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ABSTRACT

MSA-level estimates of a housing supply schedule must offer a solution to the twin problems of simultaneity and stationarity that plague the time series data for local housing prices and stock. An Error Correction Model (ECM) is shown to provide a solution to stationarity, but not simultaneity. A Vector Error Correction Model (VECM) is suggested to handle both the stationarity and endogeneity problems. Such models also nicely distinguish between (very) long run elasticities and a variety of short term impacts. We estimate these models separately for 68 US MSA using quarterly data on housing prices and residential construction permits since 1980. The results provide long run supply elasticity estimates for each market that are better bounded than previous panel-based attempts and also correspond with much conventional thought. We find these elasticities are well explained by geographic and regulatory barriers, and that inelastic markets exhibit greater price volatility over the last two decades. Using the models' short run dynamics we make several forecasts of prices over the next decade. In current dollars, some MSA will still not recover to recent peak (2007) house price levels by 2022, while others should exceed it by as much as 70%.

I. Introduction

There has been a revival of interest in the supply schedule that characterizes urban housing markets. It has been argued that variation in the elasticity of this schedule may explain the wide differences observed across US metropolitan statistical areas (MSA) in house price levels, their growth and also volatility [(Campbell-Davis-Martin (2009), Capozza-Hendershott-Mack (2004), Cannon-Miller-Pandher (2006), Glaeser-Gyourko-Saiz (2005), Paciorek (2013), Davidoff (2013)]. It has also been argued that housing supply elasticities impact the allocation of labor across MSAs and can affect aggregate productivity [Nieuwerburgh-Weil (2009), Eckhout-Pinheiro-Schmidheiny (2010)]. Thus there is much interest in the possible "determinants" of local housing supply elasticities, be they related to intrinsic geographic land supply [Saiz (2010)], local land use regulations [Gyourko-Saiz-Summers (2008)], or the organizational structure of the homebuilding industry [Somerville (1999)]. Despite all this interest, much of the discussion is conducted in an empirical vacuum, for there are no *individual time series* estimates of long or short run housing supply elasticities in San Francisco versus Dallas or any of the other 300 US MSAs. The literature review section that follows will make this more apparent.

One purpose of this study therefore is to apply modern time series analysis to quarterly data on MSA constant dollar (repeat sale) house prices, new housing construction and the growth of the stock – covering 1980:1 through 2012:2. We do this individually for each of the largest 68 MSA. At the start, we find that (real) house price levels and stock are not stationary - in all but a few MSA. This calls into question much of the early empirical research on this topic. Both series, however, are stationary in differences, or I(1). Most importantly house prices and stock (measured in levels) are cointegrated (again in all but a handful of markets). This suggests that an error-correction methodology is the proper framework for understanding the relationship between these two variables – at least at the MSA level.

Within this framework we estimate a single equation Error Correction Model (ECM) in which stock determines prices, and then a Vector Error Correction Model (VECM) in which both variables are simultaneously determined as well as determining. The cointegrating vector between the two variables yields a consistent estimate of the long run elasticity of supply and across our 68 MSA the results are extremely plausible: ranging from .2 to 3.1. The short run dynamic impacts estimated through both models are also significant however and provide us with an alternative short-run measure of housing supply elasticity. With the ECM we ask what recovery in prices – from their current (2012:2) levels - will be needed to support anticipated new supply over the next decade. To allow for the possibility that demographic aging will slow long run growth of housing demand from its historic trend, we set the anticipated new supply at 80% of that built in previous decades. With the VECM we simply do an out-of-sample forecast of both stock and price for the next 10 years. The ratio of the stock/price forecasts then provides a measure of the effective short run elasticity to be observed over the next decade.

We find great consistency between these supply elasticities, with correlations in the .9 range. We also find that they relate statistically to those "determinants" of supply elasticity recently hypothesized in the literature. Larger cities, with geographic land constraints, that have high scores on a survey of regulatory barriers have significantly lower supply elasticities – as we have measured them.

We then investigate the role of supply elasticity in an MSA's price experiences over the 2001-2012 period characterized by the housing "boom" and "bust". Consistent with the conventional thinking that this period was marked by housing demand shocks, markets with more inelastic supply exhibit both greater price increases over 2001-2007, and greater price declines from 2007 to 2012.

Finally, we use the short run forecasts generated by the models to assess the degree of housing price growth and eventual price recovery that is likely across our 68 MSA, beginning in 2012:3. We find that markets with inelastic supply will experience faster price growth between 2012 and 2022, thus exhibiting similar dynamics to the prior decade. That said inelastic markets generally have no greater tendency to recover or exceed their 2007 "bubble" peak levels – in constant dollars. We suspecte that this finding is due to the fact that areas with inelastic supply generally experience slower demand growth than areas with more elastic supply.

In the next section we review the empirical literature on housing supply and its determinants. Section III reviews the standard model of land development that underlies much of the supply elasticity discussion, while Section IV then examines the data series available on prices, construction and the stock – testing for stationarity and cointegration. Section V lays out our ECM and VECM models, along with some alternative estimation strategies. Section VI presents results from estimating the various models, and displays their long and short run implied elasticities. In section VII we examine whether these elasticities line up with often used supply "instruments". Section VIII examines the relationship between these elasticity estimates and market behavior from 2001 through 2012, while Section IX examines the magnitude and patterns in housing price recovery over the next decade that is likely across our 68 MSA.

II. Housing Supply Literature

There is an early literature on housing supply [Alberts (1962), Burns-Grebbler (1982)] that looks at housing construction as a "business" in which the level of price relative to some opportunity cost (including credit) drives housing "investment" or unit flows (permits, starts or completions). The most recent elaboration of this approach is Topel-Rosen (1988) in which great attention is given to the expectation mechanism for future prices. Following Abel-Blanchard (1986), DiPasquale-Wheaton (1992, 1994) add to this approach with the notion that expected price levels determine a "desired" stock towards which the actual stock adjusts slowly with new investment. In this approach the existing stock is a critical additional variable (to prices) in explaining new investment. Much of this early literature is summarized in Blackley (1999), who notes that it contains little or no application of true time series analysis. For example the series are rarely tested for stationarity or cointegration, and regressions contain mixed I(0) and I(1) series.

Mayer-Somerville (2000) redefines the entire discussion of supply elasticity and links it more explicitly to land development. In their framework the key ingredient necessary for cities to grow through new construction is the development of additional land. Following a long and voluminous literature on urban spatial models - this requires higher land values which are simply a residual from housing prices. Thus like DiPasquale-Wheaton the underlying "supply" relationship is between housing price levels and housing stock, rather than price levels and housing flows. They also argue that any empirically estimated relationship between house price levels and stock is likely to be miss specified as both variables are I(1) and not I(0). They present estimates of a relationship between *changes* in both housing stock and price that they argue is reflective of that between housing price and stock levels. We return to this specification issue in the next section.

All of the literature above uses US national data to estimate some supposed national supply elasticity. But if the supply elasticity is really about land development, then surely there should be significant variation across cities of different sizes, with different geographies, transportation systems and regulatory processes. The availability of widespread MSA-level housing price indices has prompted a series of more recent analysis of differences in price movements across MSA. Capozza-Hendershott-Mack (2004), Cannon-Miller-Pandher (2006) and Campbell-Davis-Martin (2009) all examine the movement in prices to see if there is any relationship between price appreciation and price volatility across (respectively) MSA, ZIP codes and US census regions. None of these studies explicitly include study of housing supply or stock.

Harter-Drieman (2004) opens up a new line of inquiry by using panel data analysis from 1980 to 1998 to compare 49 MSA. She develops a VECM model relating prices to *income* (rather than stock or households) and does not test for cointegration between these two variables. By allowing for a market specific constant term in the long run cointegrating relationship, she is able to calculate a price response to an income shock that is unique to each market. Then *assuming* a common price elasticity of demand, she is able calculate an implicit estimate of each market's supply elasticity. Not surprising, the result is a very narrow range of implicit supply elasticities; for example, she finds that no markets are inelastic.

Saiz (2010) adopts a similar panel approach, but with limited time series: there are only 3 decadal changes (observations) for each MSA. He develops an estimating equation wherein price changes are predicted using household (housing stock) changes, fixed effects, and two variables that logically would impact a supply elasticity: the Wharton Land Use Regulatory Index (WLURI) [Gyourko-Saiz-Summers (2008)] and a newly constructed measure of geographic land *un*availability. By interacting these variables with household changes he again is able to calculate an implicit supply elasticity for each market – yielding estimates of between .6 and 5.0.

Over this time span there is only one attempt to separately estimate a supply elasticity uniquely by market: Green-Malpezzi-Mayo (2011). Their paper simply presents the elasticity resulting from a series of simple bivariate regressions with no statistical specification tests, and no resulting statistics. The elasticities vary widely (-.3 to 29.0) and half are reported as insignificant. A second stage cross-section regression explaining the elasticities contains 9 variables, most of which likely to be endogenous to a housing supply process. The approach of this paper is in principle similar to Green-Malpezzi-Mayo, but with far greater series detail and testing. Such testing suggests the need for a very different model – one following an error correction framework.

