1.66000
191	St. Louis, MO-IL	35	4.0957	1.4476	7.1917	4.3889	1.57600
192	State College, PA	25	4.7282	1.4434	7.2685	4.8092	1.67536
193	Stockton, CA	35	6.3347	3.5074	14.4126	6.1711	1.17358
194	Syracuse, NY	35	2.4883	0.8750	5.0090	2.3757	1.52618
195	Tacoma, WA	35	6.9714	2.4628	13.1216	7.2960	2.38845
196	Tampa-St. Petersburg-Clearwater, FL	35	9.0088	4.8544	18.6030	8.0704	2.24293
197	Toledo, OH	35	2.9184	1.2216	5.7676	3.0082	0.81075
198	Trenton-Ewing, NJ	34	3.2342	2.1744	11.4265	3.1383	0.73453
199	Tucson, AZ	35	9.2241	5.4762	21.6843	8.6312	1.97349
200	Tulsa, OK	35	5.2756	2.6906	15.5788	4.5053	2.01937
201	Tuscaloosa, AL	24	5.6084	2.3379	12.8630	4.9077	2.70746
202	Tyler, TX	28	2.3891	1.1128	4.6843	2.1463	0.76884
203	Utica-Rome, NY	27	1.6216	0.6294	3.8688	1.4506	0.79419
204	Vallejo-Fairfield, CA	35	6.4610	5.3373	20.1632	5.3170	0.92859
205	Vineland-Millville-Bridgeton, NJ	27	2.5578	1.1500	4.7885	2.1729	1.15391
206	Visalia-Porterville, CA	35	5.2152	2.1394	11.5006	5.2092	1.49210
207	Waco, TX	27	3.3330	1.3938	6.9715	2.9052	1.08099
208	Washington-Arlington-Alexandria, DC-VA-MD-WV	35	6.7549	2.3931	11.7093	7.2804	2.32010

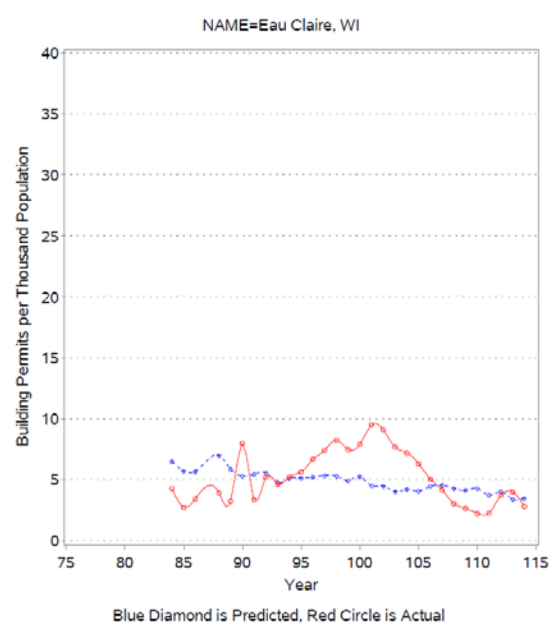
Obs	NAME	NCases	Mean	Std	Max	Median	Min
209	Waterloo-Cedar Falls, IA	30	2.4873	1.1435	4.5409	2.2927	0.25743
210	Wausau, WI	27	5.6311	2.3640	11.0364	5.8447	1.95428
211	West Palm Beach-Boca Raton-Boynton Beach, FL	35	13.5243	11.3648	47.8951	9.5862	1.11801
212	Wichita Falls, TX	27	2.0246	1.0993	5.1674	1.6031	0.66154
213	Wichita, KS	35	5.1527	1.9178	9.8078	5.1767	1.69337
214	Williamsport, PA	24	2.3215	0.6582	3.2967	2.5059	1.00993
215	Wilmington, DE-MD-NJ	34	4.4321	2.2592	10.7501	4.9345	0.77516
216	Wilmington, NC	29	9.8668	3.6909	17.6771	9.9068	1.66420
217	Worcester, MA	34	3.8150	2.6828	12.6470	4.2554	0.46986
218	Yakima, WA	27	2.9412	1.0038	5.2693	2.9742	1.44913
219	York-Hanover, PA	30	5.3390	2.3101	8.8021	5.8228	0.00000
220	Youngstown-Warren-Boardman, OH-PA	28	2.0300	0.9477	3.1184	2.2558	0.45548
221	Yuba City, CA	27	5.2911	5.0036	20.3025	3.6579	0.69201
222	Yuma, AZ	26	6.6814	3.3191	15.5172	5.9648	1.78350

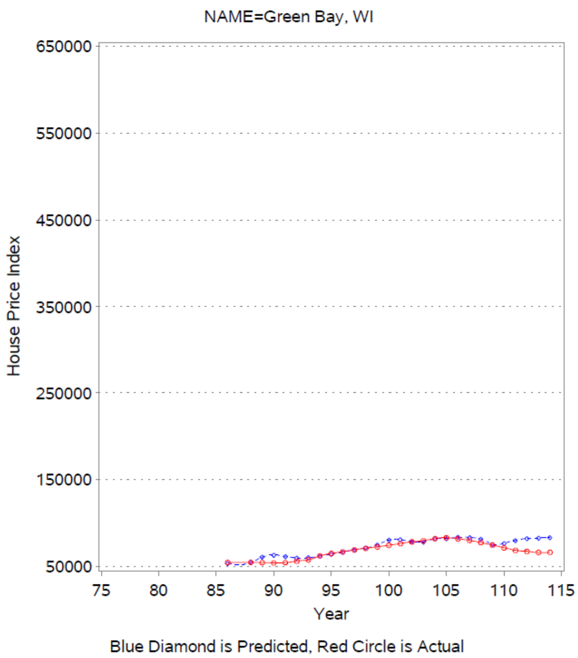
Appendix 4: Selected MSA Additional Price and Permits Charts







