

Testing for Bubbles in Housing Markets: A Panel Data Approach

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Abstract

We employ recently developed cross-sectionally robust *panel data tests* for unit roots and cointegration to find whether house prices reflect house related earnings. We use U.S. data for Metropolitan Statistical Areas, with house price measured by the weighted-repeated-sales index and cash-flows by market tenants' rents. In our full sample period, an error-correction model is not appropriate, i.e. there is a bubble. We then combine overlapping ten-year periods, price-rent ratios, and the panel data tests to construct a bubble indicator. The indicator is high for the late 1980s, early 1990s and since the late 1990s. Finally, evidence based on panel data Granger causality tests suggests that house price changes are helpful in predicting changes in rents and vice versa.

KEY WORDS: cointegration, panel data, unit root, bubble, house prices, rents

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Introduction

Very few studies use panel data methodology to assess potential bubble occurrence in housing markets. Malpezzi (1999) conducts the Im, Pesaran, and Shin (2003) panel data unit root test (IPS henceforth) to study the long-run relationship between house prices and income in U.S. Metropolitan Statistical Areas (MSA). He rejects the no-cointegration hypothesis. Gallin (2006) employs Pedroni (1999, 2004) panel data cointegration tests to account for the first-stage estimation of a cointegrating parameter and reverses the conclusion. Our paper is the first study to investigate the relationship between U.S. house prices and *rents* using panel data stationarity tests. Contrary to Malpezzi (1999) and Galin (2006), we explicitly test for cross-sectional dependence among regions and implement recently available panel data unit root tests robust to the cross-sectional correlation. Our results are conveniently summarized in a newly constructed bubble indicator. In addition, we adopt a novel approach to examine mutual predictability of house prices and rents. This approach is based on panel data Granger causality tests not yet applied in this context.

The concentration on cash-flows in our analysis naturally leads to the present-value model as the appropriate theoretical framework. Campbell and Shiller (1987) derive implications of this model for stationarity between financial assets and their cash flows: (i) they should be of the same order of integration, and (ii) if they are both non-stationary in levels but stationary in first differences, the two series should be cointegrated. Wang (2000) implements this methodology in the U.K. property market for aggregated house prices and rents. We focus on the U.S. housing market. The Bureau of Labor Statistics (BLS) is our source of the rent index for the U.S. MSA. It is defined as actual tenants' rent and calculated as a part of a CPI calculation. The rent series is combined with the house price index from the Office of Federal Housing Enterprise Oversight (OFHEO).

We first test for cross-section dependence using a test from Pesaran (2004),¹ which

¹Pesaran M.H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. CESIFO

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6 indicates the existence of a strong mutual correlation among regions for both prices and
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8 rents. We then conduct the cross-sectionally augmented IPS test (CIPS) from Pesaran
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10 (2007). We find that both the house prices and rents are non-stationary in levels but
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12 stationary in first differences. Consequently, we test for cointegration using the Pedroni
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14 (1999, 2004) tests. The house prices and rents are not cointegrated in our sample. In
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16 such a case, the price-to-rent ratio should be non-stationary as well. As expected, the
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18 CIPS test cannot reject the null hypothesis of the unit root in this variable. We conclude
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20 that an error-correction model is not appropriate for modelling house prices and rents.
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22 A broader interpretation is that it may take more than three decades for house prices to
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24 return to fundamentals.
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27 While our full-sample evidence suggests long swings of house prices from their funda-
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29 mental values, we would like to have a measure of how far away they are at a given point
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31 in time. Hence we conduct our tests using ten-period overlapping data windows. Based
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33 on the results, we define a “bubble indicator.” We set it equal to unity if house prices
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35 are non-stationary while rents are stationary, and to zero if prices are stationary. For
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37 the other possibilities we test for the stationarity of the price-rent ratio, which is more
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39 convenient than a cointegration test that is often not applicable due to the different order
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41 of integration of the involved series. The bubble indicator is then set equal to the p-value
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43 of the CIPS test. There are several periods in the U.S., when the bubble indicator is close
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45 to 1 or 1: the late 1980s and early 1990s plus a period since the year 1999.
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48 The non-stationarity of the price-to-rent ratio also has implications for research study-
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50 ing its predictive power with respect to either rents or house prices. For example, Capozza
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52 and Seguin (1996) argue that a rent-price ratio predicts capital appreciation in the hous-
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54 ing market and Clark (1995) concludes that the rent-price ratio reflects the expectations
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56 of future rent growth. To analyze this issue further, we first test for the stationarity of a
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58 simple average of price-rent and rent-price ratios across regions using standard univariate
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6 tests. All the considered aggregate series have unit roots. Panel data stationarity tests
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8 confirm this result.
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10 The presence of unit roots prevents us from using standard regressions to investigate
11 the predictive power of the price-to-rent ratios. Instead, we focus on a looser interpretation
12 of the present-value formula, which suggests that house prices should have predictive
13 power with respect to changes in rents, and vice versa. These ideas translate directly
14 into testing for Granger causality in house prices and rents. This is only plausible for
15 stationary series, in our case the differences in prices and rents. The recently developed
16 methodology in Hurlin (2004)² and Hurlin and Venet (2004)³ enables us to test for Granger
17 causality in the panel data context. Our results suggest that changes in prices are helpful
18 in predicting changes in rents and vice versa.
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29 The rest of this paper is organized as follows. We explain the idea behind bubbles in
30 the housing market using the present-value model for house prices as a discounted stream
31 of future rents in Section “Bubbles in Houseing Markets.” We describe in detail our data
32 in Section “Panel Data.” Section “Panel Data Stationarity Tests” gives a survey of the
33 panel data stationarity tests, introduces the bubble indicator and reports our results of
34 their application to our data. Section “Predictability of House Prices and Rents” analyzes
35 the mutual predictive power of changes in rents with respect to changes in prices and vice
36 versa. Section “Summary” summarizes our findings.
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47 **Bubbles in Housing Markets**

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51 So far, studies on the non-stationarity of house prices have only used regionally aggregated
52 data. Two notable exceptions are Malpezzi (1999) and Galin (2006) who investigate the
53 plausibility of error correction models for house prices and income. This paper considers
54 rents in Metropolitan Statistical Areas and augments the existing econometric framework
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59 ²Hurlin, Ch. (2004). Testing Granger Causality in Heterogeneous Panel Data Models with Fixed
60 Coefficients. Working Paper 2004-05, Laboratoire d’Economie d’Orléans.