III. Long-Run models of Local Housing Supply.

As discussed above, newer models of housing supply are actually models of land development and city expansion – rather than of "investment" in housing. In this literature, monocentric land use models yield relationships between equilibrium city size (housing stock) and the difference between central housing prices and edge housing prices[1]. This latter can be thought of as a crude "average" city price. This relationship begins with the set of variable definitions in (1) below.

$$\begin{aligned}
&B: \text{travel distance from the urban center to edge in a circular city.}\\
&T: \text{capitalized cost of traveling a unit distance (fixed across locations)}\\
&L: \text{lot size of house (fixed across location)}\\
&\text{K}: \text{Capital cost of a house (fixed across location)}\\
&r_a: \text{price of ubiquitous agricultural land outside the circle}\\
&P_0, P_B: \text{house Prices at urban center and edge}\\
&S: \text{stock of housing (population)}\\
&A: \text{fraction of land (at all locations) that is developable} \qquad (1)
\end{aligned}$$

[1] Here we use the most simple of monocentric models where transport costs are constant and exogenous, and where land consumption is similarly. The voluminous literature on such models often has land consumption determined by agent utility and prices, while congestion can make transport costs non-linear and endogenous.

The equations below derive a set of equilibrium relationships between these variables. Equation (2) requires that house price differences between the center and edge equal the capitalized value of traveling from the edge to center. This is a spatial equilibrium condition. Equation (3) links edge prices to replacement costs using capital and agricultural land (both exogenous), while (4) links the urban border with total housing stock. Combining equations, we get the result in (5) where equilibrium average house prices (the difference between center and edge prices) depend positively on the size of the housing stock. While (5) expresses price as a function of stock, it is equally true that to provide a larger stock of urban land prices must rise and hence stock is a function of price; in other words equilibrium implies joint causality. Expression (5) has often been interpreted as an inverse housing "supply" schedule [Saiz (2010), Mayer and Somerville (2000)]. Expression (5) illustrates that the long term relationship between house prices and stock may also depend on land availability and the efficiency of the city transportation system (Saiz, 2010).

$$P_0 = P_B + TB \tag{2}$$

$$P_B = K + Lr_a \tag{3}$$

$$B = \left(\frac{SA}{\pi}\right)^{1/2} \tag{4}$$

$$P_0 - P_B = T\left(SA/\pi\right)^{1/2} \tag{5}$$

Economists also have modeled a competitive system of cities [Weil and Nieuwerburgh-Weil (2009), Eckhout-Pinheiro-Schmidheiny (2010)]. In these models a "national" population selects where to reside among cities. Jobs or employment do likewise. In addition to productivity and amenity considerations, these choices are influenced in no small part by house prices. Thus through the migration of population and the relocation of employment there can arise a parallel (but negative) "demand" relationship D(…) between prices and stock. *Ceteris paribus*, *lower* prices eventually attract an expanding population and job base (E). In equilibrium this base must equal the stock (S). Expressions (6) and (7) can be combined with (5) to complete any full model of a system of cities.

$$E = D(P_0)\,,\quad D' < 0 \qquad (6)$$
$$S = E \qquad (7)$$

In recent years monocentric models have given away to "polycentric" theory wherein a city has multiple centers or locations of economic activity. Each such center however behaves like a "sub-center" – following similar conditions as in (2)-(5). The main difference from the monocentric framework is that some sub centers compete with each other over land, rather than just with agricultural uses. Some theory of "agglomeration" is also necessary to determine whether the city is composed of many small sub centers or a few very large ones. With endogenous employment location, this family of models does not always yield the same comparative static results as with single centered city models. For example, in monocentric models higher transportation costs raise land rent and generate more dense cities. In polycentric models, higher transportion costs lead to greater employment dispersal and little or no increase in land rents [McMillen-Smith (2003), Helsley-Sullivan (1991)]. The empirical implication of these models is that often they have almost infinite long run housing (land) supply. With a single fixed center, increasing the supply of land requires greater commuting and hence land rent. With multiple endogenous centers more land can be had by expanding the number of centers with little attendant increase in commuting since the dominant pattern of commutes is within a center and not between centers. Hence land rents also need not increase.

Finally, it is important to remember that (1) – (7) inform us only about long run equilibrium relationships and provide very little guidance in terms of short term dynamics. Short run dynamics are often thought to involve the capital portion of housing rather than land: the difficulty of constructing new structures and their durability once built. Glaeser-Gyourko (2005) for example convincingly show that even over decade long intervals the derivative of house prices with respect to stock is asymmetric: falling prices do little to shrink the stock, but rising prices are needed to expand it. Put differently, the identity between S and E in (6) rarely holds over short run intervals, when the stock of housing adjusts slowly.

While this discussion is certainly not new, it does highlight a range of important issues that any empirical study of *local* housing supply elasticities must address. The first such issue is that estimation must be flexible enough to accommodate a full range of potential long run elasticity values, matching the variation anticipated from polycentric as opposed to monocentric urban models. Secondly, the estimation should allow for short run dynamic effects that may be distinct from long run equilibrium impacts. For example, if the stock increases from a true "shock" then prices may fall in the short run rather than rise along the long run schedule. Finally, stock and prices are jointly determined in equilibrium and so there is a high likelihood of simultaneity between the series Using local economic data as an instrument to resolve this simultaneity is certainly not valid in the long run. Given that structural identification is difficult, non-structural macroeconomic time series analysis may offer more viable solutions.

IV. Empirical Tests of MSA House Price and Housing Stock Series

The data used in this analysis consists of two time series for each of 68 US metropolitan areas, at quarterly frequency, covering 1980:1 through 2012:2. The first is the Federal Housing Finance Agency's (FHFA) all-transactions house price index (HPI) based on repeat transactions involving conventional mortgages purchased or securitized by Fannie Mae and Freddie Mac. The second is a series of total housing stock, starting with the 2010 Decennial Census and adding (for post 2010) or subtracting (for pre 2010) housing permits each quarter. It should be noted that this estimated stock series will not produce values for 1980, 1990 or 2000 stock that match the Decennial Census unit counts for those years, due largely to the effects of demolitions and undercounting. It would be possible to calculate a 3-decade average quarterly stock adjustment for each MSA and apply this to the estimated stock series, but such scalar adjustment would not impact the statistical results, although it could alter slightly the estimated elasticities.

To test for stationarity we undertake augmented Dickey-Fuller tests (ADF) of house price and stock in levels, using 4 and then 8 lags. For house prices, we can reject the null of a unit root in only 15 of 68 MSA – using 4 lags and a liberal 10% criterion[2]. With 8 lags the null is rejected in only 16 of 68 MSA. With the housing stock, the results are not much better, with only 18 of 68 MSA exhibiting stationarity using 4 lags and 14 of 68 using 8 lags (again applying a 10% criterion). However, the first differences of both the stock and price series are stationary in all but a handful of MSA (7 and 6 with the 4 and 8 lags respectively). These are clearly very noisy series with surprisingly little mean reversion in levels. We note that this contrasts sharply with the much smoother national time series on prices and stock (Case and Shiller (1988)).

With two non-stationary series any direct regressions of prices on stock would be subject to a range of problems – as would any derived estimates of a long run elasticity (such as in much early literature). Recognizing this possibility Mayer-Somerville (2000) suggest a regression (using national data) in first differences, but obtain a very small short run elasticity since only a few lags of price (changes) are included. With a model estimated in differences a permanent alteration of price levels has an impact on stock that lasts only as long as the number of lagged price changes included in the model. In our MSA level data the vast majority of the series are I(1), or stationary in differences, but using such an approach would preclude estimating our main objective - a true long run elasticity.

An alternative approach for using statistical analysis with variables that are still measured in levels would be to apply an error-correction framework. This approach does not require that each variable be stationary in levels, but does necessitate that they exhibit co-integration. To this end, Appendix 1 presents the results of several augmented cointegration tests. The first two columns essentially test for whether the errors from a regression of price on stock – a simplified version of equation (5) - are stationary. Differences in the errors (of price predicted by stock) are regressed against previous error levels controlling for lagged changes in the errors. The results depend considerably on the number of lags used – a common dilemma with such tests. We experimented using both the Akaike Information Criteria (AIC) for the number of lags, as well as selecting the

[2] For these ADF tests we used the following critical values from Mackinnon, (1996): 1% 3.49, 5% 2.89, 10% 2.58, 20% 2.21.

number of lags that gives the highest test statistic. These two criteria yielded very similar results in terms of lag selection which is shown in the 1st column of Appendix 1. In the 2nd column we present the R2 of the error regression and in the next two columns the coefficient on lagged error level (the cointegration test) and its T value. It's clear that in 10 of 68 markets, the series are just not cointegrated, while in 49 they are (at 10% or higher criteria). In 9 markets the results suggest some weak cointegration (passing at between 10% and 20%). [3]

V. Error Correction Models of Housing Supply.

With these tests validating cointegration for virtually all of the markets, the first approach would be to estimate a simple version of equation (5) directly – ignoring the possible specification issue raised by equations (6) and (7). This has not been done in the literature, despite the fact the application of an ECM not only gets around the issue of non-stationarity, but also nicely separates long run relationships from short run dynamics. Our statistical ECM version of equation (5) is illustrated in (8), where the β parameters represent the long run cointegrating relationship between the variables in levels. The parameter α_0 estimates the speed (or degree) of reversion back to the cointegrating relationship. The α_i and λ_i account for short run impacts on price movements that arise from lagged price movements or stock changes.

$$\Delta P_t = \alpha_0 [P_{t-1} - (\beta_1 + \beta_2 S_{t-1})] + \sum_{i=0}^{n} \alpha_i \Delta S_{t-i} \sum_{i=1}^{n} \lambda_i \Delta P_{t-i} \tag{8}$$

The issue with this single equation ECM is that it assumes that the right hand variable (stock) is exogenous. There are two reasons why this is not likely to be true. First, while (5) expresses price as a function of stock (households must be compensated for farther commutes), it is equally true that to provide a larger stock of urban land prices must be higher. Here stock is a function of price. Secondly, if long run equilibrium exists between cities, equations (6) and (7) suggest a negative relationship between prices and