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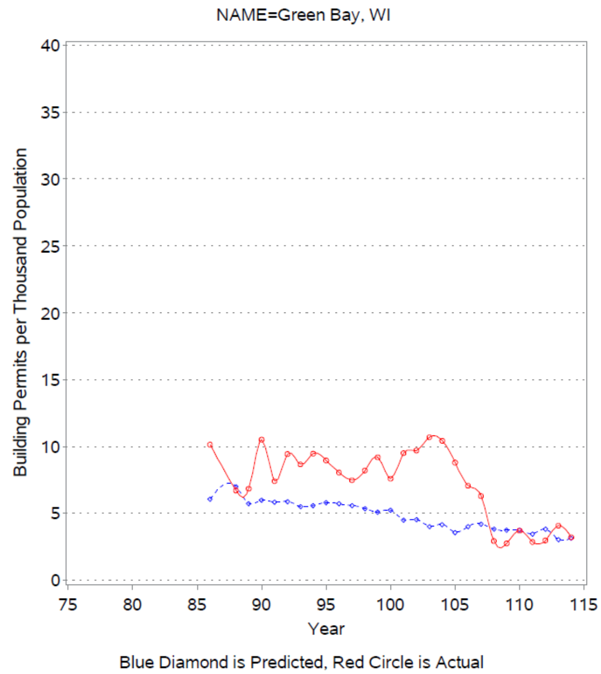
Year
Blue Diamond is Predicted, Red Circle is Actual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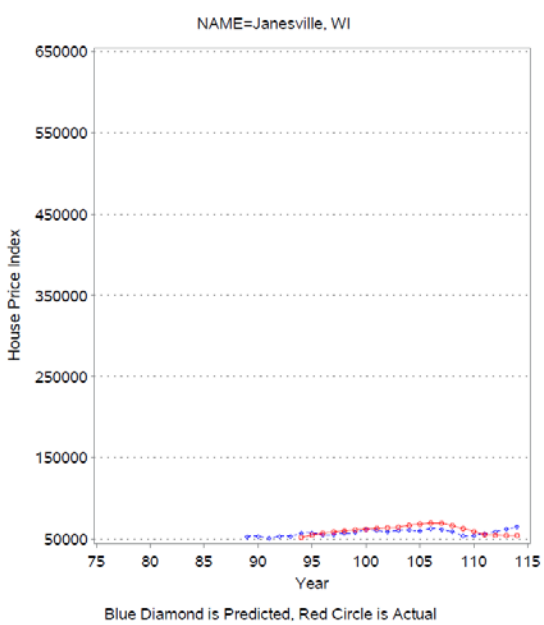
Building Permits per Thousand Population
Year
Blue Diamond is Predicted, Red Circle is Actual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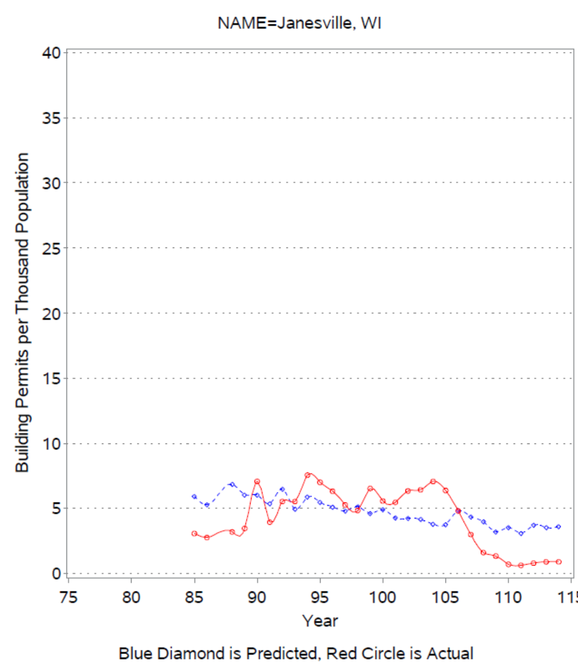
Blue Diamond is Predicted, Red Circle is Actual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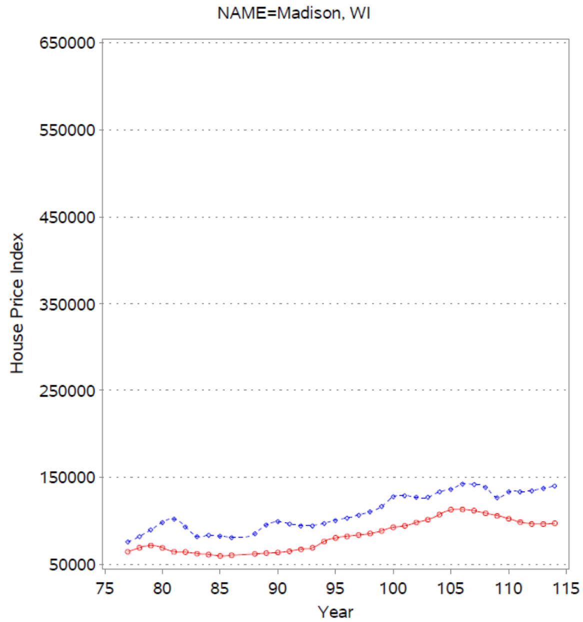
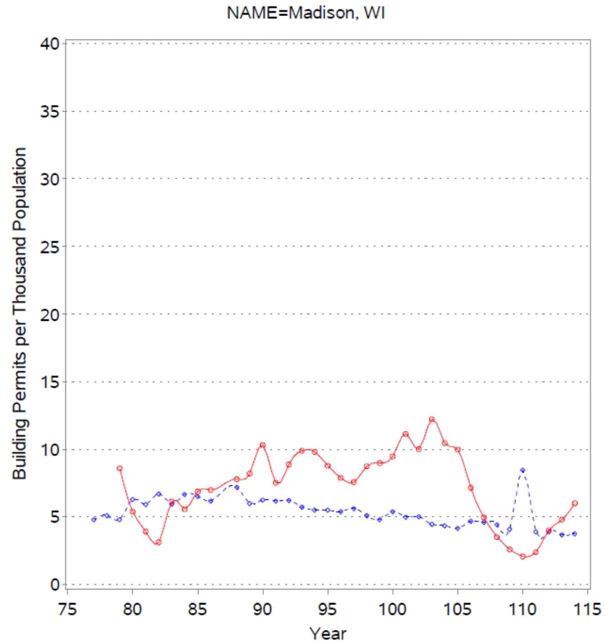
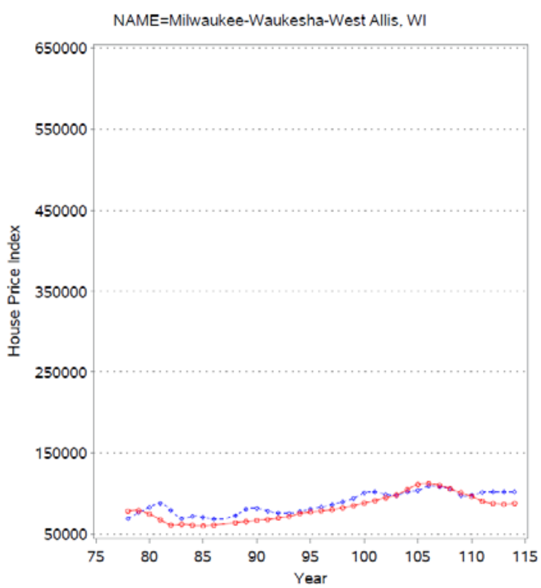
Building Permits per Thousand Population
Year
Blue Diamond is Predicted, Red Circle is Actual