61 ³Hurlin, Ch. and B. Venet (2004). Financial Development and Growth: A Re-examination Using a
62 Panel Granger Causality Test. Working Paper 2004-18, Laboratoire d’Economie d’Orléans.
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6 by constructing a bubble indicator and by implementing Granger causality panel tests in
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8 the context of housing markets. We view a house as an investment vehicle, use a standard
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10 present-value formula to derive implications for the relationship between house prices and
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12 cash flows, and illustrate the consequences of a bubble presence in an economy. These
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14 consequences are later employed to test for rational bubbles using U.S. panel data on
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16 house prices and rents.
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18 The standard present-value formula is:

$$19 \quad P_{i,t} = E_t \left[\frac{C_{i,t+1} + P_{i,t+1}}{1 + D} \right], \quad i = 1, \dots, N, \quad (1)$$

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21 where $P_{i,t}$ is the price of a house i or, more in the light of our subsequent analysis, a
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23 regional house price index and E_t is mathematical expectation conditional on information
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25 at time t . $C_{i,t}$ is a cash-flow associated with owning a house, i.e. a rent r_{it} . The formula
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27 (1) can be viewed as an implication of a Lucas (1978) endowment economy with risk
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29 neutral investors. In the equilibrium of this economy, income coincides with the cash-
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31 flow, which suggests that a study of the relationship between house prices and income is
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33 also appropriate.⁴ D denotes a constant discount rate. This formula holds for all periods
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35 t . Invoking the law of iterated expectations results in the following formula:
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$$40 \quad P_{i,t} = E_t \left[\frac{C_{i,t+1}}{1 + D} + \frac{C_{i,t+2}}{(1 + D)^2} + \dots + \frac{C_{i,t+k}}{(1 + D)^k} + \frac{P_{i,t+k}}{(1 + D)^k} \right]. \quad (2)$$

41 We impose for a moment the no-bubbles condition

$$42 \quad \lim_{k \rightarrow \infty} E_t \left[\frac{P_{i,t+k}}{(1 + D)^k} \right] = 0, \quad (3)$$

43 which yields

$$44 \quad P_{i,t}^F = \sum_{j=1}^{\infty} \frac{1}{(1 + D)^j} E_t [C_{i,t+j}], \quad (4)$$

45 which is often referred to as price reflecting fundamentals.

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47 Following Campbell and Shiller (1987) and Wang (2000), we define the spread between
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49 the house price and cash flows as $S_{i,t} \equiv P_{i,t} - \frac{1}{D}C_{i,t}$. If the cash-flow process is $I(1)$ and
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61 ⁴Fundamentals (including income) can also be motivated by considering omitted variables in the
62 present value formula as in Hamilton (1986) or via a general supply-demand model as in Gallin (2006).
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(3) holds, then $P_{i,t}$ is also $I(1)$ (i.e. $\Delta P_{i,t}$ is stationary) and $S_{i,t}$ is stationary (i.e. house prices and cash flows are cointegrated). To illustrate this result we rewrite $S_{i,t}$ as:

$$S_{i,t} = \frac{1}{D} E_t \sum_{j=1}^{\infty} \frac{\Delta C_{i,t+j+1}}{(1+D)^j} = \frac{1}{D} E_t [\Delta P_{i,t+1}]. \quad (5)$$

The first equality stems from the fact that the conditional expected value of the future cash-flow is given by its current value. The second equality follows from equation (4). Note also that the stationarity of $S_{i,t}$ implies the stationarity of $P_{i,t}/C_{i,t}$ (and its inverse) since if $S_{i,t} = 0$ then $P_{i,t}/C_{i,t} = 1/D$.

Let us assume that the no-bubbles condition (3) is violated. In this case, both the house price $P_{i,t}$ and the spread $S_{i,t}$ are non-stationary.⁵ Our previous discussion then suggests a strategy to determine empirically whether there is a bubble or not. A first natural step is to test for unit roots in series for house prices and cash-flows. There are four possible results of this test:

Case 1: $P_{i,t}$ stationary and $C_{i,t}$ stationary,

Case 2: $P_{i,t}$ stationary and $C_{i,t}$ non-stationary,

Case 3: $P_{i,t}$ non-stationary and $C_{i,t}$ stationary,

Case 4: $P_{i,t}$ non-stationary and $C_{i,t}$ non-stationary.

In Case 1, equation (1) passes a basic empirical test. While it can still fail to explain the behavior of house prices and cash-flows for other reasons, it is unlikely that the failure is due to the presence of a bubble. Case 2 indicates the failure of the present value model, since explosive cash-flows should be reflected in house prices. However, we are only interested in the failure of the model due to run-away prices and hence focus mainly

⁵An example of such a violation is a solution of the stochastic differential equation (1), which contains a “bubble” term that satisfies

$$B_{i,t} = \frac{1}{1+D} E_t B_{i,t+1}. \quad (6)$$

Consequently, the house price with a bubble may be written as:

$$P_{i,t} = P_{i,t}^F + B_{i,t}. \quad (7)$$

It is easy to show that the price obtained in equation (7) satisfies equality (1) and in this sense this bubble is “rational”. See for example Hamilton (1986) for a survey of speculative bubbles.

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6 on the two remaining cases. In Case 3, there is clearly a bubble. Case 4 calls for a test of
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8 the cointegration between house prices and cash-flows, assuming that first differences are
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10 stationary. Alternatively, one can test for the stationarity of P/r . In Section “Panel Data
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12 Stationarity Tests,” we explicitly discuss panel data unit root and cointegration tests, and
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14 formulate a “bubble” indicator, which summarizes the results of these tests in a simple
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16 manner.
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19 The present value formula is often used to justify the use of the rent-to-price ratio as
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21 a predictor for either the expected capitalization of investment in a house or the growth
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23 rate of rents (see Capozza and Seguin 1996 and Clark 1995). To illustrate, let us assume
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25 that a house is sold after one period. We can re-write (1) as
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$$27 \quad E_t \frac{\Delta P_{i,t+1}}{P_{i,t}} = D - E_t \frac{C_{i,t+1}}{P_{i,t}}. \quad (8)$$

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31 One can regress the capitalization on the rent-to-price ratio. Capitalization can be re-
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33 placed by the growth rate of rents since the two should be closely related. Statistically,
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35 regression (8) can be run if either both price differences and the rent-to-price are station-
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37 ary or if they are of the same order of integration but cointegrated. Theory restricts the
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39 relationship further: Under the no bubbles condition and unit root in cash flows, both the
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41 price differences and rent-to-price ratio are stationary. Therefore, different means should
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43 be used to study predictability for a non-stationary rent-to-price ratio. If first differences
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45 in prices and rents are stationary we can test for Granger-causality in panel data. If the
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47 changes in prices Granger-cause changes in rents, price differences are useful in predicting
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49 the rent differences. The same principle applies in the opposite direction. We investigate
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51 this issue in Section “Predictability of House Prices and Rents.”
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56 Panel Data

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59 The empirical analysis carried out in this study utilizes the house price and rent indices.
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61 The house price index (HPI) is from the Office of Federal Housing Enterprise Oversight and
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6 the rent of primary residence index (RI) is estimated by the Bureau of Labor Statistics.⁶
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8 According to OFHEO (Calhoun 1996), the HPI is computed quarterly for the period 1975-
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10 2006 as the weighted repeat sales index based on the data on mortgage contracts recorded
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12 by the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National
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14 Mortgage Association (Fannie Mae).⁷ The RI data for 25 Metropolitan Statistical Areas
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16 is available from the BLS for the period 1975-2006 in monthly, semi-annual, and annual
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18 frequency.
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21 In order to harmonize the data in the frequency dimension and leave as many data
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23 points as possible, both the HPI and RI are recalculated to a semi-annual frequency.
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25 Particularly, the HPI is computed as an arithmetic average of two quarterly values of
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27 this index, and the RI is estimated as the average of all monthly values of the index if
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29 monthly values are available or as a semi-annual value if such a value is available. After
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31 all recalculations, the HPI and RI are matched based on the names of the largest cities
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33 in the MSA because definitions of these areas are slightly different in OFHEO and BLS
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35 databases. The resulting dataset consists of 23 MSA and covers the period from the first
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37 half of 1978 to the second half of 2006. Both house prices and rents are adjusted for
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39 inflation using regional BLS CPI's.
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42 The base period for the HPI is by definition the first half of 1995. The base year for
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44 the regional CPI and RI is in the second half of 1983. We recalculated the latter two
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46 indexes so that the CPI=100 and RI=100 in the first half of 1995. Our recalculation
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48 makes it easier to compare the two series with the HPI as well as to compare the series
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50 for real house prices with real rents. Such a renormalization results in the price-to-rent
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52 ratio equal to 1 in 1995 h1. This does not imply that prices are equal to rents, it only
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54 makes 1995:h1 our reference point. The P/r greater than one indicates that the ratio of
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57 ⁶A description of the method of gathering data and calculating the rent index is presented in Fact
58 Sheet No. BLS 96-5 "How BLS Uses Rent Data in the Consumer Price Index."