[3] We use the following test statistic critical values [MacKinnon (1996)] : 1% 4.02, 5% 3.39, 10% 3.07, 20% 2.71.

stock. An approach that is far more agnostic regarding causality is the application of a Vector Error Correction Model (VECM). This is represented in (9). In this system, we allow for the same single cointegrating vector (with parameters β), but there are two sets of adjustment coefficients (with parameters α, λ versus α', λ').

$$\Delta S_t = \alpha_0[S_{t-1} - (\beta_1 + \beta_2 P_{t-1})] + \sum_{i=0}^{n} \lambda_i \Delta P_{t-i} + \sum_{i=1}^{n} \alpha_i \Delta S_{t-i}$$

$$\Delta P_t = \alpha'_0\,[(S_{t-1} - (\beta_1 + \beta_2 P_{t-1})] + \sum_{i=0}^{n} \alpha'_i\, \Delta S_{t-i} + \sum_{i=1}^{n} \lambda'_i\, \Delta P_{t-i} \qquad (9)$$

The estimation of equation (8) or the pair of equations (9) generally can be done in one of two ways, both of which are found in the literature. The first is to estimate the β parameters with a 1st stage OLS, and then use the actual residuals in a 2nd stage equation to estimate the α (and λ) parameters, again by OLS. This 2-step procedure, originally suggested by Engle and Granger (1987) provides super-consistent estimates of the β values – provided that P and S are cointegrated controlling for their own autocorrelation. Hence the number of lags in either (8) or (9) should be the same or similar to that which was used to establish cointegration (for example in the previous section). This same 2-stage procedure is suggested more recently by Lutkepohl (2007) as a simple and consistent way to estimate the vector system in (9). He refers to this an OLS-VECM.

An alternative has been developed by Johansen (1995) who devises a single step Maximum Likelihood Estimator (MLE) since both (8) and (9) are nonlinear in their parameters. The one-step procedure has the advantage of also testing for cointegration at the same time as estimating the model. In this procedure the model is often re-estimated multiple times, each with a different lag structure, until some criteria is met and cointegration determined (or not). A problem with the Johansen MLE estimator, however, is that its statistical properties are known *only under the assumption that the errors of (8) and (9) are normally distributed.* We initially experimented with the MLE estimator with results that were often insignificant, and with model parameters that frequently led to instability. To further investigate we applied a test for error normality (Jarque and Bera

(1987)). The p-values for this test statistic are reported in Appendix 2 and they represent the probability that the null (normality) is true given observed data. It is clear that there are just a very few market/equations that have even a modest likelihood of normal error. More than 90% of the market/equations fail the test by a wide margin.

Since OLS estimation in general is quite robust to the assumption of error normality, we proceed to estimate both models (8) and (9) with the OLS 2-step procedure originally suggested by Engle and Granger (1987) and then subsequently by Lutkepohl (2007). Our OLS VECM results exhibit none of the stability or significance problems we encountered with the Johansen procedure.

VI. Estimation Results: ECM, VECM.

Appendix 3 presents the OLS estimates of the ECM model for 68 MSA. We present the R2, the convergence coefficient $\alpha_{o,}$ and its t statistic, as well as the number of lags used on lagged stock and price changes (the same as used to establish cointegration). We also provide two measures of the "elasticity of supply". The first elasticity measure is simply equal to the coefficient β_2**,** estimated in the first stage by OLS, and converted into an elasticity using current stock and price values.

The second is a more a "short run" elasticity and is derived from undertaking a 40 period price forecast - that begins in 2012:2 – using an *assumed* trajectory for the housing stock. The trajectory assumed is the same as the average growth in each market's housing stock during the decade before the recent housing "bubble"- 1993:1-2003:1 – but scaled by 80%. This latter figure is derived from national estimates of household formation expected over the coming decade relative to that of 1993-2003 [U.S. Census (2012)]. In effect we ask what increase in price will be required to get the stock to grow in the next decade at 80% of the amount it did during the pre-bubble decade – starting from where prices and stock are in 2012:2. The required price change relative to assumed supply is then converted into a "short run" forecast elasticity. It is important to remember that if current prices are below the long run cointegrating relationship, they will have to "catch up" a bit to provide the targeted new supply. Conversely, if current prices are above the cointegrating relationship, little if any price increases may be needed to generate the assumed supply. Thus this short run elasticity could differ considerably from the long run estimates.

On the surface, the ECM elasticities look gratifyingly reasonable. Looking over the results we draw the following observations.

1). There are 6 negative elasticities, which occur in most Texas markets and two other south central cities. All these markets display continual real price declines over the last 30 years despite significant stock increases. This negative relationship, however still exhibits cointegration. Presumably cities like Dallas are able to expand with just nominal appreciation because the real cost of travel, construction costs, or the value of edge rural land has fallen over time.

2). There also are 3 “anomalies”. Baton Rouge has a positive very elastic long run (LR) cointegrating relationship but a small negative forecast price increase. This is because current prices are actually above the values implied by the cointegrating relationship and anticipated supply needs no further price increase. Charlotte’s ECM is dynamically unstable. Finally the large elasticity in Memphis is possibly due to the fact that stock and price are not well cointegrated in that market.

3). As for the rest of the markets, the short run elasticities (SR) are all well below their long run elasticity value. Without the anamolies, the R^2 between short and long run is .43 and at the means the average market short run elasticity is 32% of its long run value. *This results because virtually all markets have prices that are currently well below values implied by their cointegrating relationship; therefore to meet even modest target increases in supply, the forecast of price growth has to be quite pronounced (generating a lower forecast elasticity).*

4). The adjustment coefficient is statistically significant at the 5% level or higher in all but 2 markets and even in these MSA it passes a 10% test. Adjustment speeds back to the underlying cointegrating relationship average about 5% per quarter or 20% per annum. “Error correction” is an important feature of the relationship between stock and price.

5). The estimated elasticity values seem readily plausible. The long run values generally are between .20 and 3.1, with the usual list of hypothesized inelastic markets

(New York, Boston, the LA and San Francisco regions). Many markets in the South and Mid-West region have much more elastic supply.

With respect to the results of the OLS-VECM, the LR cointegrating relationship is by construction the same as with the ECM. The forecast however could be quite different as now the stock is endogenous. In Figures 1 and 2 below, we illustrate the ECM and OLS-VECM forecasts for two very different markets: Boston and Houston. Boston is like many coastal markets with a strong long run positive price trend, while Houston is like most Texas and South Central markets. Despite a negative relationship, prices and stock are well cointegrated in most of these areas. In Appendix 4 we compare the OLS-VECM model with the ECM. Our observations continue below.

Figure 1: ECM, VECM Forecasts

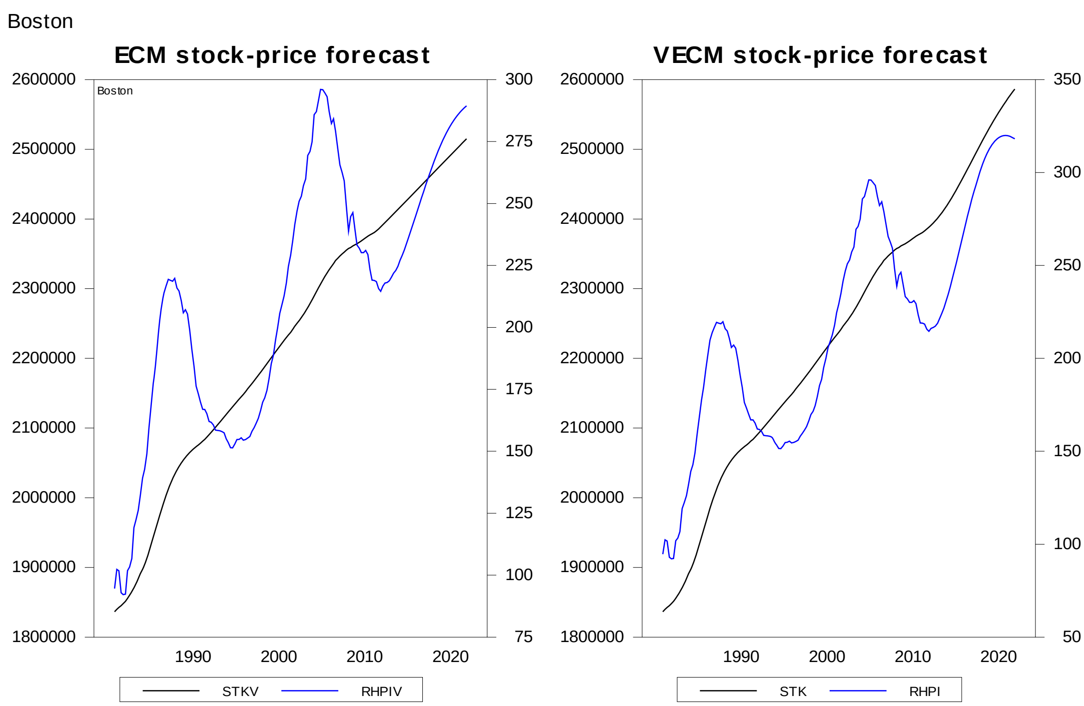
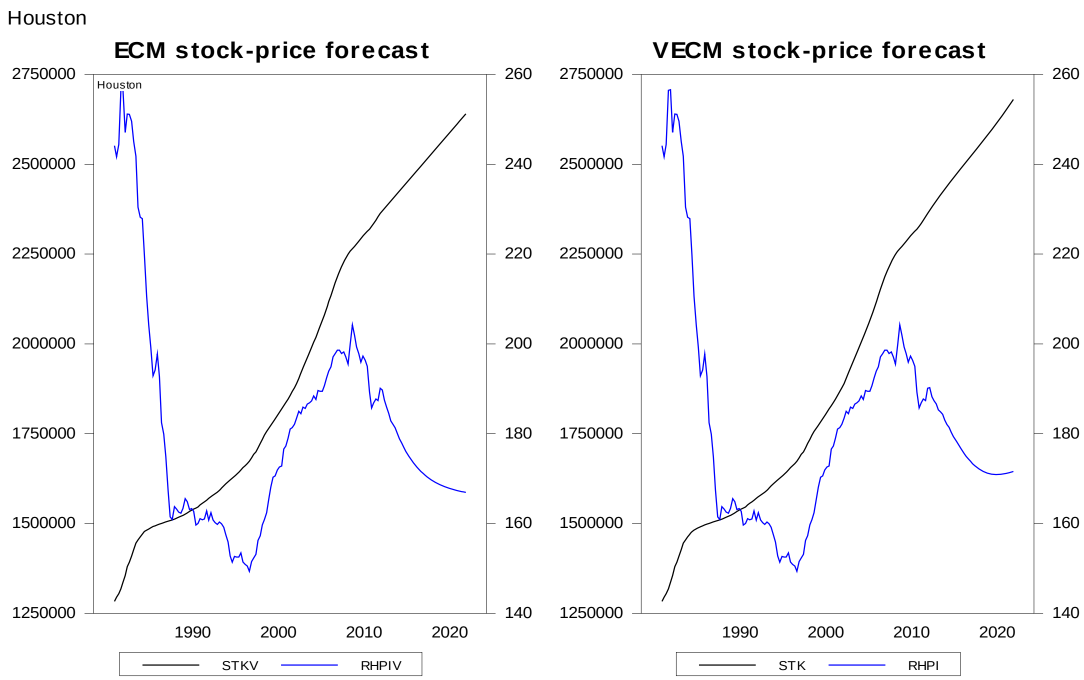


