A Time Series Test to Identify Housing Bubbles

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Abstract

In this paper we propose a new time series empirical test to identify housing bubble periods. Our test estimates the beginning and the burst of bubbles as structural breaks in the difference between the appreciation rates of the Case-Shiller price tiers. We identify the relevant periods by exploiting the common characteristic that lower-tier house prices tend to rise faster during the boom and fall more precipitously during the bust. We implement our test on 15 U.S. Metropolitan Statistical Areas during the most recent housing bubble.

Keywords: Housing Bubbles, Price Tiers, Time Series

JEL Codes: R31, C23

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1 Introduction

The recent housing boom and bust in the United States was marked by large differences in the run-up and the subsequent decline of housing prices both across metro areas and across market segments in the same area. One common phenomenon observed in many metro areas is that the low-tier homes realized the largest price gains during the boom and saw the sharpest declines during the bust of the market. There is now a consensus in the rapidly growing empirical literature on the housing boom and bust that subprime lending and low interest rates were major contributing factors to the bubble (see e.g., Mayer 2011 for a recent survey). These factors, however, have a differential effect on the price tiers. Landvoigt, Piazzesi, and Schneider (2011) present a theoretical model in which movers of different age, income and wealth, demand houses that differ in quality. These three dimensions of mover characteristics and the quality of houses are then mapped into an equilibrium distribution of house prices. Applying micro data on buyer characteristics and house prices from San Diego to this model, Landvoigt et al conclude that "cheap credit for poor agents was most important in generating higher capital gains at the low end of the market."

In this paper, we present a new empirical test for the existence of housing bubbles which exploits the specific feature that low tier homes appreciate more during the boom and fall faster during the bust of the market. We use time series data of the S&P home price tiers to identify the exact dates at which housing market bubbles emerge and burst. Our methodology does not require information on market fundamentals. Instead, it analyzes the differences in the rate of change of the tiered price indices to identify breaks, which correspond to the origin and the burst of the bubbles.

We implement our empirical test on the metropolitan areas covered by the Case-Shiller tiered price indices.[2] The procedure allows the data to endogenously dictate the breaks, which mark the beginning and the end of the housing market bubbles. The results show that from the metropolitan areas considered in the analysis, all bubbles started between June 1997 (with Seattle, WA) and May 2001 (with Washington DC). Moreover, all bursts occurred between June 2006 (in San Diego, CA and Tampa, FL) and July 2008 (in Portland, OR). The bubble that lasted the longest was the one in Seattle, between June 1997 and July, 2007. It was in the San Diego metropolitan area where the high-tier prices went up the most, increasing by 134.5%

[2] The S&P Case-Shiller home price indices are calculated from data on repeat sales of single-family homes and organized in three equally sized tiers depending on their resale value.

(between January, 1999 and June, 2006). In other cities the increase in high-tiered prices was less severe. For example, in Minneapolis the increase was 48.4% (between November, 2000 and September, 2007), while in Portland it was 56.3% (between June, 1997 and November, 2008).

The extant literature on market bubbles has taken two distinct approaches to identify bubbles. The main approach views bubbles as a rapid and unsustainable growth in asset prices that cannot be explained by “fundamental” factors. In his summary article on the symposium on bubbles, in the *Journal of Economic Perspectives,* Stiglitz wrote that “[I]f the reason that the price is high today is only because investors believe that the selling price will be high tomorrow—when "fundamental" factors do not seem to justify such a price—then a bubble exists” (Stiglitz, 1990, p. 13). Using this definition, a number of empirical tests have been developed to exploit the link between asset prices and various fundamental values. West (1987) proposes an empirical test for the existence of a bubble using the constant expected return model. His approach relies on comparing two sets of parameters. One set of estimates is obtained by a projection of stock prices based on past dividends, and the other is obtained by a set of equations describing the discount rate and the dividend process. This and other tests to identify bubbles are reviewed in Flood and Hodrick (1990). Meese and Wallace (1994) examine whether the real expected return on home ownership is close to the real homeowner cost of capital by studying the relationship between price, rent, and the cost of capital. Abraham and Hendershott (1993 & 1996) study the relationship between housing prices and construction cost, real income growth and interest rate. They find that these factors explain half of the historical variation in house price appreciation. The bubble, then, manifests itself in the “sustained serially correlated deviations,” yet, it remains unclear whether these deviations are due to a “bubble” or to a misspecification of the econometric model. Himmelberg, Mayer and Sinai (2005) compare the level of housing prices to local rents and incomes for a period of 25 years. They explain that changes in the price-to-rent and price-to-income ratios might suggest the existence of bubbles even when the houses are reasonably priced because they fail to account, for example, for differences in risk, property taxes and maintenance expenses, and anticipated capital gains from owning a home. Glaeser, Gyourko and Saiz (2008) present a theoretical model of housing bubbles which predicts that areas with more elastic supply will have fewer bubbles with shorter duration and smaller price run-ups. Their data indicate that the price increases in the 1980s were almost exclusively experienced in areas with inelastic supply. The alternative approach, promoted by Case and Shiller, views housing bubbles as a result of unrealistic expectations of future prices sustained by speculative feedback and social contagion. In addition to the analysis of “fundamentals” —including personal per capita income, population, and employment— for the time period 1985-2003, Case and Shiller (2003) present the results of a survey of people who bought houses in 2002. This survey asked respondents a set of questions about their expectations of future prices and whether they feared that houses will become unaffordable in the future. The article reports that the term “housing bubble” had essentially no popularity prior to 2002 while the term “housing boom” had been in much more frequent use since the 1980s. An extensive overview of these approaches to understanding housing bubbles, and housing dynamics in general, is presented in Mayer (2011).

