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# 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 10-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.

**Keywords** Cointegration · Panel data · Unit root · Bubble · House prices · Rents

## Introduction

Very few studies use panel data methodology to assess potential bubble occurrence in housing markets. Malpezzi (1999) conducts the Im et al. (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

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(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 Gallin (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 indicates the existence of a strong mutual correlation among regions for both prices and rents. We then conduct the cross-sectionally augmented IPS test (CIPS) from Pesaran (2007). We find that both the house prices and rents are non-stationary in levels but stationary in first differences. Consequently, we test for cointegration using the Pedroni (1999, 2004) tests. The house prices and rents are not cointegrated in our sample. In such a case, the price-to-rent ratio should be non-stationary as well. As expected, the CIPS test cannot reject the null hypothesis of the unit root in this variable. We conclude that an error-correction model is not appropriate for modelling house prices and rents. A broader interpretation is that it may take more than three decades for house prices to return to fundamentals.

While our full-sample evidence suggests long swings of house prices from their fundamental values, we would like to have a measure of how far away they are at a given point in time. Hence we conduct our tests using ten-period overlapping data windows. Based on the results, we define a "bubble indicator." We set it equal to unity if house prices are non-stationary while rents are stationary, and to zero if prices are stationary. For the other possibilities we test for the stationarity of the price–rent ratio, which is more convenient than a cointegration test that is often not applicable due to the different order of integration of the involved series. The bubble indicator is then set equal to

[1] Pesaran M.H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. CESIFO Working Paper 1229.

the $p$-value of the CIPS test. There are several periods in the U.S., when the bubble indicator is close to 1 or 1: the late 1980s and early 1990s plus a period since the year 1999.

The non-stationarity of the price-to-rent ratio also has implications for research studying its predictive power with respect to either rents or house prices. For example, Capozza and Seguin (1996) argue that a rent–price ratio predicts capital appreciation in the housing market and Clark (1995) concludes that the rent–price ratio reflects the expectations of future rent growth. To analyze this issue further, we first test for the stationarity of a simple average of price–rent and rent–price ratios across regions using standard univariate tests. All the considered aggregate series have unit roots. Panel data stationarity tests confirm this result.

The presence of unit roots prevents us from using standard regressions to investigate the predictive power of the price-to-rent ratios. Instead, we focus on a looser interpretation of the present-value formula, which suggests that house prices should have predictive power with respect to changes in rents, and vice versa. These ideas translate directly into testing for Granger causality in house prices and rents. This is only plausible for stationary series, in our case the differences in prices and rents. The recently developed methodology in Hurlin (2004)[2] and Hurlin and Venet (2004)[3] enables us to test for Granger causality in the panel data context. Our results suggest that changes in prices are helpful in predicting changes in rents and vice versa.

The rest of this paper is organized as follows. We explain the idea behind bubbles in the housing market using the present-value model for house prices as a discounted stream of future rents in Section "Bubbles in Housing Markets." We describe in detail our data in Section "Panel Data." Section "Panel Data Stationarity Tests" gives a survey of the panel data stationarity tests, introduces the bubble indicator and reports our results of their application to our data. Section "Predictability of House Prices and Rents" analyzes the mutual predictive power of changes in rents with respect to changes in prices and vice versa. Section "Summary" summarizes our findings.

## Bubbles in Housing Markets

So far, studies on the non-stationarity of house prices have only used regionally aggregated data. Two notable exceptions are Malpezzi (1999) and Gallin (2006) who investigate the plausibility of error correction models for house prices and income. This paper considers rents in MSA and augments the existing econometric framework by constructing a bubble indicator and by implementing Granger causality panel tests in the context of housing markets.

[2]Hurlin, Ch. (2004). Testing Granger Causality in Hetergoeneous Panel Data Models with Fixed Coefficients. Working Paper 2004-05, Laboratoire d'Economie d'Orléans.

[3]Hurlin, Ch. and B. Venet (2004). Financial Development and Growth: A Re-examination Using a Panel Granger Causality Test. Working Paper 2004-18, Laboratoire d'Economie d'Orléans.

We view a house as an investment vehicle, use a standard present-value formula to derive implications for the relationship between house prices and cash flows, and illustrate the consequences of a bubble presence in an economy. These consequences are later employed to test for rational bubbles using U.S. panel data on house prices and rents.

The standard present-value formula is:

$$P_{i,t} = E_t\left[\frac{C_{i,t+1} + P_{i,t+1}}{1+D}\right], \quad i = 1, \ldots, N, \tag{1}$$

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

$$P_{i,t} = E_t\left[\frac{C_{i,t+1}}{1+D} + \frac{C_{i,t+2}}{(1+D)^2} + \ldots + \frac{C_{i,t+k}}{(1+D)^k} + \frac{P_{i,t+k}}{(1+D)^k}\right]. \tag{2}$$

We impose for a moment the no-bubbles condition

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

which yields

$$P^F_{i,t} = \sum_{j=1}^{\infty} \frac{1}{(1+D)^j} E_t[C_{i,t+j}], \tag{4}$$

which is often referred to as price reflecting fundamentals.

Following Campbell and Shiller (1987) and Wang (2000), we define the spread between 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 Eq. 3 holds, then $P_{i,t}$ is also $I(1)$ (i.e. $\triangle P_{i,t}$ 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:

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

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

[4]Fundamentals (including income) can also be motivated by considering omitted variables in the present value formula as in Hamilton (1986) or via a general supply-demand model as in Gallin (2006).