Figure 2: ECM, VECM Forecasts



6). We find that the stock equation within the OLS-VECM does not have the stock re-equilibrating around the cointegrating relationship - as do prices in the price equation. In 62 of 68 markets the cointegrating coefficient in the stock equation is insignificant. In 6 markets it is significant negative and in 1 market significant positive. A significant negative coefficient implies that when prices are above the value implied by the long term cointegrating value the stock tends to grow more slowly (or declines). This would be illustrative of the migration relationship hypothesized in (6)-(7). A significant positive relationship would be consistent with supply "mean reversion". In general there is no strong pattern as to how the stock behaves - other than to short run price shocks and its own momentum.

7). Despite the estimation results for the stock equation, the overall OLS-VECM produces remarkably similar forecast elasticity estimates to the ECM model with its exogenous stock targets. Excluding two "anomalies" (Baton Rouge and Charlotte again) the simple average forecast price appreciation between 2012:2 and 2022:3 is 29.5% with the ECM using an assumed average stock growth of 10.9% (based on the 80% rule discussed in the previous section). Under the OLS-VECM framework the average forecast price appreciation is 39.2%, with an endogenous average forecast growth in stock of 13.3%. The OLS-VECM has generally greater price appreciation since it forecasts slightly greater stock growth - as opposed that we assumed based on a national demographic slowdown in household formation.

8). The small differences in the supply forecasts translate into very similar short run supply elasticity estimates between the two models. The average forecast-based supply elasticity with the ECM is .276 as opposed to .257 with the OLS-VECM. Furthermore the correlation between the two elasticities (across 66 markets) is .92. This degree of similarity is interesting because the OLS-VECM derived elasticity is theoretically a different concept from the ECM one. The former is an equilibrium –based derivative as opposed to a partial derivative for a structural equation in the ECM. This suggests that joint endogeneity just makes little difference.

VII. Correlates of Market Supply Elasticity

This paper presents several alternative ways of estimating supply elasticities at the MSA level when the underlying data is non-stationary, and arguably subject to bi-directional causality. The error-correction framework also allows us to distinguish between true long run elasticities and short run ones (here 10 years). The results provide a wide range of elasticities across our 68 MSA, and again open up the question of what determines the housing market elasticity in any given area.

The literature on this question completely focuses on barriers to the development of land: Saiz (2010) on natural geographic barriers, and Gyourko et. al (2008) on regulatory barriers. Several authors also argue that larger metropolitan markets have inherently smaller elasticities, although in a simple circular monocentric model (such as in equation 5), the elasticity turns out to be scale invariant.

In Table 1, we examine how our elasticity estimates vary with these three common variables. WRI is the Gyourko et. al regulatory index and the land constraint variable is the Saiz measure of land *un*availability. Population is measured as of 2012. We report equations for each of our three elasticities: the long run and the two short run measures based on the ECM and OLS-VECM 10 year forecasts. The results are all significant, and in the anticipated direction. The fact that the LR elasticity is more highly explained also seems plausible as it filters out short run market dynamics, and disequilibrium. Using the equation for the long run elasticity, the difference in geographic land *un*availability between Boston (index value of 33.9) and Washington DC (index value of .14) lowers the Boston housing supply by -.24. Similarly the regulatory differences between these two markets (1.7 versus .3) generate a further reduction in the elasticity of -.63. The actual elasticity in the Boston MSA is .36 versus Washington's .70

Table 1: Cross Section Determinants of Elasticities

(t statistics in parenthesis)

Equation	LR Elasticity	ECM Elasticity	VEC Elasticity
R2	0.463	0.309	0.254
Constant	1.77 (10.4)	.694 (7.78)	.712 (6.55)
WRI	-.447 (-3.65)	-.144 (2.190)	-.177 (2.25)
Land Constraints (Saiz)	-.012 (3.56)	-.0043 (-2.45)	-.0038 (-1.76)
MSA Population	-.000071 (-2.1)	-.000040 (-2.23)	-.000042 (-1.93)

VIII. House Price Elasticities and the Housing "Bubble".

In virtually all of our 68 markets, the period from 2000:1 through 2007:2 exhibits an unprecedented rise in real house prices, followed by a huge decline over 2007:2 to 2012:2. There is consensus that this resulted from a positive shock to housing ownership, although there is disagreement over whether this shock originated with the relaxation of mortgage underwriting standards, or simply changed expectations about the returns from housing [Foote-Gerardi-Willen (2012)]. With a national housing finance system, these shocks are widespread, impacting all markets to some extent. In such a case we should expect that the degree of housing price rise and then fall would naturally depend (negatively) on the supply elasticity of each market. The relationship, however, could be quite imperfect as there were nuances to the rise and fall that were unique to each area. For example second home havens seem to have experienced a larger “bubble [Chinco-Mayer (2012)].

In Figures 3 and 4, we compare each market’s price rise (2000:1–2007:2) and then fall (2007:2–2012:2) against their supply elasticity. In this comparison we have excluded the 6 markets with negative elasticities located in Texas and the south central US. In some sense a downward sloping supply curve (in real prices) is most similar in economic behavior to a horizontal curve (a high elasticity). Numerically, however a negative elasticity is proximate to a small positive (inelastic) value. The relationships become much clearer if we restrict our sample to those 62 MSA with estimated positive elasticities.

It is quite apparent in both figures that markets with generally lower supply elasticities have both higher increases in prices over this period and also greater subsequent declines. In this sample of MSA, the average increase in real prices over 2000:1-2007:1 is 48%. The decline from 2007:1 to 2012:2 is 30% - leaving the average market value in 2012:2 at about 4% above 2000:1 levels (in constant dollars). Both Paciorek (2013) and Davidoff (2013) attempt link recent housing volatility to metrics that approximate a local supply elasticity.