59 ⁷The repeat sales approach to real estate index calculation was described first by Bailey, Muth, and
60 Nourse (1963) and further advanced in Case and Shiller (1987, Prices of Single Family Homes since
61 1970: New Indexes for Four Cities, NBER Working Paper 2393) and Case and Shiller (1989). For more
62 information on the HPI see Calhoun (1996).
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6 prices to rents is greater than it was in 1995:h1. What matters in our analysis is whether
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8 P/r is increasing or not, its actual value is irrelevant. This is determined with the help
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10 of panel data stationarity tests in Section “Panel Data Stationarity Tests.”
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13 The price-rent ratios are graphed in Figures 1 to 4. Based on the path of these ratios
14 for 1978:h1-2006:h2, it is possible to divide metropolitan areas into four groups. The
15 dynamics of the price-rent ratio in the first group (Figure 1) may hint that this group
16 has experienced an increasing discrepancy between home prices and rents with peaks in
17 the early 1980s, at the end of the 1980s, and in the late 1990s. These are the “usual
18 suspects,” large cities such as New York or San Francisco, with cycles of booms and busts
19 on the real estate market. The second group (Figure 2) consists mainly of Midwestern
20 cities and has experienced a peak in the price-rent ratio again around 1980 and also since
21 1999-2000. The third group (Figure 3) are cities that have experienced three increases
22 similar to the first group but less pronounced. Finally, the fourth group (depicted in
23 Figure 4) are cities that are difficult to categorize but with the exception of Portland
24 have been experiencing a rise in the price-rent ratio. The average price-rent ratio for the
25 23 MSA presented in Figure 5 also has the three peaks with a substantial increase since
26 1999-2000. Interestingly, in all the above pictures, one can identify a slight decrease of
27 the price-rent ratio growth at the end of the sample.
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44 We also investigated whether our results were sensitive to the choice of a measure of
45 rent and to the dimensions of the employed panel of data. Our second measure of rent
46 was the fair market rent from the U.S. Department of Housing and Urban Development
47 which was again combined with the HPI from OFHEO. The second panel uses data on
48 273 MSA from 1986 to 2006 at a yearly frequency. In other words, it spans a greater
49 time period for a smaller cross-section, while the latter spans a shorter period for a large
50 number of regions. The results of our tests using this dataset are very similar to those
51 obtained using our main dataset and are omitted for brevity.⁸
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62 ⁸A working paper with a complete set of results is available upon request.
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Panel Data Stationarity Tests

In this section, we investigate whether there is a long-run equilibrium relationship between house prices and rents corresponding to the present value formula (1). To do so, we conduct the IPS and CIPS tests for unit roots and the Pedroni test for cointegration. Our test results are then interpreted in accordance with Section “Bubbles in Housing Markets” and we also formulate a simple procedure designed to detect a bubble using a moving ten-year data window.

Unit Roots

Assume that the law of motion for panel data is the following AR(1) process:

$$y_{it} = \mu_i + \omega_i t + \rho_i y_{i,t-1} + \epsilon_{it}, \quad (9)$$

where $i = 1, \dots, N$ is the cross-sectional dimension of the data and $t = 1, \dots, T$ is the number of observed periods. μ_i is a fixed effect, $\omega_i t$ is an individual trend and ρ_i is an autoregressive coefficient. ϵ_{it} denotes an i.i.d. error term. The dependent variable y_i is said to contain a unit root if $|\rho_i| = 1$. We will consider two dependent variables, the house price $P_{i,t}$ and $r_{i,t}$, and their first differences.

There is an additional dimension here not present in univariate time series. ρ_i can be the same across cross-sections (i.e. $\rho_i = \rho$) or it can differ. Tests in Levin, Lin, and Chu (2002), Breitung (2000) and Hardi (2000) rely on the former assumption, while the Im, et al. (2003), Maddala and Wu (1999) and Choi (2001) tests rely on the latter. Assuming that autoregressive parameters cannot vary across individual series means the only alternative to a common unit root is the stationarity of all the series. This may be fairly restrictive in the context of our study since property prices (or rents for that matter) can rise substantially in some places while they stagnate or even decline in others. The tests which are based on the assumption of individual persistence parameters allows one to test the null hypothesis of a unit root in all series with the alternative hypothesis of

unit roots in some (but not necessarily all) of the series. Therefore we decided to employ these tests in our empirical investigation.

Specifically, the Im, et al. (2003), Maddala and Wu (1999), and Choi (2001) tests combine the results of individual unit root tests. To see how, let us consider a standard specification, the augmented Dickey Fuller test (see Hamilton 1994, Ch. 17 for a textbook treatment; ADF henceforth):

$$\Delta y_{it} = \mu_i + \omega_i t + \alpha_i y_{i,t-1} + \sum_{j=1}^{p_i} \lambda_{ij} \Delta y_{i,t-j} + \varepsilon_{it}, \quad (10)$$

where ε_{it} is an error term. Note that $\alpha_i = \rho_i - 1$ and the lag order p_i vary across cross-sections. The respective null and alternative hypotheses for this test can be expressed as:

$$H_0 : \alpha_i = 0, \quad (11)$$

$$H_1 : \begin{cases} \alpha_i = 0 & \text{for } i = 1, 2, \dots, N_1 \\ \alpha_i < 0 & \text{for } i = N_1 + 1, N_1 + 2, \dots, N. \end{cases} \quad (12)$$

The ordering of regions may be changed as needed. H_1 states that at least one (a non-zero fraction) series is stationary.