The main innovation in this paper lies in identifying bubbles without observing fundamentals and without the reliance on surveys or on measurements of sentiment. This approach can be implemented in housing markets due to the availability of the tiered price indices.

Defining the relevant periods in which bubbles grow and collapse opens new venues for future research on the impact of fundamentals on housing price movements both in and outside of the bubble periods. There is a rapidly growing strand in the recent literature on housing price dynamics which tries to identify the effects of various fundamental values on prices. Using simulation of the US housing market, Khandani, Lo, and Merton (2007) find that the declining interest rates and the growth of the refinancing business contributed significantly to the recent housing boom and the massive defaults during the bust. Favilukis (2010) argues that much of the housing price appreciation can be explained by relaxation of credit constraints and Mayer and Sinai (2009) show that markets with the highest subprime lending experienced the greatest growth in price-to-rent ratios. In contrast, Glaeser, Gottlieb, and Gyourko (2010) present evidence supporting the view that easy credit, in the form of low real interest rates and permissive mortgage approval standards is not a strong contributor to the rising house prices. Our approach permits these relationships to be revisited in the context of the relevant time period in each metropolitan area because we do not use fundamental factors to determine the bubble periods.

The organization of the paper is as follows. In Section 2 we describe the data. The empirical model, the estimation methods, and the identification strategy are outlined in Section 3. Section 4 presents the estimation results and Section 5 concludes.

2 Data and Intuition of the Testing Methodology

The data utilized in this paper are the time series S&P Case-Shiller seasonally adjusted Tier Price Indices. Our study covers the time period between January 1992 and August 2011 with 15 Metropolitan Statistical Areas (MSA): Atlanta, Boston, Chicago, Denver, Los Angeles, Miami, New York, Minneapolis, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa, and Washington DC. For each MSA we have three indices, the Low-, Medium-, and High-Tier.[3]

The indices we employ are constructed using a three month moving average, where home sales pairs are aggregated in rolling three month periods. This methodology assures the indices account for delays in data recording at the county level.[4] As is detailed in S&P Indices (2011), for the construction of the three tier indices, the S&P Case-Shiller methodology selects price breakpoints between low-tier and middle-tier houses and price breakpoints between middle-tier and upper-tier houses. The breakpoints are smoothed through time to eliminate seasonal and other transient variation. Depending on the sale prices, a transaction is allocated to one of the three tiers.

[Figure 1, here]

To illustrate the dynamics of the price tiers during the period of study, we present in Figure 1 the Low-, Mid-, and High-Tier indices for four of the metropolitan areas: Chicago, New York, San Diego, and Tampa. All indices are adjusted to have January 1992 as the base month. Two apparent observations can easily be made from examining these figures. First, all tiers increased during the housing bubble years and then decreased once the housing bubble busted. And second, the low tier increased the most during the bubble period, and decreased the most once the bubble burst. The vertical lines mark the beginning and end of the bubble and in the following section we will discuss how they are estimated.

[Table 1, here]

[3] While S&P Case-Shiller also constructs the indices for Cleveland and Las Vegas, we dropped them from our sample because Las Vegas did not have information prior January 1993, and Cleveland only had data until August 2011.

[4] For a more detailed discussion on the construction of the indices see Miao, Ramchander and Simpson (2011).

The summary statistics of the tiers for all the MSA that we examine are presented in Table 1. The higher averages in the lower tiers are consistent with the observation that during this period the low tier displays a larger appreciation than the high tier.

4 Empirical Strategy

4.1 The Housing Bubble and Identification Strategy

Let the price of a house be given by p_t, and, following the literature on testing for speculative bubbles (see, e.g. Flood and Hodrick 1990), let us assume that it consists of a *market fundamentals* term, p_t^f, and a bubble term denoted by B_t:

$$p_t = p_t^f + B_t. \qquad (1)$$

The bubble term B_t, thus, represents the deviation of the current market price from the value implied by market fundamentals. The market price in Equation (1) can be used for different price tiers $i, j = L, M, H$, where L, M, and H denote the low, medium, and high price tear, respectively. Hence we can write the difference between any two price tiers as follows:

$$y_t^{ij} \equiv p_{i,t} - p_{j,t} = \left(p_{i,t}^f + B_{i,t}\right) - \left(p_{j,t}^f + B_{j,t}\right) \qquad \text{for } i, j = L, M, H, \text{ and } i \neq j. \qquad (2)$$

We want to test whether the difference in the price tiers follows a trend stationary with a nonzero mean process. That is,

$$\lim_{k\to\infty} E_t\left(p_{i,t+k} - p_{j,t+k} \middle| I_t\right) = \beta_0 + \beta_1 t \qquad \text{for } i, j = L, M, H, \text{ and } i \neq j, \qquad (3)$$

which implies that after taking into account the nonzero mean and trend, the price sequences must be cointegrated with cointegrating vector $[-1, 1]$. I_t denotes the information set at time t. Because by the definition of the tiers there must be a difference between the prices of different tiers, we allow for the sequence $\{y_t^{ij}\}$ to have a nonzero mean. Stationarity has an interesting convergence interpretation; it says that shocks to the differences in the prices have to be temporary and that the long-term forecast of prices in both tiers can only differ by $\beta_0 + \beta_1 t$ at a finite fixed time t.