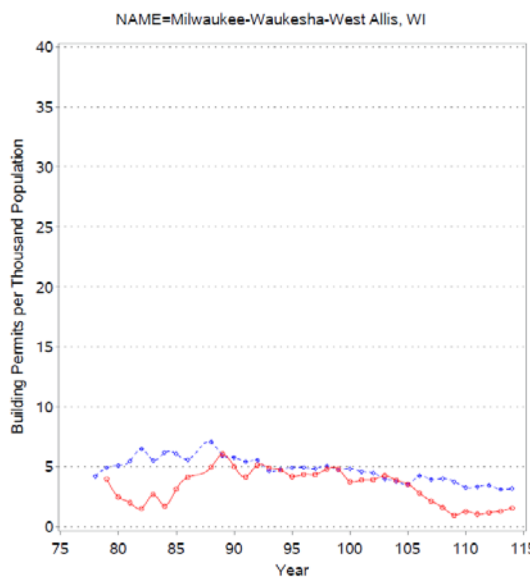
Blue Diamond is Predicted, Red Circle is Actual



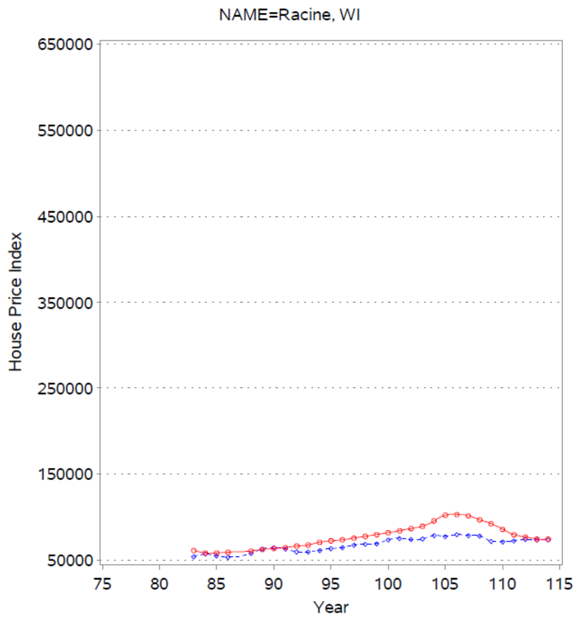
Blue Diamond is Predicted, Red Circle is Actual