Im, et al. (2003) first calculate the t-statistics for the α_i 's in the individual ADF regressions (denoted as $t_{iT_i}(p_i)$) and then compute their average:

$$\bar{t}_{NT} = \frac{\sum_{i=1}^N t_{iT_i}(p_i)}{N}. \quad (13)$$

For the general case with a non-zero p_i for some cross-sections, the following statistic is asymptotically normally distributed:

$$W_{\bar{t}_{NT}} = \frac{\sqrt{(N)} \left(\bar{t}_{NT} - N^{-1} \sum_{i=1}^N E[t_{iT}(p_i)] \right)}{\sqrt{N^{-1} \sum_{i=1}^N Var[t_{iT}(p_i)]}} \rightarrow N(0, 1). \quad (14)$$

Im, et al. (2003) (see Table 3 of the paper) provide $E[t_{iT}(p_i)]$ and $Var[t_{iT}(p_i)]$ for various combinations of T and p_i . To calculate the statistic, one needs to specify the deterministic components and the number of lags for each ADF regression. The set of choices for exogenous regressors consists of no regressors, an individual constant (a fixed effect) or an

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6 individual constant with a linear trend. As indicated in our specification (10), we opt for
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8 the most general case with the number of lags set to unity in each case. A complementary
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10 approach to the IPS test is used in Maddala and Wu (1999) and Choi (2001). They
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12 define a test based on functions of the p-value associated with the ADF test in individual
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14 regressions. As the results based on these tests are similar to the IPS test results, we do
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16 not report them here.
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19 The IPS test is valid under the assumption of no cross-section dependence in the data.
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21 In other words, the residuals in the ADF regression equation (10) are not correlated. This
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23 may be a very strong assumption and Pesaran (2007) demonstrates that its violation often
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25 leads to undesirable finite sample properties of the IPS test. Therefore, we use the general
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27 diagnostic test for cross section dependence in panels proposed by Pesaran (2004) to find
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29 whether the dependence is present in the data. The test statistic
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$$31 \quad CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \text{Corr}(\hat{\epsilon}_i, \hat{\epsilon}_j) \right) \Rightarrow N(0, 1), \quad (15)$$

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33 where $\hat{\epsilon}_i, i = 1, \dots, N$ is a $(T \times 1)$ vector of estimated residuals from equation (10). This
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35 test exhibits much less size distortions than the standard Lagrange multiplier test based
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37 on squared correlation coefficients. Our test results are reported in Table 1 and clearly
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39 indicate strong dependence in our data in levels for both prices and rents.
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43 Pesaran (2007) suggests a way of constructing a test robust to the presence of cross-
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45 section dependence in a panel. The test uses a cross-sectionally augmented Dickey-Fuller
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47 regression (CADF):
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$$49 \quad \Delta y_{it} = \mu_i + \omega_i t + \alpha_i y_{i,t-1} + v_i \bar{y}_{t-1} + \sum_{j=1}^{p_i} \lambda_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p_i} \varpi_{ij} \Delta \bar{y}_{i,t-j} + \varepsilon_{it}, \quad (16)$$

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51 where \bar{y}_t is a cross-section mean. The presence of the lagged cross-section mean and its
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53 differences suffices to filter out the effect of an unobserved common factor. Let us denote
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55 $\tilde{t}_{i,T_i,N}(p_i)$ as the t-statistic for α_i in the CADF regression. Note that the t-statistic depends
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57 on the N-dimension here as well, reflecting the cross-sectional dependence. Pesaran (2007)
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59 shows that in a standard ADF regression, the t-test has a high empirical size in the
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6 presence of cross-sectional dependence, while it does not have this in the CADF regression.
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8 Assuming a balanced panel, $T_i = T$ for all i 's. We also set $p_i = p = 1$ for all i 's. Our
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10 notation then simplifies to $\tilde{t}_{i,T_i,N}(p_i) = \tilde{t}_i(T, N)$. We employ a truncated version of this
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12 statistic, restricting it to the interval between -6.42 and 1.70, which improves its finite
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14 sample properties. The CADF t-statistic is then used to construct a cross-sectionally
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16 augmented version of the IPS test:
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$$19 \quad \bar{t}^\dagger = \frac{1}{N} \sum_{i=1}^N \tilde{t}_i(N, T). \quad (17)$$

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23 Critical values for this statistic are available in Pesaran (2007).
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25 We use Gauss code to conduct our empirical analysis. The IPS test is implemented
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27 using Nonstationary Panel Time Series Module 1.3 for Gauss (NPT 1.3) written by Chihwa
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29 Kao. We programmed the CADF and CIPS tests ourselves.⁹ We report our results for the
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31 CADF t-tests in Table 2. The MSA are in alphabetical order and we calculate $\tilde{t}_i(T, N)$
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33 for prices, rents, and price-rent ratios. As expected, the t-CADF statistic rejects much
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35 less often than the standard t-ADF (not reported). Only two price-rent ratios are deemed
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37 stationary for the whole sample period. Table 3 gives a summary of all conducted panel
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39 data unit root tests. The tests indicate that using the whole sample period in both cases,
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41 prices and rents are integrated of order one and the price-rent ratio is non-stationary. P/r
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43 inverse (results not reported here) is not stationary either. Results based on the IPS test,
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45 while quantitatively different, are qualitatively the same as the results based on the CIPS
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47 test. Given that prices and rents series have the same order of integration, the natural
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49 next step is testing for cointegration in panel data. The cointegration test can indicate
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51 whether it is appropriate to formulate a dynamic model of the dependence of house prices
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53 on rents in terms of first differences or whether we should formulate an error-correction
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55 model.
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61 ⁹Our code was cross-checked with the Gauss procedures kindly provided by professor Pesaran and his
62
63 research assistant Takashi Yamagata. They yielded identical results.
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Cointegration

The cointegration tests employed in this paper rely on the results of Pedroni (1999, 2004). Pedroni (1999) describes the framework for testing for cointegration in panel datasets with $m = 2, \dots, M$ explanatory variables and Pedroni (2004) covers the case for just one regressor. The hypothesized cointegrating regression is

$$y_{i,t} = \mu_i + \omega_i t + \psi_i x_{i,t} + \zeta_{i,t} \text{ for } t = 1, \dots, T, i = 1, \dots, N. \quad (18)$$

Again, T is the time dimension and N the cross-sectional dimension. The slope coefficient ψ_i and the fixed-effects parameter μ_i are allowed to vary across individual panel members. Also included is an individual time trend with a coefficient ω_i . We substitute house prices for y and rents for x in the regression equation.

There are seven residual-based statistics proposed by Pedroni (1999).¹⁰ The first four are based on pooling along the within-dimension and test the null hypothesis of no cointegration: $H_0 : \gamma_i = 1$ for all i where γ_i is the autoregressive coefficient of the residual $\hat{\zeta}_i$ extracted from estimating the regression equation (18). The alternative hypothesis is $H_1 : \gamma_i = \gamma < 1$ for all i 's, i.e. it assumes a common value for γ_i 's. These four statistics are a non-parametric variance ratio statistic, non-parametric statistics similar to the Phillips and Perron rho- and t-statistics, and a parametric statistic similar to the augmented Dickey-Fuller t-statistic.

The remaining three statistics are based on pooling along the between-dimension and again test the null hypothesis of no cointegration: $H_0 : \gamma_i = 1$ for all i , this time versus the alternative hypothesis $H_1 : \gamma_i < 1$ for all i , i.e. no common value for the autoregressive coefficient is presumed in this case. The statistics use a group mean approach and are again respectively analogous to the Phillips and Perron rho- and t-statistic, and to the augmented Dickey-Fuller t-statistic. Similarly to testing for unit roots in panel data, the group statistics are of main interest since a potential failure to reject the null hypothesis

¹⁰For explicit formulae, see Table 1 in Pedroni (1999).

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6 of a unit root in residuals from the panel data regression may be due to heterogenous
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8 autoregressive coefficients rather than due to the presence of a unit root. Pedroni (2004)
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10 also conducts some Monte Carlo experiments that show that the finite sample properties
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12 of the group ADF t-statistic dominate the properties of the other two group tests and
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14 hence we employ this one in our analysis.