Combining Equations (2) and (3) we obtain,

$$\lim_{k\to\infty} E_t\left(p_{i,t+k} - p_{j,t+k} \middle| I_t\right) = \lim_{k\to\infty} E_t\left(p^f_{i,t+k} - p^f_{j,t+k} \middle| I_t\right) + \lim_{k\to\infty} E_t\left(B_{i,t+k} - B_{j,t+k} \middle| I_t\right)$$

$$\text{for } i,j = L,M,H, \text{ and } i \neq j. \quad (4)$$

One concern in the identification of the housing bubbles is that the two additively separable components on the right-hand side in Equation (4) cannot be separately observed. We only observe the sequence $\{y_t^{ij}\}$. Our identification strategy models the first term on the right-hand side to have a nonzero mean and a constant trend. Then, any structural break in the mean and trend of $\{y_t^{ij}\}$ is assumed to come from the second term on the right-hand side of Equation (4). That is, the boom and bust of the housing bubble are identified under the assumption that the beginning and end of the bubble cause a significant difference (a structural break in the mean or trend of the price difference across tiers) in the rate at which the tiers appreciate and depreciate.

4.2 Testing Methodology

Our identification strategy has a natural testable analog in the cointegration literature that allows for structural breaks. In particular, we test whether the observed sequence $\{y_t^{ij}\}$ is a nonzero mean trend stationary with process, while allowing for structural breaks in the mean and trend. To do this we use the minimum LM unit root test proposed by Lee and Strazicich (2003) which assumes the following data-generating process:[5]

$$y_t = \delta' Z_t + e_t, \qquad \text{where} \qquad e_t = \beta e_{t-1} + \varepsilon_t \qquad (5)$$

[5] As explained in Lee and Strazicich (2003), one common issue in unit root tests that allow for structural breaks (such as the ones presented in Zivot and Andrews (1992), Lumsdaine and Papell (1997), and Perron (1997)) is that they assume no break(s) under the unit root null and the alternative is 'structural breaks are present.' This includes the possibility of having a unit root with break(s) (Perron (1989) and Perron and Vogelsang (1992) do allow for the possibility of breaks in both, the null and the alternative). This implies that the rejection of the null is rejection of a unit root without breaks and not necessarily the rejection of a unit root. Strazicich et al. (2004) point out that these endogenous break unit root tests might conclude that a time series is trend stationary, when in fact the series is nonstationary with break(s). To overcome this limitation the two-break minimum Lagrange Multiplier (LM) unit root test proposed by Lee and Strazicich (2003) has an alternative hypothesis that unambiguously implies trend stationary.

and for convenience we drop the superscript ij in y_t^{ij}. Z_t is a vector of exogenous variables and $\varepsilon \sim iid\ N(0, \sigma^2)$. We will use Model C, as in Perron (1989), which includes two changes in levels and trends:

$$Z_t = [1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]' \qquad \text{where } DT_{mt} = t - T_{Bm} \text{ for } t \geq T_{Bm} + 1,\ m = 1,2$$

$$DT_{mt} = 0 \text{ otherwise.}$$

The first break should identify the beginning of the bubble, while the second break should identify the bust. The two-break LM unit root statistic is obtained from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta \tilde{S}_{t-i} + u_t \tag{6}$$

where $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t \tilde{\delta}$ for $t = 2, 3, \ldots, T.$,

and where $\tilde{\delta}$ denotes the estimated coefficients from the regression equation of Δy_t on ΔZ_t; $\tilde{\psi}$ is given by $y_1 = Z_1 \tilde{\delta}$ as shown in Schmidt and Phillips (1992), and $\Delta \tilde{S}_{t-i}$ are included as required to correct for serial correlation. The unit root test is described by $\phi = 0$ in equation (4) and the LM test statistics are:

$\tilde{\rho} = T\tilde{\phi}$,

$\tilde{\tau}$ = t-statistic testing the null hypothesis $\phi = 0$.

The important element in this test is that the breaks LM_ρ and LM_τ that identify the boom and the bust of the bubble, are determined endogenously by the test using:

$$LM_\rho = \inf_\theta \tilde{\rho}(\theta)$$

$$LM_\tau = \inf_\theta \tilde{\tau}(\theta)$$

where $\theta_m = T_{Bm}/T$, for $m = 1,2$, denotes the dates of the breaks relative to the total number of observations T. The breaks are determined when there is more evidence of stationarity in the sequence $\{y_t^{ij}\}$; that is, where the test statistic is minimized. Even when the series is found to have a unit root, the breaks can still be used to identify significant differences in the rates at which the tiers appreciate or depreciate.

4 Empirical Results

For comparison purposes we first test for stationarity in the $\{y_t^{ij}\}$ sequence for $i, j = L, M, H$ using two popular unit root tests that do not account for breaks, the Augmented Dickey Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The results are reported in Table 2, where the null in the ADF is unit root and the null in the KPSS is trend stationary. The first two columns show the results for the difference in the mid and low tiers. At standard significance levels, the ADF tests—which were carried out with trend—fail to reject the unit root null for every metropolitan area. Moreover, the KPSS tests reach a similar conclusion, as they reject the null of trend stationarity at a 10% significance level for every market. A similar story is true for the difference between the prices of the high and middle tiers shown in the last two columns. The only evidence of stationarity when no breaks are allowed appears when comparing the prices of the high and low tiers for the Los Angeles, San Diego and Washington DC markets. The ADF tests for these cities reported in the third column reject the unit root null at a 10% significance level. Overall, the results with no breaks find very little evidence of stationarity and, of course, cannot identify the bubble.