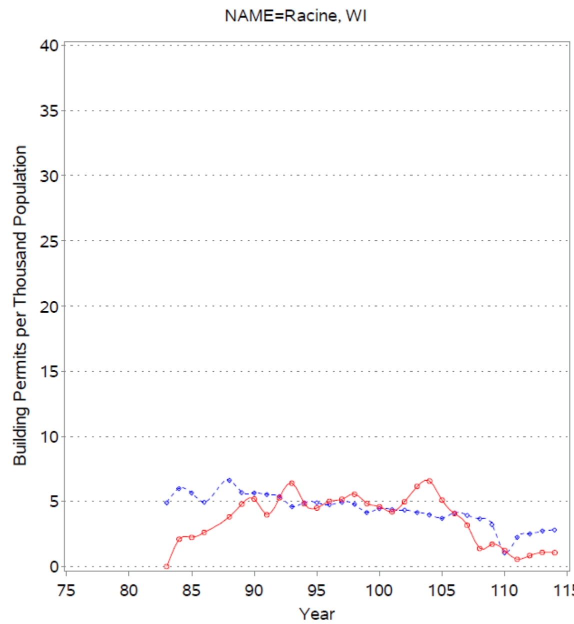
Blue Diamond is Predicted, Red Circle is Actual



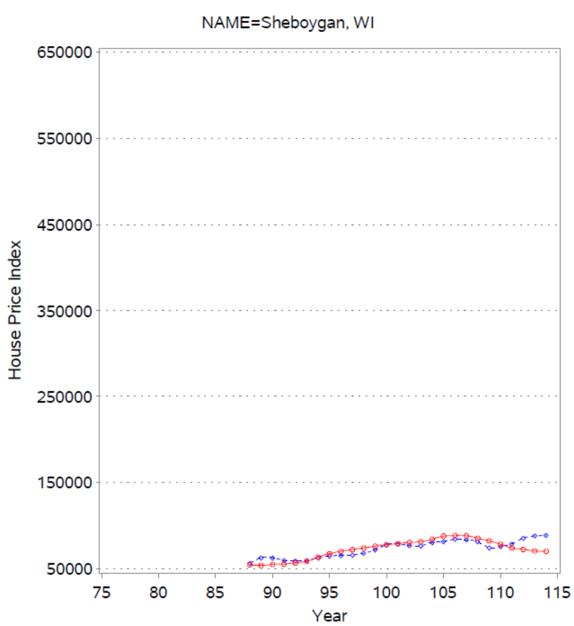
Blue Diamond is Predicted, Red Circle is Actual



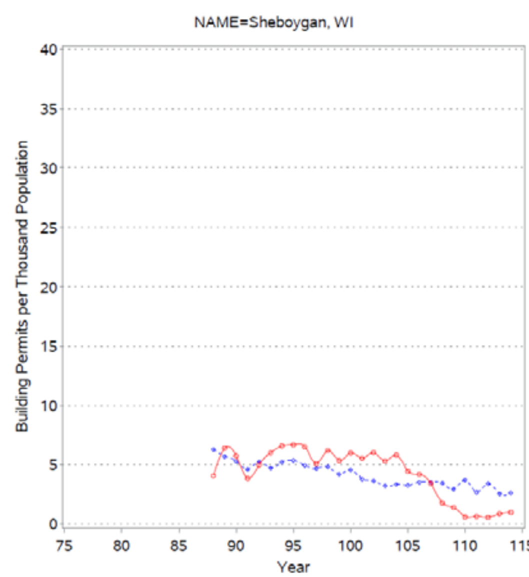
Blue Diamond is Predicted, Red Circle is Actual



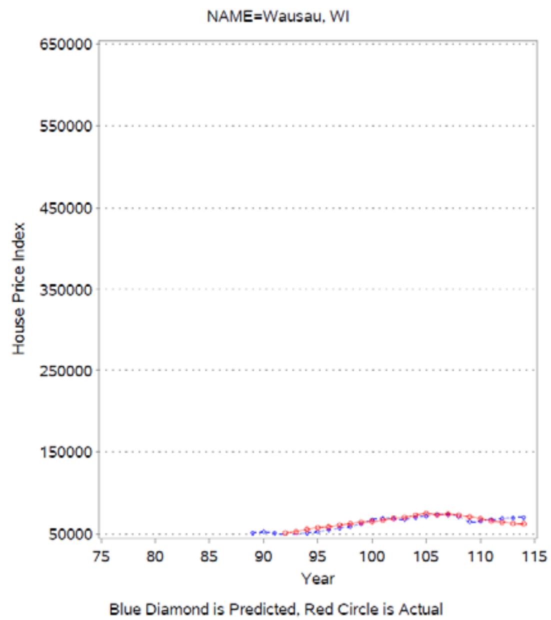
Blue Diamond is Predicted, Red Circle is Actual