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16 To calculate the values of the Pedroni test statistic, we used Gauss code from Wagner
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18 and Hlouskova (2007).¹¹ Since a panel data cointegration test robust to the presence of
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20 cross-correlation is not yet available, we used the bootstrapping methodology from Gallin
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22 (2006) and Maddala and Wu (1999) to calculate critical values for the cointegration test.
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24 The bootstrapping methodology preserves the cross-sectional dependence in the residuals
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26 from equation (18) observed in the data. The Pedroni ADF-t statistic is 1.82, much higher
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28 than the 10% critical value -2.03. Therefore, prices and rents are clearly not cointegrated
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30 and the use of an error-correction model is not appropriate.
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36 **Bubble Indicator**

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39 Here we combine the previously described methodology of testing for unit roots and
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41 cointegration in panel data and further analyze the relationship between house prices
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43 and rents in levels. We propose an indicator summarizing the implications of the present
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45 value model. The theory suggests that there is a bubble if either (i) the price-level is
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47 non-stationary while the rent-level is stationary, or (ii) both series are of first order of
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49 integration but they are not cointegrated. In both cases, the relationship between the two
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51 variables breaks down and there is a bubble on the house market. The latter case prevails
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53 using the whole sample period. However, we would also like to be able to assess how
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55 the likelihood of a bubble changes over time. We define overlapping ten-year intervals
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57 covering our sample period. In accordance with the theory, we define a bubble indicator
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61 ¹¹Wagner, M. and J. Hlouskova (2007). The Performance of Panel Cointegration Methods: Results
62 from a Large Scale Simulation Study. Institute for Advanced Studies Vienna, Working Paper.
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6 to be 0 for stationary prices and one for non-stationary prices and stationary rents. For
7 cases in between, one would ideally use a cointegration test. However, this is potentially
8 problematic since the test is often not well defined in a given sub-sample due to a different
9 order of integration of the two series and it is cumbersome to check (one has to conduct
10 unit root tests for higher order differences in many cases). Therefore we propose to replace
11 the cointegration test with a test for the stationarity of the price-rent ratio, which has an
12 intuitive appeal. We equate the bubble indicator to the p-value of the CIPS test for P/r
13 if it is not already 1 or 0.
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23 We calculate the Pedroni tests and the CIPS unit root tests, which respectively allow
24 for the possibility of different autocorrelation coefficients in the residuals of the cointe-
25 grating regression and in a given time series. We present our results in Table 4. Looking
26 at the CIPS unit root tests, we can see that house prices were non-stationary and rents
27 stationary from 1987 to 1988 when we use ten prior years of data in each year. This results
28 in the indicator being 1. In 1990, the rents become non-stationary but the price-rent ratio
29 is stationary, resulting in a bubble indicator of 0.03, below the 5% level of significance.
30 Overall, the periods when the indicator is higher correspond to rising average price-rent
31 ratios in Figure 5 prior to 1990 and prior to 2000. The indicator decreases by the end of
32 a sample, which reflects a potential stagnation of the housing market.
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44 While the number of observations for our bubble indicator is fairly small for a thorough
45 time series analysis, we at least provide an illustrative comparison to major house market
46 indicators. First, we use existing home sales, sale price of existing homes, and the housing
47 affordability index from the National Association of Realtors. Second, we use new home
48 sales sold and for sale, total construction spending, and total housing units started from
49 the Census Bureau, Department of Commerce. Finally, we use the Housing Market Index
50 (HMI) from the National Association of Home Builders. A survey of these indicators is
51 given in Bauhmol (2005).
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62 We split the indicators into three groups and depict their values together with our
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6 indicator in graphs 6, 7 and 8 (all indicators are normalized to 1 in 1995). Interestingly,
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8 all of the indicators show a cooling of the housing market at the end of 2006. Figure 6
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10 shows the correspondence of the indicator with existing home sales and new home sales,
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12 which is consistent with correlations in Table 5. Figure 7 demonstrates visually the
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14 positive correlations from Table 5 for existing home prices and HMI. Not surprisingly, the
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16 correlation between the indicator and the affordability index is negative. Interestingly,
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18 there is a strong positive correlation of the bubble indicator with housing starts and the
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20 value of construction (see Table 5 and Figure 8).
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25 Predictability of House Prices and Rents

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29 The aggregate average price-to-rent ratio and its inverse are non-stationary. This prevents
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31 us from using the standard regression methodology and brings us to statistical predictabil-
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33 ity formulated in terms of Granger causality. First differences for both house prices and
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35 rents are stationary according to our panel data tests for unit roots. Therefore, we are in
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37 a position to test for causality between the two. Testing for causality gives an indication
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39 of whether changes in prices predict rents and vice versa. Similarly to recently devel-
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41 oped panel data unit root and causality tests, there exists an analogous test for Granger
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43 causality in panel data with a short time-series dimension. This test is described in Hurlin
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45 (2004) and applied in Hurlin and Venet (2004).
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48 Let y_i and x_j be two stationary variables. Consider the following linear model:

$$49 \quad y_{it} = \mu_i + \sum_{l=1}^L \varphi_i^{(l)} y_{i,t-l} + \sum_{l=1}^L \delta_i^{(l)} x_{i,j,t-l} + \xi_{it}. \quad (19)$$

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51 ξ_{it} are normally i.i.d. with zero mean and finite heterogeneous variances and $\xi_i =$
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53 $(\xi_{i1}, \dots, \xi_{iT})'$ are independently distributed across groups. The null hypothesis assumes
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55 that x does not help in predicting y for any of the N individual units in the panel. It is
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57 referred to as Homogeneous Non Causality (HNC) and can be formally stated as:
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$$61 \quad H_0 : \delta_i = 0, \quad \forall i = 1, \dots, N, \quad (20)$$

where $\delta_i = (\delta_i^{(1)}, \dots, \delta_i^{(L)})'$. The alternative hypothesis encompasses the possibility that there are N_1 individual units with no causality and is defined as:

$$H_1 : \begin{aligned} \delta_i &= 0, & \forall i &= 1, \dots, N_1, \\ \delta_i &\neq 0, & \forall i &= N_1 + 1, \dots, N, \end{aligned} \quad (21)$$

where $N_1 \in [0, N)$ is not known. Let $W_{NT}^{HNC} = (1/N) \sum_{i=1}^N W_{iT}$ where W_{it} denotes the Wald statistic associated with the individual test of H_0 for each $i = 1, \dots, N$. Hurlin (2004) shows that the approximated standardized statistic

$$Z_{NT}^{HNC} = \sqrt{\frac{N}{2 \times L} \times \frac{(T - 2L - 5)}{(T - L - 3)}} \times \left[\frac{(T - 2L - 3)}{(T - 2L - 1)} W_{NT}^{HNC} - L \right] \quad (22)$$

converges in distribution to $N(0, 1)$ as $N \rightarrow \infty$ for a fixed $T > 5 + 2L$.

We first verify that there is no cross-sectional dependence in the residuals from regression (19). See the results of the *CD* test in Table 6. We then use Intercooled Stata 9.2. to run panel data Granger causality tests with $L = 1$. Results in Table 6 show that the null of HNC can only be rejected for in the direction from differences in rents to differences in prices. Even in this case, the p-value is barely above the 10% level of significance.¹² In other words, there is a (statistically speaking) causal two-way relationship between changes in house prices and changes in rents, in spite of the fact that the connection between the levels of the two variables breaks down due to the presence of a bubble.