[Table 2, here]

The first set of results that allow for breaks are presented in Table 3, where the analysis focuses on the difference in prices between the middle and the low tiers. These results correspond to Model C that allows for two breaks in the levels and the trends. The first column reports the estimate of ϕ from Equation (4). Its LM test statistic is reported in the second column, while the third column has the number of lags $\Delta\tilde{S}_{t-i}$ included in the estimation. Given that we are using monthly data, the maximum number of lags we allow to correct for serial correlation is $k = 12$. Moreover, lags are being dropped if they are not different from zero at at least 10% significance level. $\hat{T}_{B1}$ and $\hat{T}_{B2}$ denote the two key estimates of interest: the estimated breaks expressed in years and months. We restrict $\hat{\lambda}_1$ and $\hat{\lambda}_2$ to be in the interval $[0.1T, 0.9T]$ to assure that we have enough observations at the end and at the beginning of the sample. The results show that nearly all the estimated boom and bust are statistically significant at at least 10% level. We have that for Denver the bust is not significant, and for San Francisco neither the boom nor the bust are significant.[6]

[6] Comparing the results from Tables 2 and 3 we see a clear difference in terms of the stationarity of the difference between the middle and low tiers when allowing for breaks. While there is no evidence of stationarity when no

[Table 3, here]

Tables 4 and 5 report the results for the differences between the high and low tiers, and the high and middle tiers, respectively. In Table 4 we see that there is less evidence of stationarity between the high and the low tiers. Only Phoenix, Portland, and Tampa reject the unit root null. Moreover, there is even less evidence of stationarity in the difference between the high and middle tiers. Only Atlanta and Portland reject the unit root null. In terms of the significance of the identified boom and bust, less breaks are significant in the difference between the high and low tiers, where six of the thirty breaks are not significant. For the difference between the high and the middle tiers, just the bust for Washington DC is not statistically significant.

[Table 4, here]

[Table 5, here]

We can now explain the intuition behind these results and the key idea behind the estimated dates for the structural breaks. Figure 1 not only shows the price indices for the low, middle and high tiers discussed earlier, but the vertical lines in the graphs denote the endogenously determined boom and bust using the difference between the high and low tiers, as reported in Table 4. For example, in Chicago the boom of the housing bubble started in April 1999 and the bust was in September 2006. A very similar pattern can be observed in New York, San Diego, and Tampa, all shown in Figure 1. The identified date of the bust for the bubbles in Tampa and San Diego is the same, June of 2006. In New York the bubble busted in February 2006. Notice that the identified breaks are not always the same across different $\{y_t^{ij}\}$ when different tiers are considered. We illustrate the results for the difference between the high and low tiers because it is this difference that was most pronounced during the housing bubble.

The last column in Table 4 shows the percentage change in the price of the high tier homes between the beginning and the end of the identified housing bubbles. For example, in Chicago the prices of the high tier homes went up by 62.5% between April, 1999 and September, 2006.[7]

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breaks are allowed, the results in Table 3 show that at 10% significance level we reject the unit root null for six cities: Chicago, Miami, Phoenix, Portland, San Diego, and Tampa.

[7] Notice that the Lee and Strazicich (2003) methodology allows for the identification of only *two* breaks, while some of the series appear to have more than two. In those cases (i.e., Atlanta, Denver, Los Angeles, Phoenix, and

The figures in this last column show that the appreciation was most pronounced in San Diego with an increase of 134.5%, followed by Seattle and Tampa with 119.2% and 103.4%, respectively. The cities in which the appreciation was lower were Minneapolis with a 48.4% increase and Portland with a 56.3%. The identified beginning and end of the bubbles are very similar across cities. The beginning of the bubbles that are statistically significant at a 10% level are all between June 1997 and May 2001, starting with Seattle and finishing with Washington DC. On the other hand, the statistically significant end-of-bubble dates are all between June, 2006 (San Diego and Tampa) and July 2008 (Portland).

[Figure 2, here]

Figure 2 plots the logarithm of the difference between the high and low price tiers (y_t^{HL}) for Miami, Portland, Seattle and Washington DC. In addition to the actual y_t^{HL} series, the figures also show the Ordinary Least Squares fitted lines to illustrate the dates of the breaks. The figures clearly show how the Lee and Strazicich (2003) procedure select the dates of the boom and bust of the bubbles. While the vertical lines denote the estimated beginning and end dates, the downward trend in the period between the two lines shows how during the bubble years the low tier prices increased faster than the high tier prices. Once the bubble bursts, the break in the trend shows how the lower tier prices dropped at a much higher rate than the high tier prices.[8]

6. Conclusion

The traditional approach to test for housing market bubbles is to examine deviations from market fundamentals. This paper presents an alternative approach that does not rely on an analysis of fundamental values. Instead, we exploit the property that low tier homes increase at a faster pace during the boom and depreciate more during the bust. This insight serves as a basis for the development of our empirical strategy which employs cointegration techniques that allow for structural breaks to estimate the dates of boom and bust of the bubbles. Using data for

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San Francisco) one of the identified breaks may correspond neither to the beginning nor the end of the bubble. Hence, in those cases we do not report the percentage increase in the prices of the high tear.