Figure 3: Prices 2007/2000 versus Elasticities

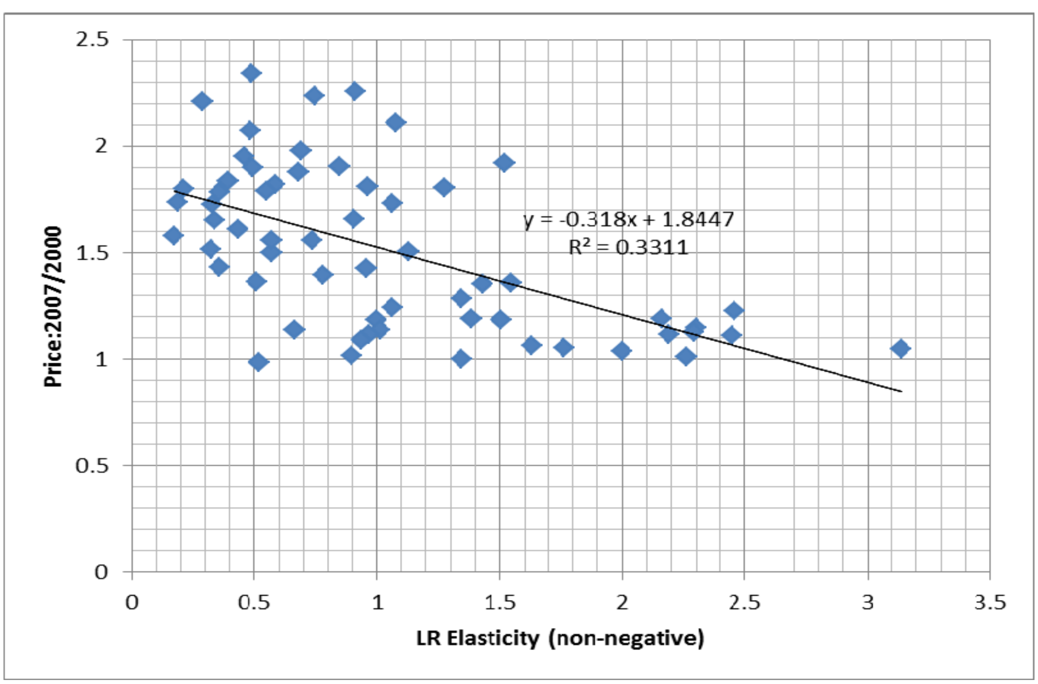
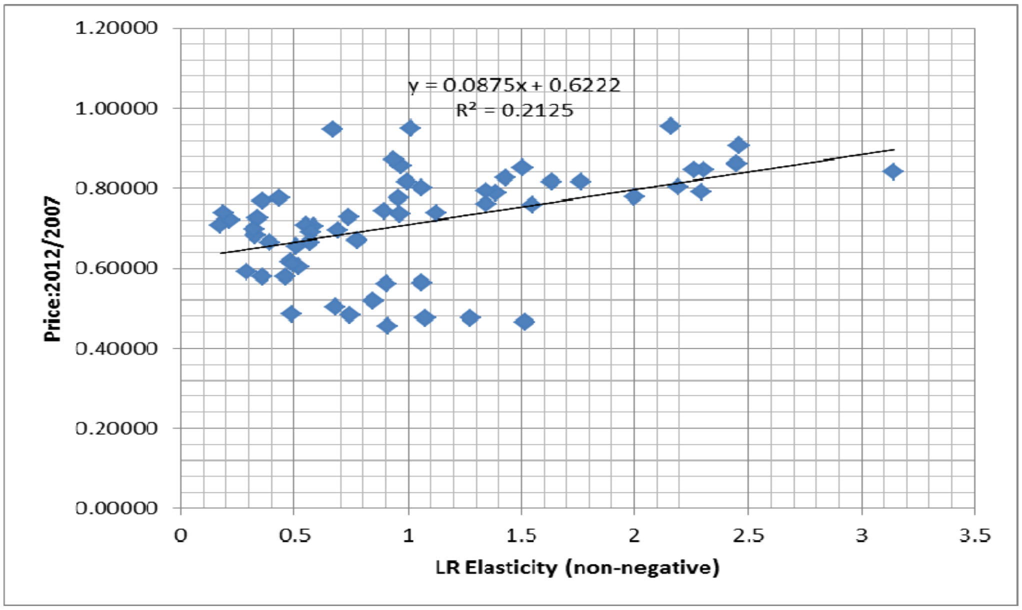


Figure 4: Prices 2012/2007 versus Elasticities



IX. House Price Recoveries from the Great Recession

The advantage of the error correction approach is not confined solely to its ability to provide unbiased estimates of long run parameters, but also in the fact that it offers an excellent mechanism for out of sample forecasting with its flexible handling of short run dynamics. The unprecedented rise in house prices from 2000 to 2007 and the almost equal fall over 2007-2012 has many asking whether, when and by how much prices will recover. This is not just of academic interest, for as many as 21% of American homes may have mortgage balances that exceed their current prices (Core Logic, 2012). Furthermore, the future balance sheets of many financial institutions, as well as Federal housing policy certainly will be influenced by the shape and extent of the housing price recovery.

Against this background, we take our preferred model (the OLS-VEC approach) with its joint forecast of housing stock and housing prices in each of our 68 MSA. The forecast is for a decade beginning in 2012:3. In almost all markets the forecasts look as realistic and plausible as the right hand frames of Figures 1 and 2. The results for each market are presented in Appendix 5. Here we display the peak level of prices (uniformly assumed to occur in 2007:1), and trough price levels (assumed to occur close to the base period of 2012:2). Following this are two ratios. The first is the forecast of 2022:2 price levels relative to 2007:1 in real dollars (used throughout the models). The second is the same in nominal dollars. This conversion uses actual CPI inflation from 2007.1 to 2012:2 and assumes 2% annual CPI inflation from 2012:2 through 2022:2. Given current yields on Treasuries and TIPS this estimate of future inflation is a bit conservative, but our analysis is only meant to be illustrative of what might happen to nominal house prices over the next decade. This is the more relevant metric for assessing the future of US mortgage leverage ratios.

In Appendix 5 we can see that out of 68 markets, *nominal* prices will fail to get back to 2007:1 levels by 2022:2 in only 7 markets. Four of these markets are in Florida, while the other three are in Arizona, Nevada and inland California. Adjusted for expected CPI inflation, however, 30 out of 68 markets will fail to recover in real price levels. This includes many markets in California, Florida, Arizona and Nevada as well as Texas and some of the South Atlantic states.

To help see patterns across markets we present Figures 5 and 6. In Figure 5 we see that the average market will appreciate about 40% - in real terms -over the next decade and that those markets which are forecast to have the highest rates of price appreciation from 2012:2 to 2022:2 are again those with lower supply elasticity. This relationship is quite significant statistically and is consistent with the historic pattern of greater volatility for such markets over the last decade (Figures 3 and 4). In Figure 6 we see that by 2022:2 the average market will be back to 2007 price levels (adjusted for inflation), but that there is no relationship between this rate of price *recovery* and a market's long run supply elasticity. Markets with inelastic supply should appreciate more in real terms over the long run – but only if demand growth is the same as in elastic markets. The OLS-VECM forecasts tend to have the stock growing somewhat faster in elastic markets – generating comparable price levels relative to 2007:1 as in inelastic markets with slower forecast stock growth.

Figure 5: Forecast Price Growth 2022/2012 versus Elasticity

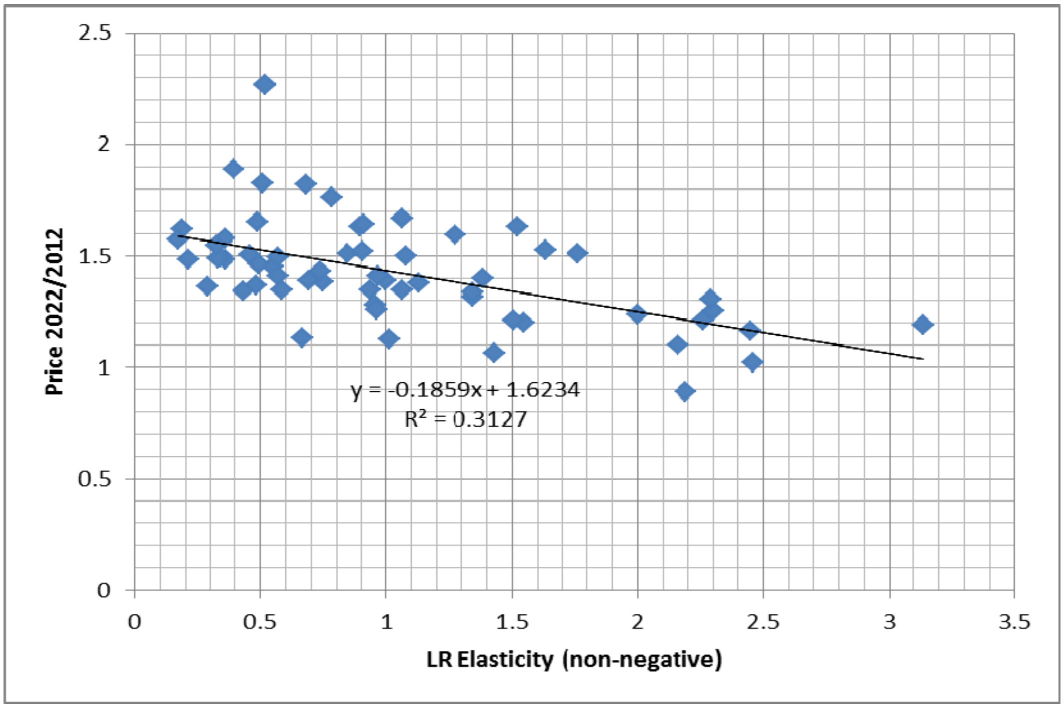
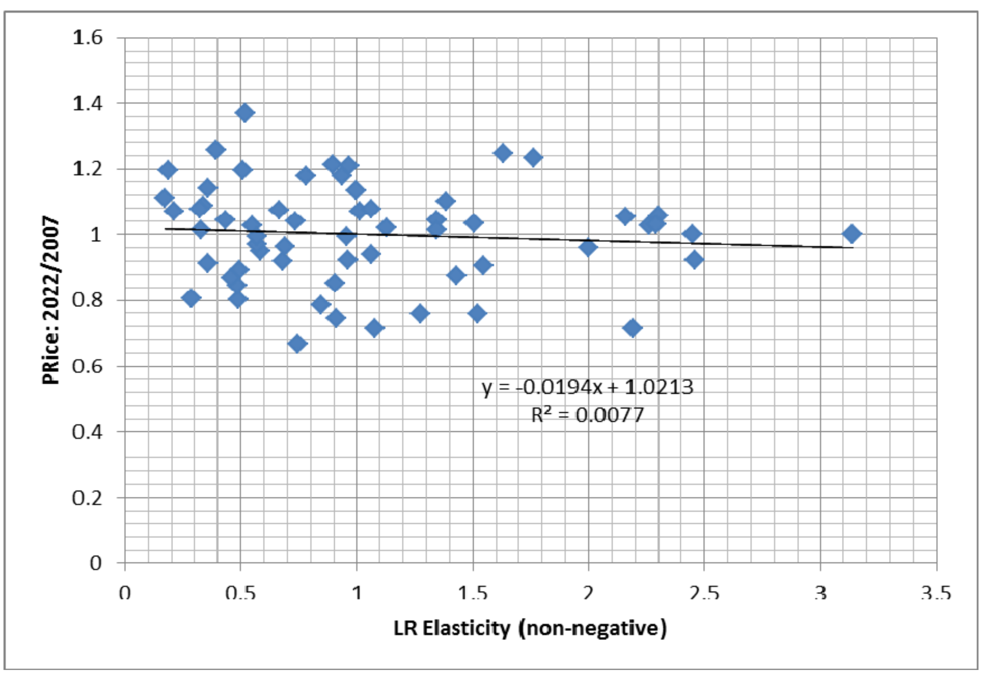


Figure 6: Forecast Price Recovery 2022/2007 versus Elasticity



Finally, these forecasts suggest that housing will generally be a fine investment in most cases over the coming decade. Across our 68 markets cumulative *nominal* price inflation will average around 60% - ranging from just 10% in many Texas markets to 80% or more in many areas hard hit by the "bubble" years. With housing capital gains largely untaxed, mortgage rates in the 5% range and the mortgage interest deduction continuing, the annual long run cost of owning a home [Poterba, (1984)] should again turn negative as it did in the late 1970s, late 1990s and mid-2000s. This should help to spur future home ownership, housing consumption and new housing construction.