Summary

We study the implications of the standard present value formula for the order of integration, cointegration and Granger-causality between house prices and rents, with and without a bubble term. We conduct our analysis using recent advances in panel data econometrics. Over the whole sample period, the house prices and rents either have a different order of integration or are not cointegrated. This conclusion is confirmed using the price-rent ratio. This is consistent with the presence of a bubble term in our asset

¹²The corresponding p-values for our dataset with cash flows measured by a fair market rent are close to 0 and hence strongly support mutual predictability for changes in house prices and rents.

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6 pricing model and it implies that one cannot use an error correction model for house
7 prices with rents as the fundamental factor. We proceed a step further with our analysis
8 and formulate a simple procedure that can help to determine the extent to which there is
9 a (statistical) discrepancy between house prices and their fundamentals. At each point in
10 time, we investigate a panel of house prices and rents for the last ten years. If the prices
11 are non-stationary but rents are not, we view that as an indication of a bubble. If prices
12 are stationary, the bubble indicator is zero. In all other situations it is equal to the p-value
13 of the panel data unit root test for the price-rent ratio. Our bubble indicator coincides
14 fairly well with the pattern of price-rent ratios and several housing market indicators.
15 However, it has the advantage of being able to determine formally whether the price-rent
16 ratio is “too high.” Price-rent ratios are suggestive of rational bubbles in several periods
17 but mainly in the late 1980s and in the late 1990s up to 2005.
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32 Non-stationarity of the price-to-rent and rent-to-price ratios is documented for both
33 the aggregate series and in our panels. In such a case, standard regression techniques
34 cannot be used to investigate the predictive properties of the price-to-rent ratios for the
35 growth rates of house prices or rents. However, since prices and rents are both $I(1)$,
36 we can test for panel Granger causality. In spite of the fact that it can take over three
37 decades for house prices to revert to a fundamental value corresponding to earnings, the
38 first differences of house prices have predictive power with respect to rents and vice versa.
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47 There are several possible extensions of our study, mainly considering different mea-
48 sures of property prices or variables providing information about fundamentals. On the
49 price side, one can for instance attempt to use a quality adjusted index or correct for an
50 upward bias present in the repeated-sales index used in this paper. On the side of funda-
51 mentals, yet another measure for rents can be employed, such as the owners’ equivalent
52 rent series. Also, income and interest rates can be included as explanatory variables.
53 However, all these improvements come at a cost in the terms of reduced cross-sectional
54 and/or time dimension of the data, a more complex structural theoretical framework, and
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6 a greater computational burden.
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11 Marie Curie International Reintegration Grant # 014864 from the European Commission.
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Table 1: Diagnostic tests for cross section dependence in panels

price-level <i>CD</i>	price-diff. <i>CD</i>	rent-level <i>CD</i>	rent-diff. <i>CD</i>
75.12***	-0.69	29.13***	-0.64

¹ Sample: 23 MSA, 1978:01-2006:02 semi-annual data

² ADF regression: intercept, trend, and the first lag of the dependent variable.

³ Under the null of no cross section dependence: $CD \Rightarrow N(0, 1)$.

⁴ *** - significant at the 1 % level, ** - significant at the 5 % level, * - significant at the 10 % level.

Table 2: Cross-sectionally augmented Dickey-Fuller tests

MSA	price CADF	rent CADF	P/r CADF	P/r rank
Atlanta-Sandy Springs-Marietta, GA	-0.37	-0.41	-1.15	7
Boston-Quincy, MA (MSAD)	-1.90	-3.21	-1.69	8
Chicago-Naperville-Joliet, IL (MSAD)	-6.42 ***	-6.42 ***	-4.42 **	23
Cincinnati-Middletown, OH-KY-IN	-4.73 ***	-1.32	-2.75	19
Cleveland-Arkon, OH (MSAD)	-4.73 ***	-4.53 ***	-2.23	12
Dallas-Plano-Irving, TX (MSAD)	-2.95	-1.68	-2.93	21
Denver-Aurora, CO	0.89	-0.12	-0.78	5
Detroit-Livonia-Dearborn, MI (MSAD)	-1.08	-3.03	-0.72	3
Honolulu, HI	-0.13	-0.79	-0.49	2
Houston-Sugar Land-Baytown, TX	-3.05	-5.18 ***	-2.52	17
Kansas City, MO-KS	-0.01	-2.50	-0.76	4
Los Angeles-Long Beach-Glendale, CA (MSAD)	-1.78	-1.79	-2.5	16
Miami-Miami Beach-Kendall, FL (MSAD)	-0.45	-0.03	-0.91	6
Milwaukee-Waukesha-West Allis, WI	-4.40 **	-2.36	-2.33	15
Minneapolis-St. Paul-Bloomington, MN-WI	0.65	-5.06 ***	-0.42	1
New York-White Plains-Wayne, NY-NJ (MSAD)	-3.39	-3.90 **	-2.82	20
Philadelphia, PA (MSAD)	-1.50	-1.70	-1.87	9
Pittsburgh, PA	-3.32	-2.76	-2.27	13
Portland-Vancouver-Beaverton, OR-WA	-2.08	-2.29	-1.89	10
San Diego-Carlsbad-San Marcos, CA	-2.34	-3.18	-2.63	18
San Francisco-San Mateo-Redwood City, CA (MSAD)	-2.80	-2.00	-2.28	14
Seattle-Bellevue-Everett, WA (MSAD)	-2.96	-2.95	-3.51 *	22
St. Louis, MO-IL	-3.04	-2.08	-2.17	11

¹ Sample: 23 MSA, 1978:01-2006:02, semi-annual data, levels only.

² CADF regression: intercept; trend; the first lags of the difference of the dependent variable, the difference of the cross section mean, and the cross-section mean; the difference of the cross-section mean.

³ Critical values for the CADF t-statistic are from Pesaran (2007), Table Ic: 1% -4.52 (denoted ***), 5% -3.79 (denoted **), and 10% -3.44 (denoted *).

⁴ MSA are in alphabetical order.

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Table 3: Panel data unit root tests

23 MSA, 1978:01-2006:02, semi-annual data						
Method	price-level	price-diff.	rent-level	rent-diff.	p/r	
IPS	1.63	-20.29 ***	-2.60	-13.00 ***	5.48	
CIPS	-2.26	-5.02 ***	-2.58	-4.16 ***	-2.00	

¹ The IPS test is based on the individual ADF regressions with an intercept, trend, and the first lag of the dependent variable. The test statistic has an asymptotic standardized normal distribution.

² The CIPS test is based on the individual CADF regressions with an intercept; a trend; the first lags of the difference of the dependent variable, the difference of the cross section mean, and the cross-section mean; and the difference of the cross-section mean. Critical values for the CIPS statistic are from Pesaran (2007), Table IIc: 1% -2.85, 5% -2.71, and 10% -2.63.

³ Significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively, for both tests.

⁴ For both tests, the null hypothesis is that of a unit root and the alternative hypothesis is that at least one of the series is stationary.