[8] Figure 3 in the appendix show the y_t^{HL} sequences for the other 11 cities, including Atlanta, Denver, Los Angeles, Phoenix, and San Francisco, where the procedure cannot correctly identify the beginning or end of the bubbles.

15 metropolitan areas we find that the estimated breaks resemble quite closely the beginnings of the price increases and the subsequent downfalls of the housing prices.

Our paper offers new insights on the dynamics of housing market prices. On the one hand, it suggests that the misalignment in the appreciation rates of the home price tiered indices can be a symptom for a regime change in the borrowing and lending behavior of market agents. On the other hand, this misalignment can be interpreted as an indication for an ensuing market bubble. That is, the question of whether we are currently in a housing bubble can be addressed through a comparison of the appreciation rates of the tiers. By identifying the beginning and the ending of the housing bubbles and the intensity with which they occur without using market fundamentals, our paper provides opportunities for future research on the impact of market fundamentals on housing prices inside and outside of bubble periods.

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Figure 1.

Low, Mid and High Tiers Indexes, 1992-01 through 2011-08.

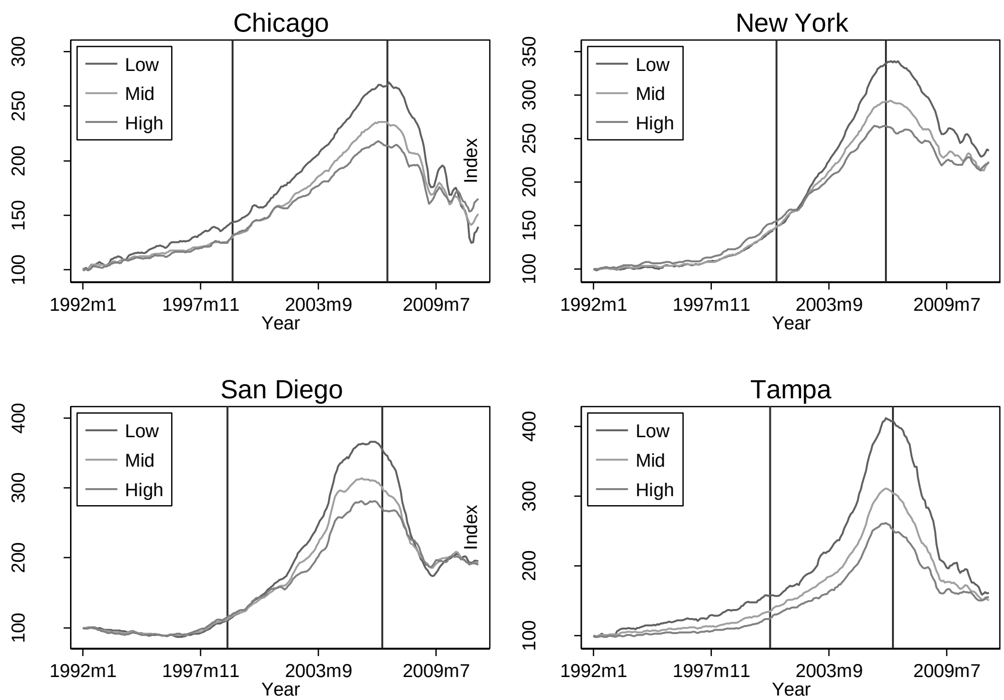

Figure 2

Differences Between High and Low Tiers with Breaks, 1992-01 through 2011-08.

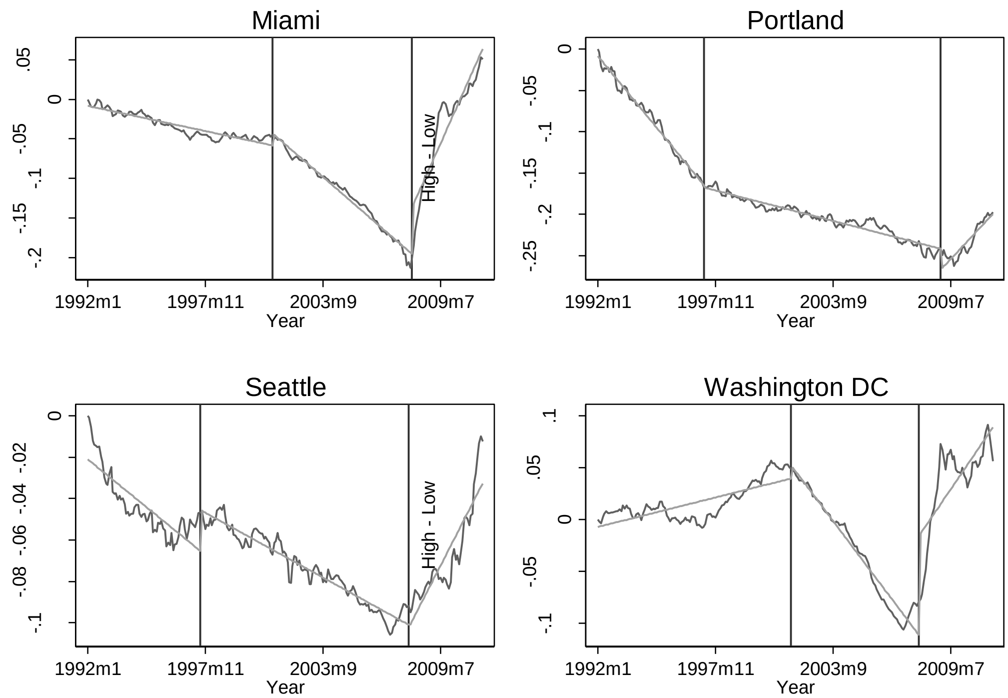

Figure 3 - Appendix

Differences Between High and Low Tiers with Breaks, 1992-01 through 2011-08.