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Appendix 1: Cointegration Tests: Price on Stock

MSA	Lags	R2	lagged error	T value
Albuquerque	6	0.32182	-0.07382	-3.75322
Atlanta	8	0.39813	-0.05132	-2.97339
Austin	8	0.16753	-0.07921	-3.54801
Baltimore	5	0.51591	-0.03355	-3.47419
Baton Rouge	12	0.21416	-0.04549	-3.12046
Birmingham	11	0.12486	-0.11224	-2.80686
Boston	7	0.61054	-0.0331	-3.51572
Buffalo	9	0.14666	-0.06008	-3.23303
Charlotte	7	0.23287	-0.08845	-3.00548
Chicago	8	0.492	-0.06016	-3.53879
Cincinnati*	10	0.28526	-0.03867	-1.80048
Cleveland*	11	0.2556	-0.0299	-1.67525
Colorado Spngs	14	0.26735	-0.04719	-2.63407
Columbia SC*	9	0.08946	-0.07726	-2.37317
Columbus*	8	0.22169	-0.02977	-1.45949
Dallas	7	0.32058	-0.02799	-2.75523
Dayton*	4	0.05905	-0.02003	-0.85016
Denver	6	0.32533	-0.0329	-3.15138
Detroit	7	0.57542	-0.02799	-3.39546
Edison	4	0.63562	-0.02579	-3.20937
Fort Lauderdale	4	0.61672	-0.03888	-4.12673
Fort Worth	11	0.27923	-0.03372	-2.83133
Greensboro	9	0.24299	-0.07625	-2.6233
Hartford	4	0.51344	-0.03281	-3.29003
Honolulu	5	0.57453	-0.03878	-3.71806
Houston	6	0.40003	-0.0348	-3.82529

Indianapolis*	6	0.06938	-0.02519	-1.25753
Jacksonville	6	0.42635	-0.04323	-3.36352
Kansas City*	10	0.32971	-0.03311	-2.48574
Las Vegas	5	0.60541	-0.04853	-3.9346
Long Island	5	0.55352	-0.02982	-3.51836
Los Angeles	3	0.69955	-0.02562	-3.35974
Louisville*	9	0.11283	-0.04123	-1.55918
Memphis*	10	0.28225	-0.10314	-2.34424
Miami	4	0.61705	-0.03812	-3.82371
Minneapolis	7	0.4976	-0.04257	-3.90853
Nashville	7	0.24371	-0.07104	-3.36986
New Orleans	12	0.20986	-0.0392	-2.85223
New York	5	0.59282	-0.03524	-3.50882
Newark	5	0.58935	-0.03517	-3.59795
Norfolk	6	0.5859	-0.02802	-3.39632
Oakland	3	0.6412	-0.02878	-3.31458
Oklahoma City	11	0.33104	-0.03903	-3.43076
Orange County	3	0.67135	-0.02594	-3.28562
Orlando	4	0.5732	-0.03685	-3.33139
Philadelphia	6	0.56465	-0.03396	-3.376
Phoenix	6	0.5947	-0.04463	-3.53703
Pittsburgh*	5	0.14086	-0.10237	-2.26634
Portland	6	0.53734	-0.07097	-4.5241
Providence	8	0.61632	-0.03522	-3.37841
Raleigh	7	0.27244	-0.08183	-3.39137
Richmond	7	0.40169	-0.0481	-3.67429
Riverside	4	0.67266	-0.02865	-2.95214
Sacramento	4	0.66132	-0.03168	-3.39783
Salt Lake City	6	0.35949	-0.05817	-3.53722
San Antonio	11	0.42625	-0.05384	-3.38143
San Diego	3	0.5963	-0.02542	-3.02031

San Francisco	3	0.55827	-0.02835	-2.87109
San Jose	3	0.52396	-0.03471	-2.87714
Seattle	6	0.61215	-0.04901	-3.7719
St Louis	9	0.43173	-0.04925	-3.45583
Tampa	5	0.50151	-0.03809	-3.27913
Tucson	5	0.3685	-0.07383	-3.56841
Tulsa	6	0.17807	-0.03803	-3.22059
Ventura	3	0.62227	-0.03067	-3.33343
Washington DC	5	0.58547	-0.03289	-3.2196
West P Beach	4	0.64575	-0.02888	-3.24114
Wilmington	6	0.48793	-0.04235	-3.74964

(* market not cointegrated)

Appendix 2: Jarque-Bera Test on Null of Normality in Residuals*

Market	P-Value for Eqn D_rhpi	P-Value for Eqn D_stk	P-Value for Joint Test on Both Eqns
Albuquerque	0.002264966	6.01E-86	2.77E-86
Atlanta	4.8299E-05	0.382991668	0.000220088
Austin	2.3787149211e-316	0.007115151	1.2400815401e-315
Baltimore	5.81E-06	1.49E-47	1.05E-50
Baton Rouge	0.960285202	1.32E-65	1.90E-63
Birmingham	0.006731155	0.000753312	6.68924E-05
Boston	1.28E-08	1.04E-27	1.09E-33
Buffalo	0.262237226	0.010431756	0.018879451
Charlotte	9.49E-12	0.009049121	2.67E-12
Chicago	7.06E-12	0.005474005	1.23E-12
Cincinnati	5.99716E-05	6.80E-13	1.58E-15
Cleveland	0.008833102	0.023350473	0.001956635
Colorado Sprgs	0.001259587	0.093055686	0.001178157
Columbia SC	0.000169894	0.784358993	0.00132235
Columbus	0.00543286	0.287783242	0.011664915
Dallas	6.31E-06	7.85E-08	1.45E-11
Dayton	0	1.47E-08	0
Denver	2.62E-06	0.000890351	4.87E-08
Detroit	3.71E-94	9.12E-07	7.79E-98
Edison	8.40E-06	0.002533053	3.97E-07
FortLauderdale	5.90E-11	5.84E-111	9.60E-119
FortWorth	0.889067301	0.00141103	0.009635842
Greensboro	0.122385037	0.865577726	0.343748837
Hartford	0.936205833	3.16E-34	2.31E-32
Honolulu	0	6.41995E-05	0
Houston	0.003938721	7.45E-06	5.39E-07
Indianapolis	6.64E-224	0.244704997	8.39E-222
Jacksonville	0.000735122	0.26168822	0.001838328
Kansas City	0.000881334	0.20280275	0.001721165
Las Vegas	4.24E-11	0.001066571	1.44E-12
Long Island	4.56E-10	1.09467E-05	1.69E-13
Los Angeles	2.11E-34	1.03E-54	4.41E-86
Louisville	1.69803E-05	0.944645102	0.000193132
Memphis	0.000121858	0.292256695	0.000400398
Miami	1.22E-15	2.88E-83	7.94E-96

Minneapolis	0.122685371	0.629407004	0.274985414
Nashville	1.44E-21	0.020202206	1.54E-21
New Orleans	0.056541011	1.04E-18	2.67E-18
New York	7.94E-14	0	0
Newark	3.36E-08	0.005575325	4.38E-09
Norfolk	0.00177531	0.333603315	0.004993599
Oakland	1.88E-19	0.002270435	2.14E-20
Oklahoma City	0.184399551	2.75E-06	7.85E-06
Orange County	9.13E-33	0.429493243	2.97E-31
Orlando	3.42E-06	0.73614544	3.4949E-05
Philadelphia	0.000325059	0.285431848	0.000954289
Phoenix	3.73E-08	0.003743776	3.30E-09
Pittsburgh	0.277957752	0.235160837	0.243664971
Portland	3.48E-08	0.030131595	2.27E-08
Providence	0.002348382	5.20E-31	9.38E-32
Raleigh	0.005760123	0.000339034	2.76258E-05
Richmond	0.001199553	0.002920793	4.75154E-05
Riverside	4.03E-14	6.26E-22	2.04E-33
Sacramento	1.43E-09	5.73E-12	3.87E-19
Salt Lake City	4.31E-33	0.128949954	4.31E-32
San Antonio	4.45E-38	0.000912799	3.82E-39
San Diego	7.67E-34	2.31E-10	1.77E-41
San Francisco	5.50E-14	0.589145806	1.04E-12
San Jose	2.26E-08	0.000314474	1.89E-10
Seattle	1.04E-29	0.043541031	3.22E-29
St Louis	5.33E-11	0.000339227	5.90E-13
Tampa	1.03E-12	0.535734153	1.62E-11
Tucson	1.02E-29	0.297427577	2.10E-28
Tulsa	2.68256E-05	9.76E-13	1.03E-15
Ventura	2.35E-64	0.02918028	1.04E-63
Washington DC	4.05E-13	0.897212944	1.08E-11
West P Beach	4.61E-07	0.230991055	1.81E-06
Wilmington	0.117280726	4.82E-14	1.91E-13

* This test is based on the test as discribed in Lutkepohl (2005, p 174- 181) as applied to the augmented VAR in first differences (i.e. VECM) and is implemented in Stata software.