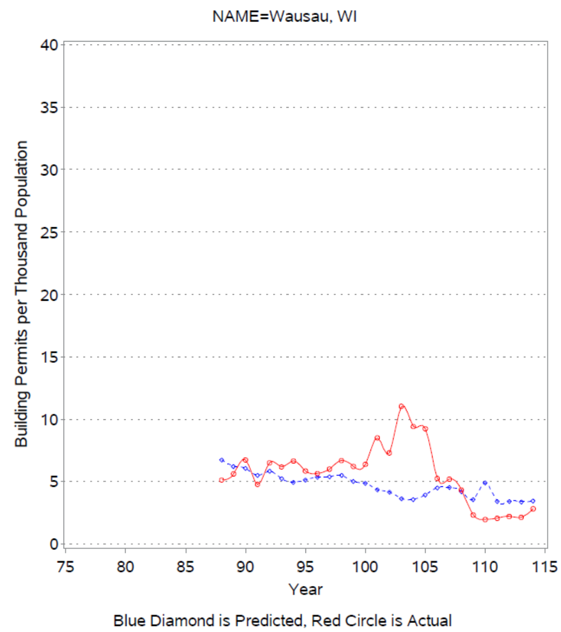


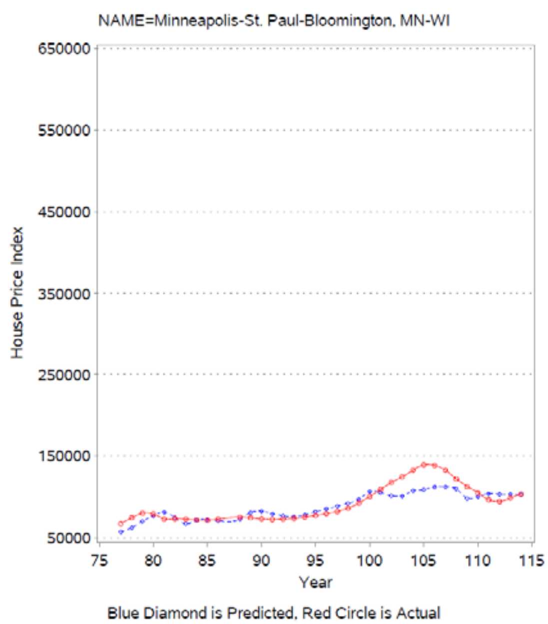
Blue Diamond is Predicted, Red Circle is Actual

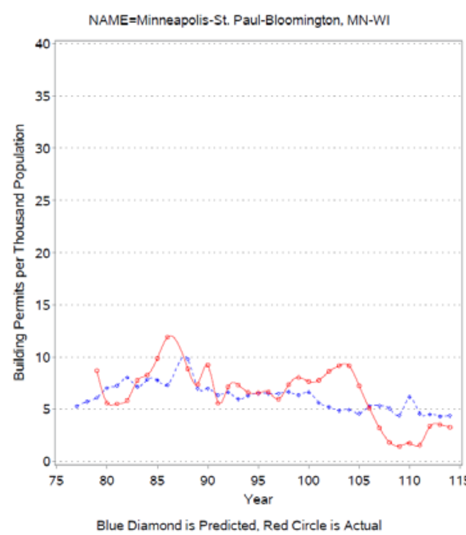


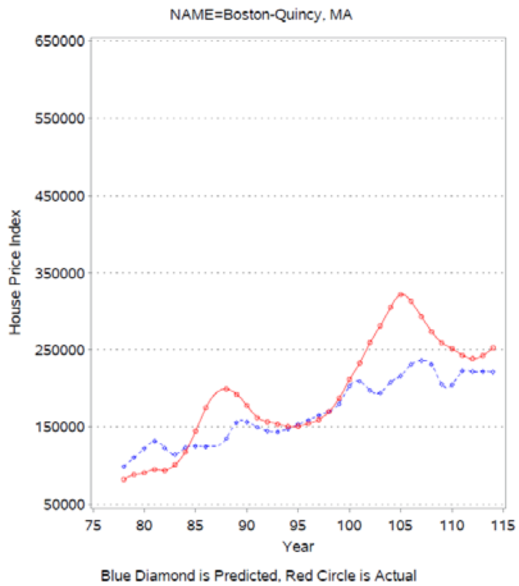
Blue Diamond is Predicted, Red Circle is Actual


NAME=Wausau, WI
House Price Index
650000
550000
450000
350000
250000
150000
50000
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual

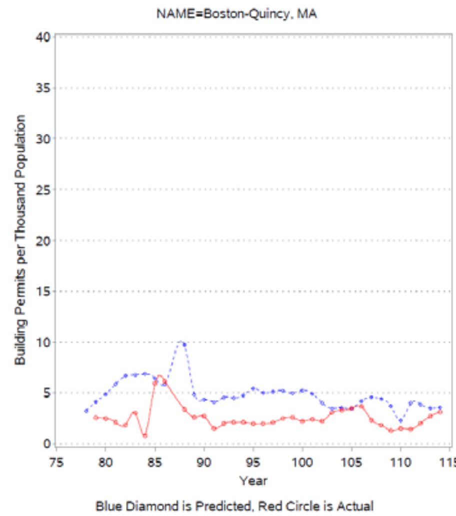

NAME=Wausau, WI
Building Permits per Thousand Population
40
35
30
25
20
15
10
5
0
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual


NAME=Minneapolis-St. Paul-Bloomington, MN-WI
House Price Index
650000
550000
450000
350000
250000
150000
50000
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual

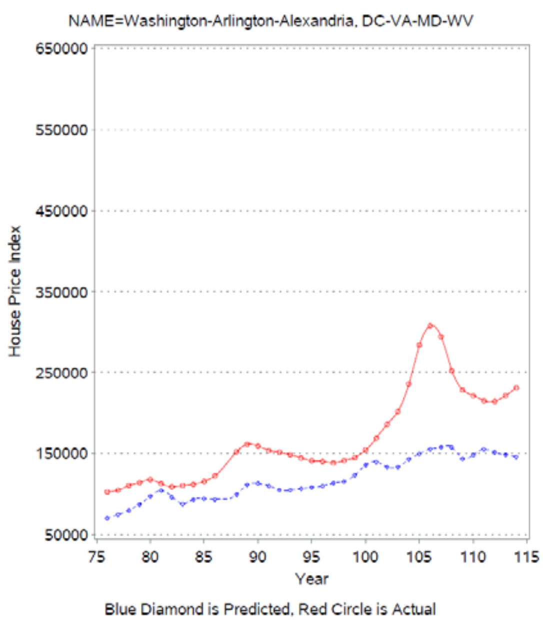

NAME=Minneapolis-St. Paul-Bloomington, MN-WI
Building Permits per Thousand Population
40
35
30
25
20
15
10
5
0
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual



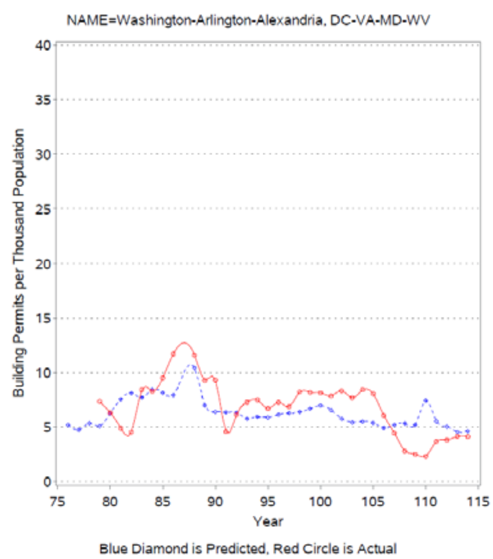
NAME=Boston-Quincy, MA
House Price Index
Year
Blue Diamond is Predicted, Red Circle is Actual



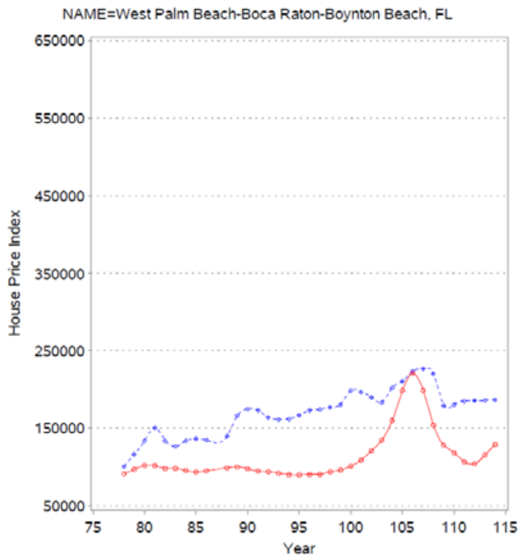
NAME=Boston-Quincy, MA
Building Permits per Thousand Population
Year
Blue Diamond is Predicted, Red Circle is Actual



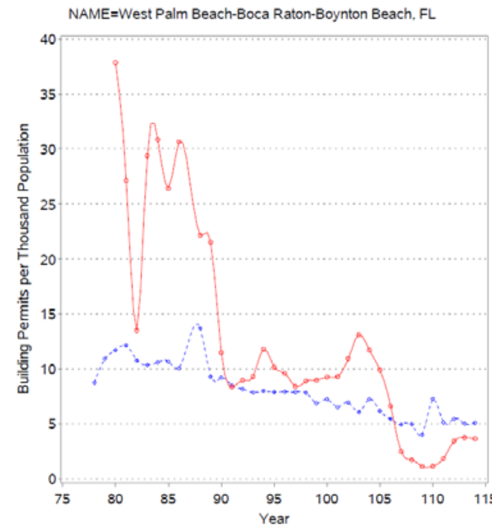
NAME=Washington-Arlington-Alexandria, DC-VA-MD-WV
House Price Index
Year
Blue Diamond is Predicted, Red Circle is Actual



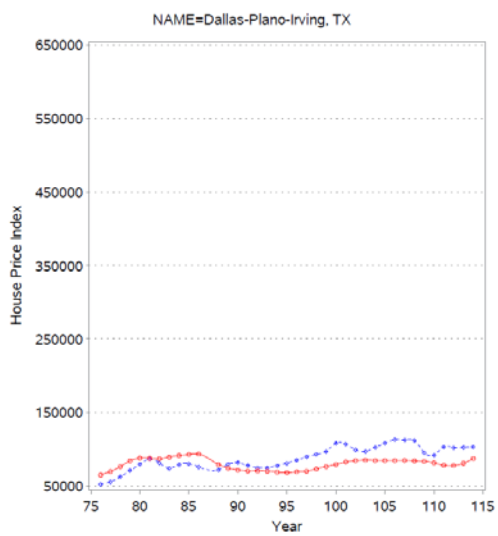
NAME=Washington-Arlington-Alexandria, DC-VA-MD-WV
Building Permits per Thousand Population
Year
Blue Diamond is Predicted, Red Circle is Actual