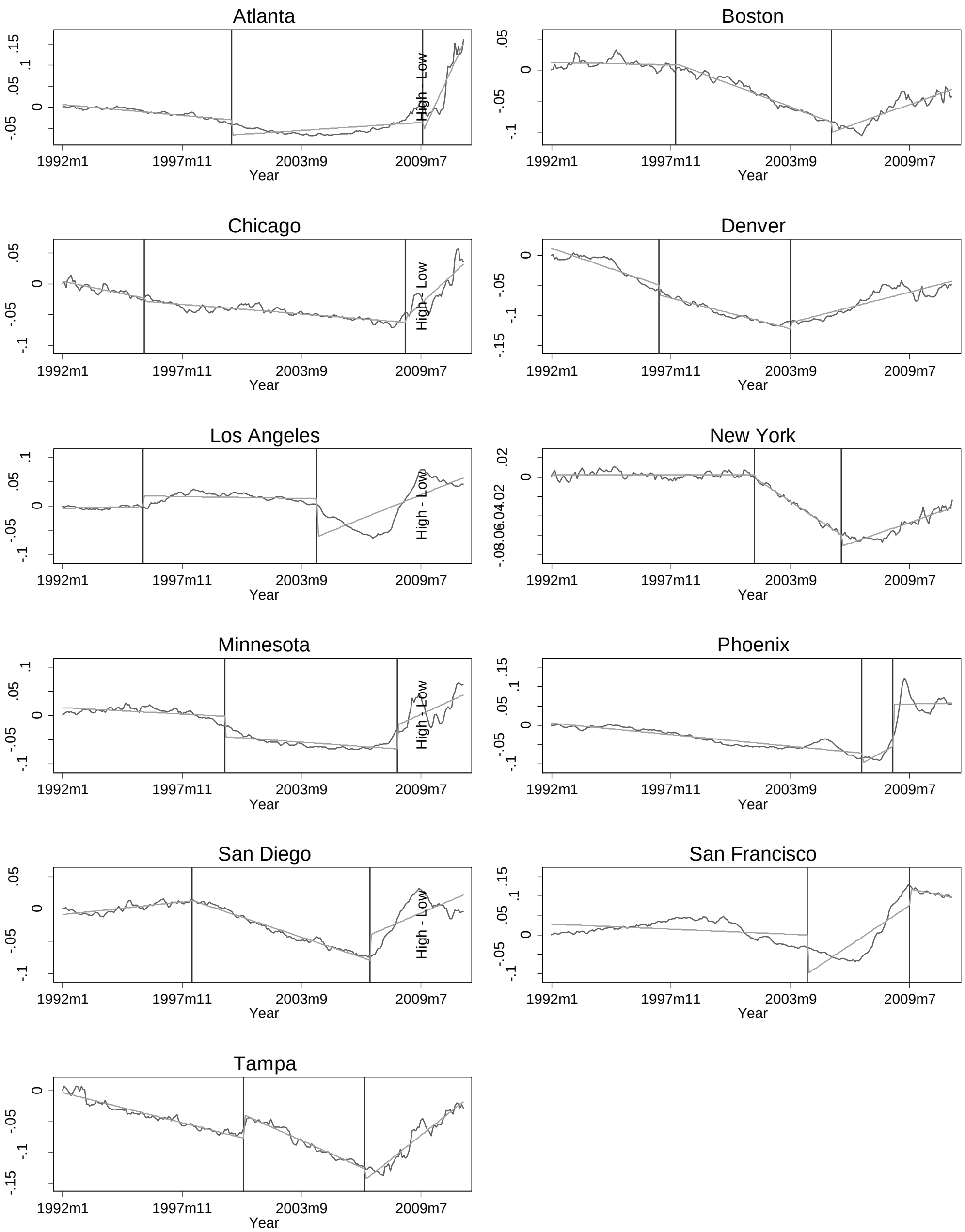

Table 1
Summary Statistics

	Mean	St.Dev	Min	Max
Atlanta				
$p_{H,t}$	144.9	27.9	99.3	193.
$p_{M,t}$	144.5	27.0	100.0	189.4
$p_{L,t}$	155.0	38.4	88.6	24.5
Chicago				
$p_{H,t}$	152.6	36.8	100.0	217.7
$p_{M,t}$	157.1	42.1	100.0	235.7
$p_{L,t}$	171.4	52.6	99.5	271.7
Los Angeles				
$p_{H,t}$	150.4	62.6	78.6	266.1
$p_{M,t}$	156.1	72.4	79.6	304.8
$p_{L,t}$	156.7	83.1	76.6	347.0
New York				
$p_{H,t}$	173.1	59.4	99.6	264.8
$p_{M,t}$	177.1	69.1	99.6	293.3
$p_{L,t}$	189.7	84.9	98.4	338.9
Phoeni				
$p_{H,t}$	179.6	68.9	100.0	341.7
$p_{M,t}$	166.7	63.4	99.3	324.6
$p_{L,t}$	180.5	82.3	99.2	386.3
San Diego				
$p_{H,t}$	164.3	65.9	88.7	281.5
$p_{M,t}$	171.1	75.6	88.5	314.3
$p_{L,t}$	182.2	92.0	86.5	366.6
Seattle				
$p_{H,t}$	170.7	55.1	99.5	279.3
$p_{M,t}$	174.9	58.7	100.0	21.6
$p_{L,t}$	200.4	72.9	99.7	348.8
Washington DC				
$p_{H,t}$	161.1	57.8	99.2	26.5
$p_{M,t}$	159.6	62.4	98.7	285.2
$p_{L,t}$	162.8	72.0	97.4	319.6