Appendix 3: ECM with Lags, Elasticities, forecast prices

MSA	lags	R2	α coef	T	LR Elast.	Stock Forcst	Price forcst	ECM Elast
Albuquerque	6	0.351	-0.066	-3.08	1.549	0.126	0.195	0.649
Atlanta	8	0.469	-0.072	-2.81	2.848	0.209	0.503	0.415
Austin	8	0.272	-0.094	-3.31	2.163	0.174	0.082	2.116
Baltimore	5	0.511	-0.033	-3.28	0.585	0.081	0.341	0.238
Baton Rouge	12	0.383	-0.170	-4.39	2.458	0.092	-0.019	-4.839
Birmingham	11	0.116	-0.087	-1.59	0.999	0.090	0.268	0.337
Boston	7	0.685	-0.029	-2.61	0.358	0.053	0.360	0.148
Buffalo	9	0.173	-0.065	-2.51	1.015	0.043	0.096	0.448
Charlotte	7	0.282	-0.127	-2.68	2.193	0.190	0.146	1.300
Chicago	8	0.555	-0.043	-1.96	0.508	0.086	0.542	0.158
Cincinnati*	10	0.398	-0.063	-2.18	1.633	0.109	0.205	0.534
Cleveland*	11	0.338	-0.046	-1.99	0.896	0.058	0.224	0.259
Colorado Sprgs	14	0.350	-0.065	-1.91	1.387	0.169	0.310	0.545
Columbia SC*	9	0.109	-0.080	-1.95	2.304	0.116	0.162	0.718
Columbus*	8	0.284	-0.067	-2.18	1.761	0.136	0.279	0.488
Dallas	7	0.350	-0.041	-3.06	-2.518	0.151	-0.123	-1.227
Dayton*	4	0.131	-0.137	-3.66	1.343	0.078	0.327	0.239
Denver	6	0.373	-0.058	-3.46	0.969	0.165	0.329	0.502
Detroit	7	0.556	-0.028	-2.21	0.517	0.083	0.853	0.098
Edison	4	0.677	-0.021	-2.41	0.550	0.090	0.323	0.280
Fort Lauderdale	4	0.606	-0.040	-3.90	0.746	0.127	0.390	0.325
Fort Worth	11	0.387	-0.050	-2.44	-1.764	0.114	-0.126	-0.906
Greensboro	9	0.298	-0.164	-3.38	3.140	0.096	0.151	0.640
Hartford	4	0.582	-0.032	-2.51	0.958	0.054	0.084	0.643
Honolulu	5	0.345	-0.048	-2.55	0.391	0.064	0.627	0.101
Houston	6	0.462	-0.049	-3.62	-31.10	0.117	-0.123	-0.952
Indianapolis*	6	0.068	-0.072	-2.00	2.261	0.146	0.266	0.549
Jacksonville	6	0.569	-0.076	-4.56	1.061	0.142	0.354	0.401

Kansas City*	10	0.403	-0.037	-2.41	2.294	0.121	0.180	0.673
Las Vegas	5	0.609	-0.055	-4.02	2.596	0.267	0.733	0.364
Long Island	5	0.597	-0.028	-3.05	0.213	0.041	0.426	0.096
Los Angeles	3	0.715	-0.027	-3.34	0.287	0.029	0.241	0.119
Louisville*	9	0.164	-0.121	-2.68	0.936	0.109	0.251	0.434
Memphis*	10	0.356	-0.183	-3.31	20.038	0.133	0.179	0.741
Miami	4	0.678	-0.049	-4.34	0.489	0.097	0.439	0.221
Minneapolis	7	0.557	-0.042	-3.65	0.779	0.123	0.464	0.265
Nashville	7	0.380	-0.129	-4.72	1.509	0.144	0.180	0.798
New Orleans	12	0.260	-0.039	-1.87	1.432	0.067	0.126	0.537
New York	5	0.709	-0.037	-3.14	0.186	0.029	0.453	0.065
Newark	5	0.637	-0.045	-3.09	0.337	0.051	0.219	0.234
Norfolk	6	0.563	-0.027	-3.08	0.965	0.101	0.225	0.448
Oakland	3	0.662	-0.031	-3.48	0.360	0.070	0.463	0.151
Oklahoma City	11	0.384	-0.030	-1.83	-1.839	0.083	-0.179	-0.461
Orange County	3	0.682	-0.027	-3.37	0.483	0.081	0.328	0.246
Orlando	4	0.632	-0.036	-3.01	1.519	0.187	0.455	0.411
Philadelphia	6	0.620	-0.025	-2.28	0.435	0.057	0.253	0.227
Phoenix	6	0.581	-0.047	-2.86	1.273	0.190	0.556	0.341
Pittsburgh*	5	0.140	-0.112	-2.44	0.667	0.047	0.111	0.423
Portland	6	0.549	-0.050	-2.67	0.571	0.141	0.431	0.326
Providence	8	0.644	-0.034	-3.09	0.327	0.050	0.468	0.106
Raleigh	7	0.360	-0.056	-1.70	2.451	0.191	0.225	0.852
Richmond	7	0.444	-0.040	-2.99	1.127	0.118	0.266	0.443
Riverside	4	0.709	-0.040	-3.39	0.911	0.107	0.368	0.290
Sacramento	4	0.695	-0.039	-3.73	0.682	0.126	0.594	0.213
Salt Lake City	6	0.348	-0.075	-3.56	1.344	0.219	0.324	0.675
San Antonio	11	0.440	-0.061	-2.48	-4.071	0.103	-0.151	-0.678
San Diego	3	0.597	-0.026	-2.97	0.494	0.080	0.402	0.199
San Francisco	3	0.612	-0.032	-3.14	0.171	0.037	0.419	0.088
San Jose	3	0.562	-0.036	-2.90	0.322	0.080	0.459	0.173

Seattle	6	0.642	-0.043	-3.09	0.570	0.116	0.575	0.202
St Louis	9	0.415	-0.038	-2.40	1.061	0.081	0.211	0.385
Tampa	5	0.558	-0.046	-3.34	0.847	0.111	0.393	0.283
Tucson	5	0.298	-0.068	-2.77	0.907	0.134	0.463	0.289
Tulsa	6	0.196	-0.036	-1.96	-2.444	0.079	-0.098	-0.803
Ventura	3	0.644	-0.032	-3.38	0.460	0.085	0.425	0.199
Washington DC	5	0.607	-0.029	-2.55	0.692	0.120	0.315	0.382
West P Beach	4	0.653	-0.030	-3.29	1.079	0.131	0.435	0.302
Wilmington	6	0.510	-0.039	-3.26	0.738	0.093	0.405	0.230

(* market not cointegrated)

Appendix 4: VECM Results, ECM comparison

MSA	lags	Price	stock	Price forcst	Stock forcst	ECM elast	Price forcst	Stock forcst	VECM elast
Albuquerque	6	151.1	377152	0.195	0.126	0.649	0.200	0.142	0.712
Atlanta	8	136.1	2170510	0.503	0.209	0.415	0.976	0.332	0.340
Austin	8	199.4	733804	0.082	0.174	2.116	0.102	0.221	2.160
Baltimore	5	198.6	1143581	0.341	0.081	0.238	0.346	0.093	0.269
Baton Rouge	12	187.6	335636	-0.019	0.092	-4.83	0.021	0.101	4.871
Birmingham	11	158.7	504057	0.268	0.090	0.337	0.390	0.149	0.381
Boston	7	214.6	2388271	0.360	0.053	0.148	0.483	0.083	0.172
Buffalo	9	149.7	522031	0.096	0.043	0.448	0.126	0.046	0.369
Charlotte	7	153.3	754279	0.146	0.190	1.300	-0.108	0.197	-1.824
Chicago	8	146.8	3509432	0.542	0.086	0.158	0.824	0.142	0.172
Cincinnati*	10	144.5	921843	0.205	0.109	0.534	0.528	0.174	0.330
Cleveland*	11	125.0	958195	0.224	0.058	0.259	0.631	0.081	0.128
Colorado Spgs	14	164.3	269065	0.310	0.169	0.545	0.399	0.197	0.494
Columbia SC*	9	158.1	338654	0.162	0.116	0.718	0.252	0.163	0.646
Columbus*	8	142.9	802415	0.279	0.136	0.488	0.511	0.199	0.389
Dallas	7	162.9	1694792	-0.123	0.151	-1.22	-0.091	0.161	-1.762
Dayton*	4	124.9	385647	0.327	0.078	0.239	0.317	0.067	0.211
Denver	6	189.5	1189418	0.329	0.165	0.502	0.411	0.184	0.448
Detroit	7	117.1	1950634	0.853	0.083	0.098	1.267	0.123	0.097
Edison	4	208.3	959312	0.323	0.090	0.280	0.453	0.119	0.262
Fort Lauderdale	4	173.1	802706	0.390	0.127	0.325	0.386	0.106	0.274
Fort Worth	11	155.8	851801	-0.126	0.114	-0.90	-0.117	0.132	-1.129
Greensboro	9	143.5	683361	0.151	0.096	0.640	0.190	0.120	0.630
Hartford	4	172.0	508007	0.084	0.054	0.643	0.281	0.080	0.284
Honolulu	5	142.2	338121	0.627	0.064	0.101	0.889	0.084	0.095
Houston	6	190.1	2363262	-0.123	0.117	-0.95	-0.098	0.134	-1.376
Indianapolis*	6	139.3	828284	0.266	0.146	0.549	0.213	0.103	0.484