Table 4: Bubble indicator

Year	price CIPS	price-dif. CIPS	rent CIPS	rent-dif. CIPS	coint. Pedroni	P/r CIPS	bubble indicator
1987	-2.21		-2.71 *		-1.32	-2.62	1.00
1988	-1.75	-2.72 *	-2.65 *	-2.42	1.64	-2.62	1.00
1989	-2.71 *	-2.46	-3.22 ***	-2.35	0.56	-2.89 **	0.00
1990	-2.41	-2.67 *	-2.14	-2.60	0.95	-2.82 **	0.03
1991	-1.51	-2.75 **	-1.89	-2.56	0.66	-2.18	0.51
1992	-1.52	-3.02 ***	-1.55	-2.64 *	-3.11	-1.63	0.97
1993	-2.11	-2.56	-1.64	-2.63 *	-2.68	-2.31	0.35
1994	-2.21	-2.61	-1.53	-2.55	-1.74	-2.32	0.34
1995	-2.71 *	-2.95 ***	-1.83	-2.44	-2.81	-2.53	0.00
1996	-2.23	-2.55	-1.83	-2.51	-2.05	-2.22	0.46
1997	-2.79 **	-3.29 ***	-1.72	-3.11 ***	-4.08	-2.44	0.00
1998	-2.96 ***	-3.15 ***	-2.08	-3.15 ***	-6.44 ***	-2.70 *	0.00
1999	-1.91	-3.07 ***	-2.25	-2.79 **	-2.35	-1.85	0.87
2000	-1.69	-2.90 **	-2.50	-2.84 **	-0.97	-1.80	0.90
2001	-2.07	-3.59 ***	-2.66 *	-2.87 **	0.16	-1.88	1.00
2002	-1.83	-3.48 ***	-1.89	-2.51	0.39	-2.13	0.58
2003	-1.46	-3.59 ***	-1.37	-2.54	0.16	-1.80	0.90
2004	-1.58	-3.23 ***	-0.81	-2.41	0.69	-1.85	0.87
2005	-1.71	-3.14 ***	-0.71	-2.69 *	-0.81	-1.75	0.93
2006	-2.28	-3.03 ***	-0.94	-3.07 ***	-3.86	-2.34	0.32

¹ Sample: 23 MSA, 1978:01-2006:02, semi-annual data, ten-year data windows end in a given year.

² The CIPS test is based on the individual CADF regressions with an intercept; a trend; the first lags of the difference of the dependent variable, the difference of the cross section mean, and the cross-section mean; and the difference of the cross-section mean. Critical values for the CIPS statistic are from Pesaran (2007), Table IIc. 1% -2.92, 5% -2.73, and 10% -2.63.

³ The Pedroni test included a constant and a trend as deterministic variables. The critical values were generated using 50,000 simulations by bootstrapping to preserve cross-sectional dependence and including autocorrelation. They are 1% -5.97, 5% -4.78, and 10% -4.13.

⁴ Significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively, for both tests.

⁵ The (price) bubble indicator is 1 if the price level is non-stationary while the rent is stationary at 10% significance level; it is 0 if the price level is stationary; otherwise, it is equal to the p-value of the CIPS test conducted for the price-rent ratio.

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Table 5: Correlation of the bubble indicator with housing indicators

Exist. home sales	New home sales	Houses for sale	Exist. home price	Afford. index	HMI	Housing starts	Value of constr.
0.37	0.35	0.12	0.24	-0.03	0.29	0.40	0.52

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Table 6: Hurlin Tests for Homogeneous Non-Causality in Panel Data

H_0	CD	P-value	Z_{NT}^{HNC}	P-value
23 MSA, 1978:01-2006:02, semi-annual data				
price-diff. does not Granger cause rent-diff.	-0.70	> 0.50	-1.70	0.09
rent-diff. does not Granger cause price-diff.	1.35	0.18	-1.58	0.11

Both CD and Z_{NT}^{HNC} asymptotically follow the standardized normal distribution. P-values for two-sided tests are reported.

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Figure 1: Price-rent ratios using indexes, Part 1/4

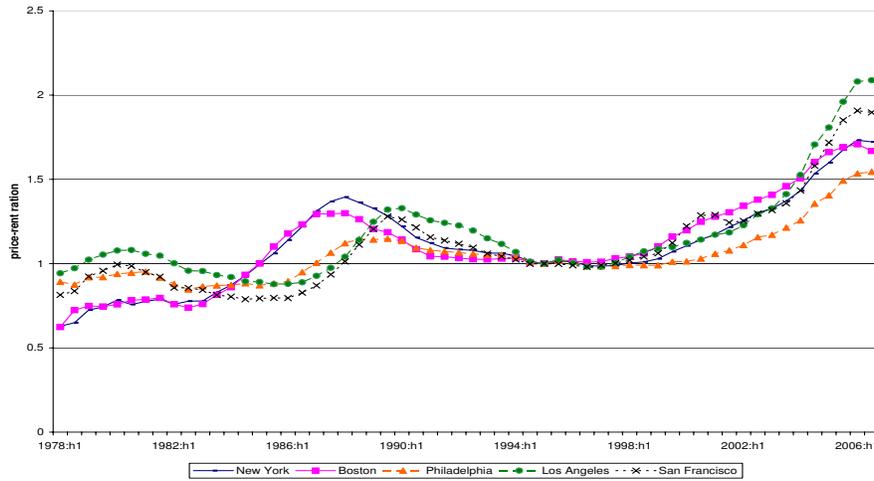
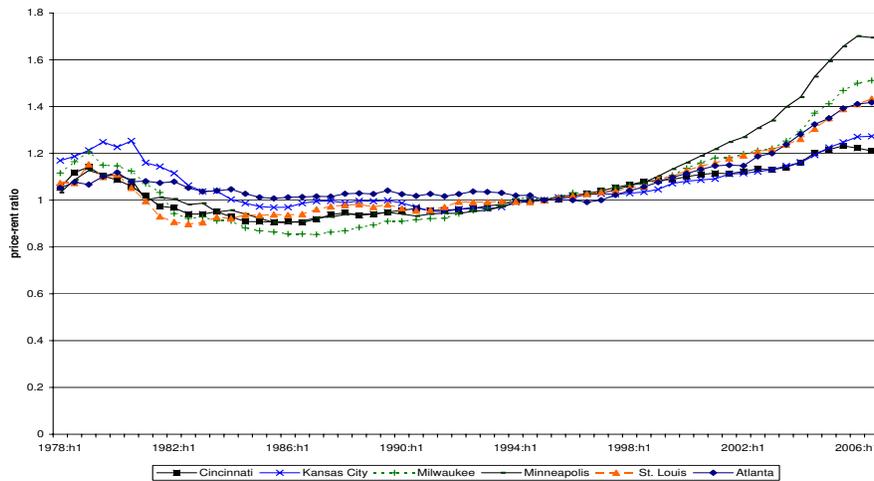


Figure 2: Price-rent ratios using indexes, Part 2/4



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Figure 3: Price-rent ratios using indexes, Part 3/4