	Mean	St.Dev	Min	Max
Boston				
$p_{H,t}$	188.0	60.2	99.6	271.8
$p_{M,t}$	187.7	67.2	99.9	288.7
$p_{L,t}$	208.3	89.7	94.5	350.4
Denver				
$p_{H,t}$	188.	48.8	100.0	254.8
$p_{M,t}$	208.0	57.5	100.0	275.3
$p_{L,t}$	247.8	80.3	100.0	342.5
Miami				
$p_{H,t}$	166.0	66.2	97.5	3153
$p_{M,t}$	183.7	84.3	99.4	379.7
$p_{L,t}$	202.8	110.9	98.2	70.0
Minneapolis				
$p_{H,t}$	163.1	44.2	100.0	237.7
$p_{M,t}$	176.7	53.8	100.0	266.2
$p_{L,t}$	189.2	71.2	100.0	311.7
Portland				
$p_{H,t}$	169.5	47.3	99.0	264.1
$p_{M,t}$	199.5	63.1	100.0	319.7
$p_{L,t}$	265.1	101.3	100.0	452.4
San Frncisco				
$p_{H,t}$	176.5	63.9	94.6	283.3
$p_{M,t}$	178.9	73.0	93.8	317.8
$p_{L,t}$	176.9	88.0	89.1	368.8
Tampa				
$p_{H,t}$	148.6	49.0	97.7	261.2
$p_{M,t}$	164.1	62.1	9.2	311.1
$p_{L,t}$	195.7	91.2	98.0	412.2

Table 2

Differences across Tiers with No breaks. ADF and KPSS tests, 1992-01 through 2011-08.

	$y_t^{ML} \equiv p_{M,t} - p_{L,t}$		$y_t^{HL} \equiv p_{H,t} - p_{L,t}$		$y_t^{HM} \equiv p_{H,t} - p_{M,t}$	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
Atlanta	-0.255	0.378[c]	-0.027	0.395[c]	-0.244	0.424[c]
Boston	-1.324	0.265[c]	-1.332	0.266[c]	-0.890	0.257[c]
Chicago	0.083	0.329[c]	-0.995	0.270[c]	-0.810	0.214[c]
Denver	-1.081	0.500[c]	-1.057	0.489[c]	-1.225	0.391[c]
Los Angeles	-2.353	0.171[a]	-2.598[a]	0.194[b]	-1.898	0.211[b]
Miami	-1.078	0.244[c]	-1.884	0.233[c]	-0.369	0.208[b]
New York	-2.093	0.231[c]	-1.930	0.240[c]	-1.965	0.241[c]
Minneapolis	-0.771	0.378[c]	-0.404	0.412[c]	0.042	0.456[c]
Phoenix	-1.736	0.316[c]	-1.592	0.315[c]	-1.204	0.272[c]
Portland	-0.421	0.466[c]	-0.463	0.411[c]	-0.843	0.215[b]
San Diego	-1.499	0.255[c]	-2.582[a]	0.247[c]	-1.813	0.214[b]
San Francisco	-1.381	0.268[c]	-1.792	0.268[c]	-1.368	0.254[c]
Seattle	0.361	0.392[c]	-0.452	0.262[c]	-1.225	0.157[a]
Tampa	-1.138	0.251[c]	-1.314	0.260[c]	-0.700	0.266[c]
Washington DC	-2.313	0.146[b]	-2.711[a]	0.165[b]	-1.989	0.179[b]

Notes: Null hypothesis in the ADF is unit root. Null hypothesis in the KPSS is trend stationary. [a], [b], and [c] denote significant at the 10%, 5%, and 1% levels, respectively. L, M, and H denote low, medium, and high tear, respectively. The critical values for the KPSS test are 10%: 0.119, 5% : 0.146, 1% : 0.216.

Table 3

Differences in Mid and Low ($y_t^{ML} \equiv p_{M,t} - p_{L,t}$) with Breaks, 1992-01 through 2011-08.

	$\hat{\phi}$	Test Statistic	$\hat{k}$	$\hat{T}_{B1}$	$\hat{T}_{B2}$	$\hat{\lambda}_1$	$\hat{\lambda}_2$
Atlanta	-0.126	-3.037	12	2000-01	2009-02	0.42	0.90
Boston	-0.217	-4.637	12	1997-12	2005-04	0.31	0.70
Chicago	-0.286	-5.724[b]	7	1995-12	2008-04	0.21	0.86
Denver	-0.138	-4.592	12	1997-03	2003-05[d]	0.27	0.60
Los Angeles	-0.044	-4.237	12	1995-11	2004-02	0.20	0.64
Miami	-0.220	-6.254[b]	10	2006-03	2008-06	0.75	0.86
New York	-0.189	-4.977	9	2001-09	2005-10	0.51	0.72
Minneapolis	-0.165	-4.606	10	1999-10	2007-11	0.41	0.83
Phoenix	-0.204	-6.460[c]	8	2006-10	2008-03	0.78	0.85
Portland	-0.421	-6.636[c]	12	1998-06	2009-02	0.34	0.90
San Diego	-0.104	-5.360[a]	12	1998-03	2006-08	0.33	0.77
San Francisco	-0.080	-3.881	11	2004-03[d]	2009-01[d]	0.64	0.89
Seattle	-0.184	-4.540	11	1994-02	2008-04	0.11	0.86
Tampa	-0.308	-5.753[b]	7	2000-08	2006-05	0.45	0.75
Washington DC	-0.148	-5.057	10	2002-01	2007-10	0.53	0.83