Jacksonville	6	168.0	604706	0.354	0.142	0.401	0.669	0.212	0.317
Kansas City*	10	158.0	888461	0.180	0.121	0.673	0.304	0.152	0.500
Las Vegas	5	102.1	850974	0.733	0.267	0.364	0.745	0.296	0.397
Long Island	5	238.3	1039320	0.426	0.041	0.096	0.484	0.051	0.105
Los Angeles	3	221.1	3443531	0.241	0.029	0.119	0.362	0.052	0.144
Louisville*	9	162.8	564779	0.251	0.109	0.434	0.350	0.129	0.369
Memphis*	10	135.8	554287	0.179	0.133	0.741	0.235	0.166	0.704
Miami	4	185.3	978620	0.439	0.097	0.221	0.652	0.138	0.212
Minneapolis	7	173.8	1359734	0.464	0.123	0.265	0.764	0.176	0.231
Nashville	7	174.3	681477	0.180	0.144	0.798	0.213	0.184	0.866
New Orleans	12	192.4	537951	0.126	0.067	0.537	0.062	0.073	1.190
New York	5	223.4	4709602	0.453	0.029	0.065	0.619	0.057	0.092
Newark	5	200.0	856319	0.219	0.051	0.234	0.497	0.076	0.152
Norfolk	6	207.1	695910	0.225	0.101	0.448	0.257	0.118	0.461
Oakland	3	199.5	983336	0.463	0.070	0.151	0.580	0.088	0.152
Oklahoma City	11	176.4	544264	-0.179	0.083	-0.46	-0.171	0.084	-0.493
Orange County	3	227.4	1050749	0.328	0.081	0.246	0.370	0.097	0.263
Orlando	4	146.5	949420	0.455	0.187	0.411	0.631	0.259	0.411
Philadelphia	6	190.0	2155803	0.253	0.057	0.227	0.344	0.073	0.213
Phoenix	6	154.8	1805925	0.556	0.190	0.341	0.595	0.204	0.343
Pittsburgh*	5	167.9	1106759	0.111	0.047	0.423	0.134	0.053	0.395
Portland	6	183.5	931818	0.431	0.141	0.326	0.408	0.154	0.378
Providence	8	193.9	694077	0.468	0.050	0.106	0.489	0.058	0.119
Raleigh	7	157.1	710975	0.225	0.191	0.852	0.163	0.255	1.568
Richmond	7	179.2	534662	0.266	0.118	0.443	0.380	0.157	0.414
Riverside	4	166.3	1502454	0.368	0.107	0.290	0.642	0.168	0.262
Sacramento	4	152.8	870028	0.594	0.126	0.213	0.822	0.160	0.194
Salt Lake City	6	169.9	420299	0.324	0.219	0.675	0.336	0.206	0.611
San Antonio	11	174.8	851659	-0.151	0.103	-0.67	-0.147	0.091	-0.618
San Diego	3	212.5	1166392	0.402	0.080	0.199	0.463	0.101	0.217
San Francisco	3	236.5	761108	0.419	0.037	0.088	0.573	0.054	0.094

San Jose	3	241.2	653581	0.459	0.080	0.173	0.546	0.104	0.190
Seattle	6	189.0	1478542	0.575	0.116	0.202	0.493	0.161	0.326
St Louis	9	166.7	1245842	0.211	0.081	0.385	0.346	0.111	0.320
Tampa	5	167.1	1349189	0.393	0.111	0.283	0.512	0.135	0.264
Tucson	5	149.7	442037	0.463	0.134	0.289	0.523	0.165	0.316
Tulsa	6	167.0	414963	-0.098	0.079	-0.80	-0.092	0.088	-0.955
Ventura	3	200.9	279572	0.425	0.085	0.199	0.506	0.103	0.203
Washington DC	5	213.5	2243342	0.315	0.120	0.382	0.387	0.150	0.387
West P Beach	4	163.5	651102	0.435	0.131	0.302	0.501	0.148	0.297
Wilmington	6	174.1	288029	0.405	0.093	0.230	0.430	0.126	0.292

(* market not cointegrated)

Appendix 5: Prices Declines and Forecast Recoveries

MSA	2007:1	2012:2	2012/2007	2022/2007	2022/2007 nom
Albuquerque	199.74	151.11	0.75653	0.90766	1.18903
Atlanta	204.07	136.10	0.66694	1.31789	1.72644
Austin	208.66	199.38	0.95552	1.05342	1.37998
Baltimore	281.88	198.59	0.70453	0.94861	1.24268
Baton Rouge	207.13	187.59	0.90567	0.92441	1.21098
Birmingham	194.60	158.65	0.81527	1.13327	1.48458
Boston	279.11	214.55	0.76872	1.13986	1.49322
Buffalo	157.59	149.73	0.95013	1.06961	1.40119
Charlotte	191.01	153.26	0.80236	0.71557	0.9374
Chicago	224.25	146.83	0.65474	1.19442	1.56469
Cincinnati	177.05	144.47	0.81599	1.24673	1.63322
Cleveland	168.42	125.04	0.74243	1.21094	1.58634
Colorado Sprngs	208.63	164.26	0.78734	1.10114	1.44249
Columbia SC	186.91	158.05	0.84560	1.05865	1.38683
Columbus	175.19	142.87	0.81550	1.23252	1.6146
Dallas	180.95	162.89	0.90019	0.81787	1.0714
Dayton	157.57	124.86	0.79243	1.0437	1.36725
Denver	221.30	189.51	0.85634	1.20866	1.58335
Detroit	193.88	117.08	0.60389	1.36888	1.79323
Edison	294.66	208.32	0.70697	1.02707	1.34546
Fort Lauderdale	358.49	173.05	0.48272	0.66893	0.87629

Fort Worth	174.69	155.78	0.89175	0.78781	1.03204
Greensboro	170.71	143.52	0.84075	1.00061	1.3108
Hartford	221.80	171.95	0.77527	0.99305	1.3009
Honolulu	213.86	142.20	0.66492	1.25605	1.64542
Houston	197.83	190.14	0.96113	0.86737	1.13625
Indianapolis	164.52	139.25	0.84643	1.02703	1.3454
Jacksonville	298.45	167.96	0.56277	0.93898	1.23007
Kansas City	199.86	158.04	0.79074	1.03147	1.35123
Las Vegas	284.17	102.09	0.35926	0.62702	0.8214
Long Island	330.79	238.26	0.72027	1.06916	1.40061
Los Angeles	374.44	221.06	0.59037	0.80435	1.0537
Louisville	186.65	162.76	0.87200	1.17708	1.54198
Memphis	174.48	135.82	0.77843	0.96142	1.25946
Miami	381.50	185.31	0.48575	0.80252	1.05131
Minneapolis	259.89	173.82	0.66882	1.1798	1.54553
Nashville	204.61	174.28	0.85175	1.03279	1.35295
New Orleans	232.92	192.37	0.82592	0.87685	1.14867
New York	302.80	223.43	0.73787	1.19474	1.56511
Newark	275.71	200.02	0.72548	1.08604	1.42271
Norfolk	281.84	207.07	0.73470	0.92337	1.20961
Oakland	344.68	199.48	0.57875	0.91433	1.19777
Oklahoma City	191.79	176.37	0.91958	0.76279	0.99926
Orange County	369.07	227.39	0.61612	0.84406	1.10572
Orlando	314.46	146.49	0.46584	0.75966	0.99515

Philadelphia	245.04	190.04	0.77554	1.04266	1.36589
Phoenix	326.13	154.84	0.47478	0.75706	0.99175
Pittsburgh	177.35	167.94	0.94694	1.07402	1.40696
Portland	266.24	183.53	0.68934	0.97051	1.27137
Providence	284.35	193.87	0.68181	1.01487	1.32948
Raleigh	182.53	157.12	0.86078	1.00092	1.3112
Richmond	242.55	179.17	0.73868	1.01914	1.33507
Riverside	366.25	166.34	0.45417	0.74566	0.97681
Sacramento	303.10	152.75	0.50395	0.9184	1.20311
Salt Lake City	223.67	169.90	0.75959	1.01516	1.32986
San Antonio	188.72	174.84	0.92646	0.79053	1.03559
San Diego	348.00	212.47	0.61055	0.89309	1.16995
San Francisco	334.47	236.45	0.70694	1.11196	1.45667
San Jose	346.14	241.22	0.69689	1.07751	1.41154
Seattle	284.08	188.99	0.66525	0.99293	1.30073
St Louis	208.49	166.72	0.79964	1.07648	1.41019
Tampa	322.21	167.13	0.51870	0.78451	1.02771
Tucson	267.11	149.72	0.56052	0.85381	1.11849
Tulsa	181.76	167.02	0.91893	0.83426	1.09289
Ventura	347.83	200.85	0.57744	0.86971	1.13932
Washington DC	307.20	213.52	0.69504	0.96413	1.26301
West P Beach	343.20	163.49	0.47637	0.7148	0.93639
Wilmington	239.12	174.06	0.72792	1.04125	1.36404