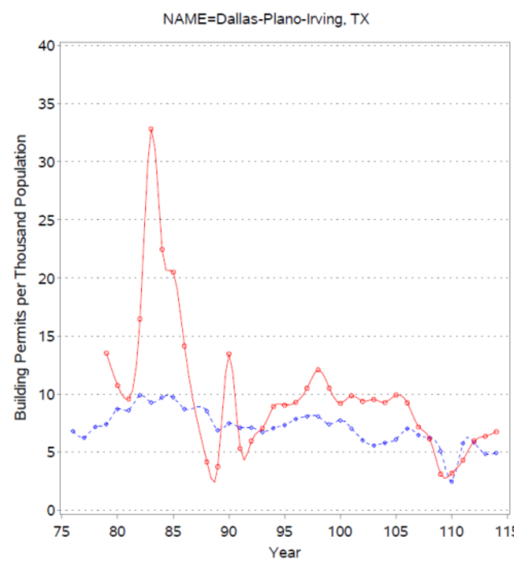
Blue Diamond is Predicted, Red Circle is Actual



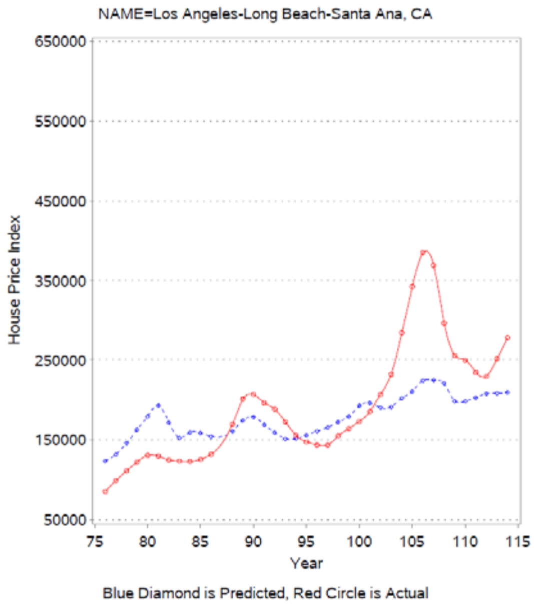
Blue Diamond is Predicted, Red Circle is Actual

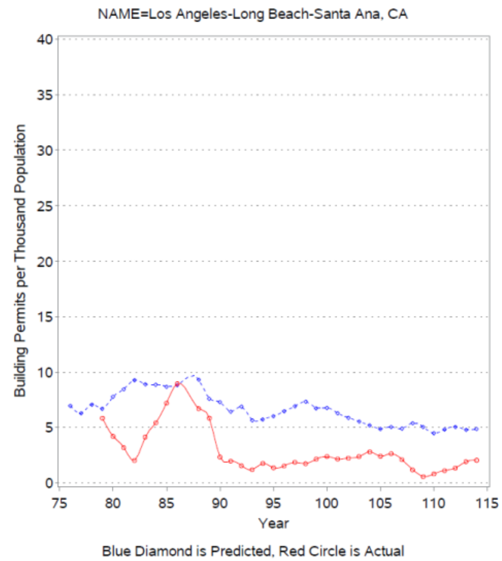


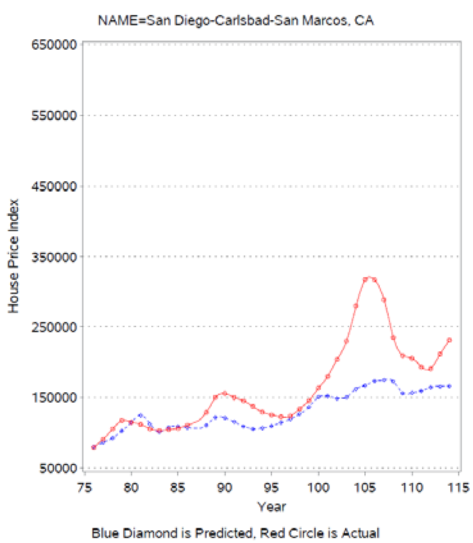
Blue Diamond is Predicted, Red Circle is Actual

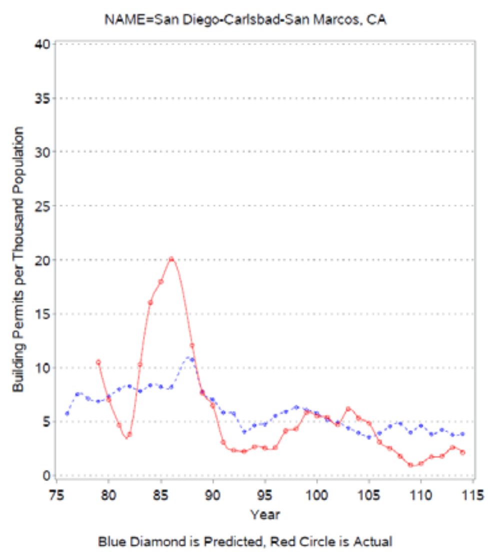


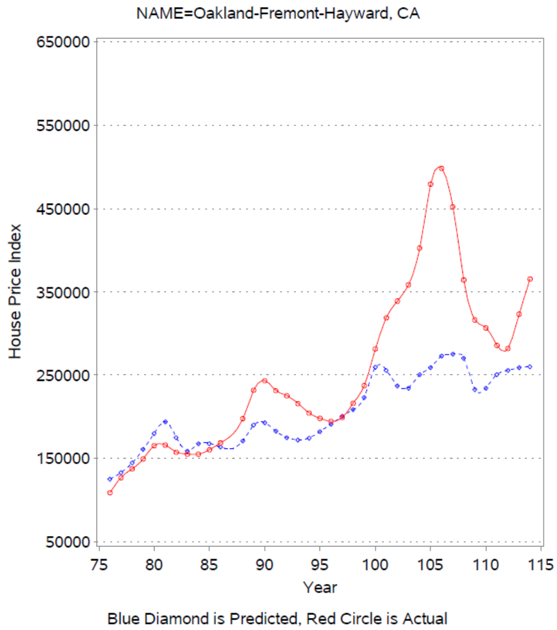
Blue Diamond is Predicted, Red Circle is Actual