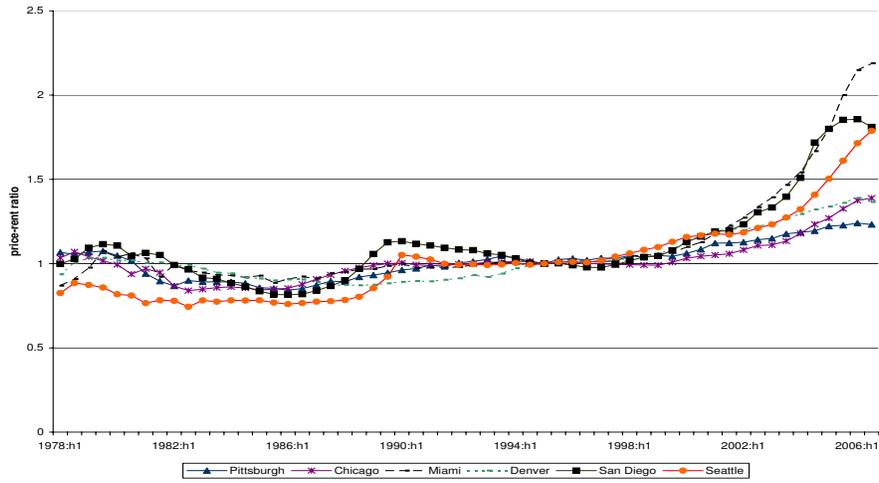
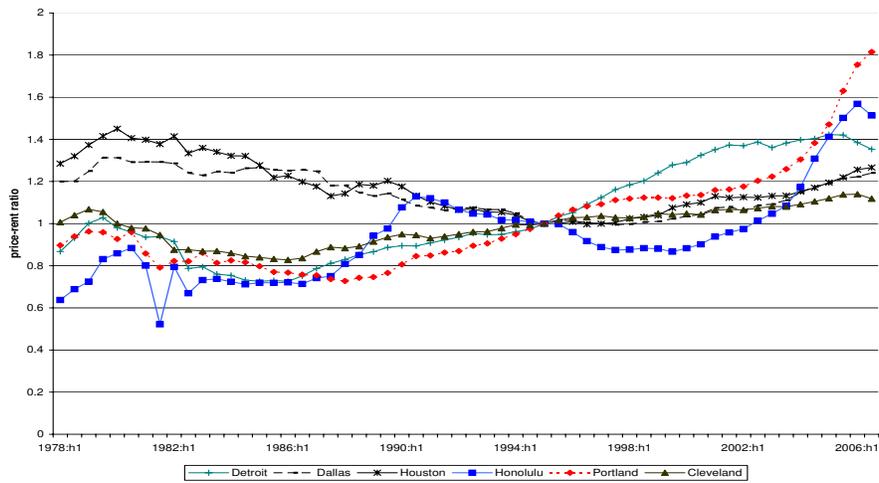
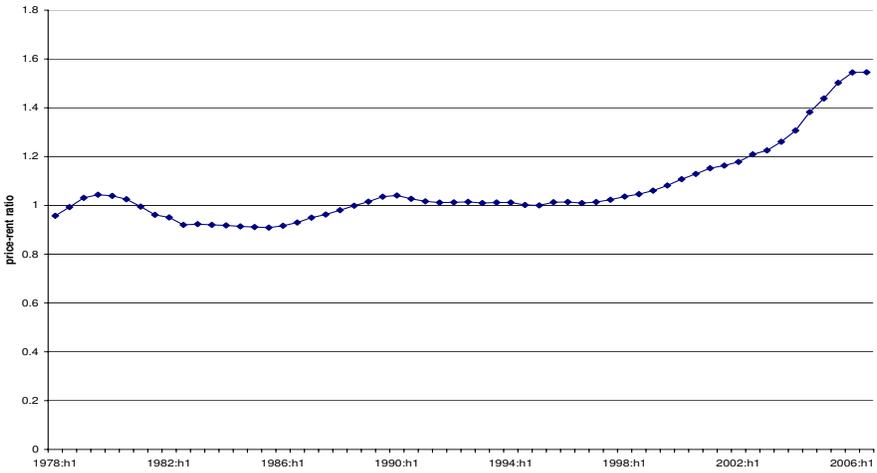


Figure 4: Price-rent ratios using indexes, Part 4/4



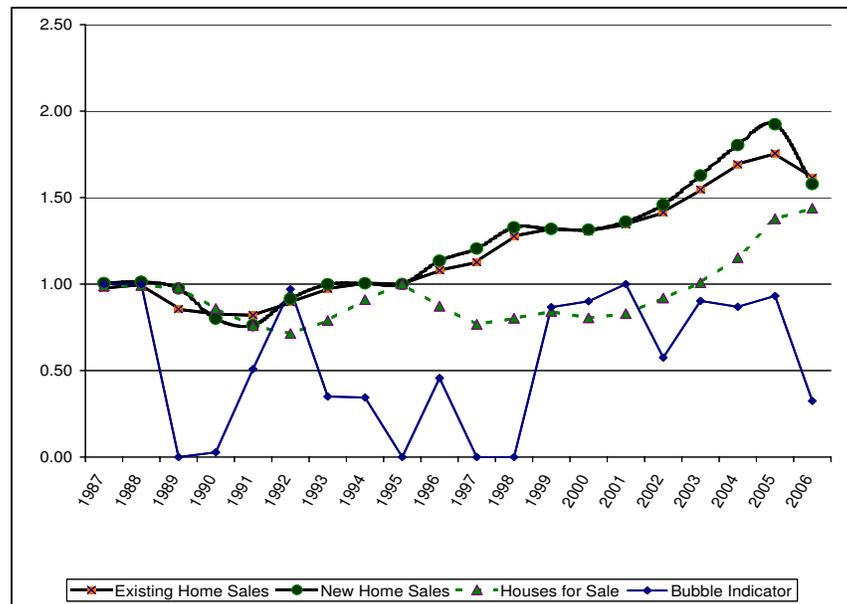
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Figure 5: Average price-rent ratios using indexes



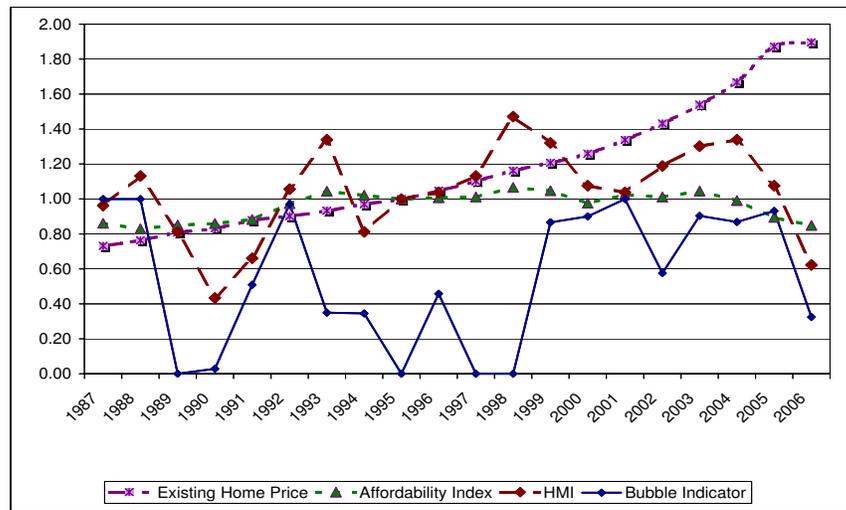
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Figure 6: A bubble indicator, existing homes sales, new home sales, and houses for sale



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Figure 7: A bubble indicator, an existing home price, an affordability index, and HMI



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Figure 8: A bubble indicator, housing starts, and a value of construction