Notes: $\hat{k}$ is the optimal lagged first-differenced terms, $\hat{T}_{Bm}$ for $m = 1, 2$ denotes the year and month of the estimated break points and $\hat{\lambda}_m = \hat{T}_{Bm}/T$ for $m = 1, 2$ denote the location of the breaks. [a], [b], and [c] denote significant at the 10%, 5%, and 1% levels, respectively. [d] denotes that the identified break point is not significant at the 10%.

Table 4

Differences in High and Low ($y_t^{HL} \equiv p_{H,t} - p_{L,t}$) with Breaks, 1992-01 through 2011-08.

	$\hat{\phi}$	Test Statistic	$\hat{k}$	$\hat{T}_{B1}$	$\hat{T}_{B2}$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\%\Delta p_{H,t}$
Atlanta	-0.188	-4.049	12	2001-01	2009-02	0.47	0.90	
Boston	-0.122	-4.358	12	1997-12	2004-08[d]	0.31	0.66	96.6%
Chicago	-0.265	-4.600	11	1999-04	2006-09	0.38	0.77	62.5%
Denver	-0.146	-4.588	11	2002-09	2007-10	0.56	0.83	
Los Angeles	-0.032	-3.761	11	1995-11	2003-10	0.20	0.62	
Miami	-0.148	-4.717	11	2000-12	2007-09	0.47	0.82	79.4%
New York	-0.226	-5.155	9	2000-11	2006-02[d]	0.47	0.74	70.4%
Minneapolis	-0.142	-4.124	12	1999-10	2007-08	0.41	0.82	48.4%
Phoenix	-0.345	-7.211[c]	8	2007-04	2008-12[d]	0.80	0.89	
Portland	-0.284	-5.919[b]	12	1997-03[d]	2008-07	0.27	0.87	56.3%
San Diego	-0.063	-5.175	11	1999-01	2006-06	0.37	0.76	134.5%
San Francisco	-0.064	-3.096	10	2003-12	2008-08[d]	0.63	0.87	
Seattle	-0.132	-3.845	12	1997-06	2007-07[d]	0.29	0.81	119.2%
Tampa	-0.271	-5.516[a]	7	2000-07	2006-06	0.45	0.76	103.4%
Washington DC	-0.078	-3.640	10	2001-05	2007-07	0.49	0.81	61.8%

Notes: $\hat{k}$ is the optimal lagged first-differenced terms, $\hat{T}_{Bm}$ for $m = 1, 2$ denotes the year and month of the estimated break points and $\hat{\lambda}_m = \hat{T}_{Bm}/T$ for $m = 1, 2$ denote the location of the breaks. [a], [b], and [c] denote significant at the 10%, 5%, and 1% levels, respectively. [d] denotes that the identified break point is not significant at the 10%.

Table 5
Differences in High and Mid ($y_t^{HM} \equiv p_{H,t} - p_{M,t}$) with Breaks, 1992m01 through 2011m08.

	$\hat{\phi}$	Test Statistic	$\hat{k}$	$\hat{T}_{B1}$	$\hat{T}_{B2}$	$\hat{\lambda}_1$	$\hat{\lambda}_2$
Atlanta	-0.468	-7.105[c]	11	2001-06	2009-01	0.50	0.89
Boston	-0.118	-4.016	5	1998-10	2005-08	0.36	0.72
Chicago	-0.116	-3.253	12	2001-06	2008-07	0.50	0.87
Denver	-0.162	-4.516	5	2003-06	2008-03	0.60	0.85
Los Angeles	-0.078	-4.024	12	1998-05	2006-09	0.33	0.77
Miami	-0.140	-4.040	6	2000-10	2007-07	0.46	0.81
New York	-0.214	-5.258	12	2000-11	2006-12	0.47	0.78
Minneapolis	-0.256	-4.599	11	2000-11	2007-09	0.47	0.82
Phoenix	-0.270	-4.831	12	2004-09	2009-02	0.67	0.90
Portland	-0.240	-5.694[a]	12	1997-06	2008-11	0.29	0.89
San Diego	-0.094	-4.057	11	2001-01	2006-10	0.47	0.78
San Francisco	-0.151	-4.606	7	2000-09	2007-05	0.46	0.81
Seattle	-0.240	-4.991	12	1997-03	2008-06	0.27	0.86
Tampa	-0.304	-4.848	10	2001-12	2007-10	0.52	0.83
Washington DC	-0.056	-3.659	11	2002-09	2008-09[d]	0.56	0.88

Notes: $\hat{k}$ is the optimal lagged first-differenced terms, $\hat{T}_{Bm}$ for $m = 1, 2$ denotes the year and month of the estimated break points and $\hat{\lambda}_m = \hat{T}_{Bm}/T$ for $m = 1, 2$ denote the location of the breaks. [a], [b], and [c] denote significant at the 10%, 5%, and 1% levels, respectively. [d] denotes that the identified break point is not significant at the 10%.

Appendix

[Figure 3, here]