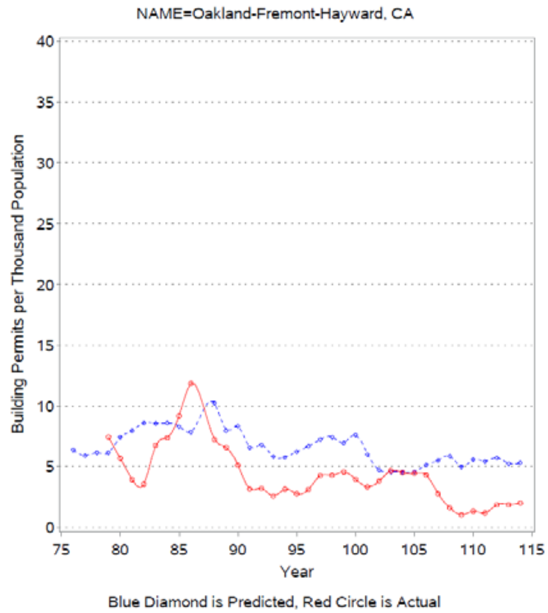

NAME=Los Angeles-Long Beach-Santa Ana, CA
House Price Index
650000
550000
450000
350000
250000
150000
50000
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual

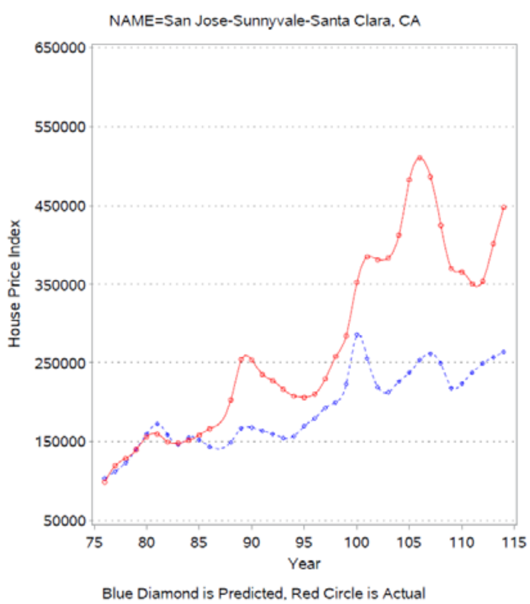

NAME=Los Angeles-Long Beach-Santa Ana, CA
Building Permits per Thousand Population
40
35
30
25
20
15
10
5
0
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual

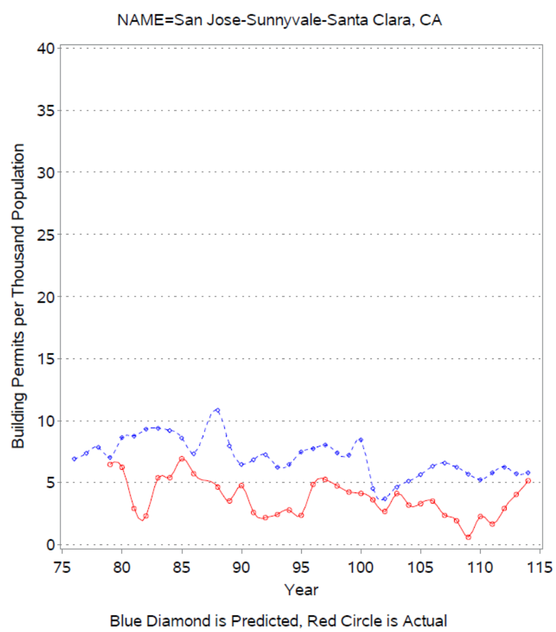

NAME=San Diego-Carlsbad-San Marcos, CA
House Price Index
650000
550000
450000
350000
250000
150000
50000
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual


NAME=San Diego-Carlsbad-San Marcos, CA
Building Permits per Thousand Population
40
35
30
25
20
15
10
5
0
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual


NAME=Oakland-Fremont-Hayward, CA
House Price Index
650000
550000
450000
350000
250000
150000
50000
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual


NAME=Oakland-Fremont-Hayward, CA
Building Permits per Thousand Population
40
35
30
25
20
15
10
5
0
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual


NAME=San Jose-Sunnyvale-Santa Clara, CA
House Price Index
650000
550000
450000
350000
250000
150000
50000
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual


NAME=San Jose-Sunnyvale-Santa Clara, CA
Building Permits per Thousand Population
40
35
30
25
20
15
10
5
0
75 80 85 90 95 100 105 110 115
Year
Blue Diamond is Predicted, Red Circle is Actual