Eq. 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 Eq. 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, Eq. 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 on the two remaining cases. In Case 3, there is clearly a bubble. Case 4 calls for a test of the cointegration between house prices and cash-flows, assuming that first differences are stationary. Alternatively, one can test for the stationarity of $P/r$. In Section "Panel Data Stationarity Tests," we explicitly discuss panel data unit root and cointegration tests, and formulate a "bubble" indicator, which summarizes the results of these tests in a simple manner.

The present value formula is often used to justify the use of the rent-to-price ratio as a predictor for either the expected capitalization of investment in a house or the growth rate of rents (see Capozza and Seguin 1996 and Clark 1995). To illustrate, let us assume that a house is sold after one period. We can re-write Eq. 1 as

$$E_t \frac{\triangle P_{i,t+1}}{P_{i,t}} = D - E_t \frac{C_{i,t+1}}{P_{i,t}}. \tag{8}$$

One can regress the capitalization on the rent-to-price ratio. Capitalization can be replaced by the growth rate of rents since the two should be closely related. Statistically, regression Eq. 8 can be run if either both price differences and the rent-to-price are stationary or if they are of the same order of integration but cointegrated. Theory restricts the relationship further: Under the no bubbles

[5] An example of such a violation is a solution of the stochastic differential equation Eq. 1, which contains a "bubble" term that satisfies

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

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

$$P_{i,t} = P^F_{i,t} + B_{i,t}. \tag{7}$$

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

condition and unit root in cash flows, both the price differences and rent-to-price ratio are stationary. Therefore, different means should be used to study predictability for a non-stationary rent-to-price ratio. If first differences in prices and rents are stationary we can test for Granger-causality in panel data. If the changes in prices Granger-cause changes in rents, price differences are useful in predicting the rent differences. The same principle applies in the opposite direction. We investigate this issue in Section "Predictability of House Prices and Rents."

## Panel Data

The empirical analysis carried out in this study utilizes the house price and rent indices. The house price index (HPI) is from the OFHEO and the rent of primary residence index (RI) is estimated by the BLS.[6] According to OFHEO (Calhoun 1996), the HPI is computed quarterly for the period 1975-2006 as the weighted repeat sales index based on the data on mortgage contracts recorded by the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Association (Fannie Mae).[7] The RI data for 25 MSA is available from the BLS for the period 1975–2006 in monthly, semi-annual, and annual frequency.

In order to harmonize the data in the frequency dimension and leave as many data points as possible, both the HPI and RI are recalculated to a semi-annual frequency. Particularly, the HPI is computed as an arithmetic average of two quarterly values of this index, and the RI is estimated as the average of all monthly values of the index if monthly values are available or as a semi-annual value if such a value is available. After all recalculations, the HPI and RI are matched based on the names of the largest cities in the MSA because definitions of these areas are slightly different in OFHEO and BLS databases. The resulting dataset consists of 23 MSA and covers the period from the first half of 1978 to the second half of 2006. Both house prices and rents are adjusted for inflation using regional BLS CPIs.

The base period for the HPI is by definition the first half of 1995. The base year for the regional CPI and RI is in the second half of 1983. We recalculated the latter two indexes so that the CPI=100 and RI=100 in the first half of 1995. Our recalculation makes it easier to compare the two series with the HPI as well as to compare the series for real house prices with real rents. Such a renormalization results in the price-to-rent ratio equal to 1 in 1995 h1. This does not imply that prices are equal to rents, it only makes 1995:h1 our reference point. The $P/r$ greater than one indicates that the ratio of prices to

[6] A description of the method of gathering data and calculating the rent index is presented in Fact Sheet No. BLS 96-5 "How BLS Uses Rent Data in the Consumer Price Index."

[7] The repeat sales approach to real estate index calculation was described first by Bailey et al. (1963) and further advanced in Case and Shiller (1989, Prices of Single Family Homes since 1970: New Indexes for Four Cities, NBER Working Paper 2393) and Case et al. (1989). For more information on the HPI see Calhoun (1996).

rents is greater than it was in 1995:h1. What matters in our analysis is whether $P/r$ is increasing or not, its actual value is irrelevant. This is determined with the help of panel data stationarity tests in Section "Panel Data Stationarity Tests."

The price–rent ratios are graphed in Figs. 1 to 4. Based on the path of these ratios for 1978:h1-2006:h2, it is possible to divide metropolitan areas into four groups. The dynamics of the price–rent ratio in the first group (Fig. 1) may hint that this group has experienced an increasing discrepancy between home prices and rents with peaks in the early 1980s, at the end of the 1980s, and in the late 1990s. These are the "usual suspects," large cities such as New York or San Francisco, with cycles of booms and busts on the real estate market. The second group (Fig. 2) consists mainly of Midwestern cities and has experienced a peak in the price–rent ratio again around 1980 and also since 1999–2000. The third group (Fig. 3) are cities that have experienced three increases similar to the first group but less pronounced. Finally, the fourth group (depicted in Fig. 4) are cities that are difficult to categorize but with the exception of Portland have been experiencing a rise in the price–rent ratio. The average price–rent ratio for the 23 MSA presented in Fig. 5 also has the three peaks with a substantial increase since 1999–2000. Interestingly, in all the above pictures, one can identify a slight decrease of the price–rent ratio growth at the end of the sample.

We also investigated whether our results were sensitive to the choice of a measure of rent and to the dimensions of the employed panel of data. Our second measure of rent was the fair market rent from the U.S. Department of Housing and Urban Development which was again combined with the HPI from OFHEO. The second panel uses data on 273 MSA from 1986 to 2006 at a yearly frequency. In other words, it spans a greater time period for a smaller cross-section, while the latter spans a shorter period for a large number of

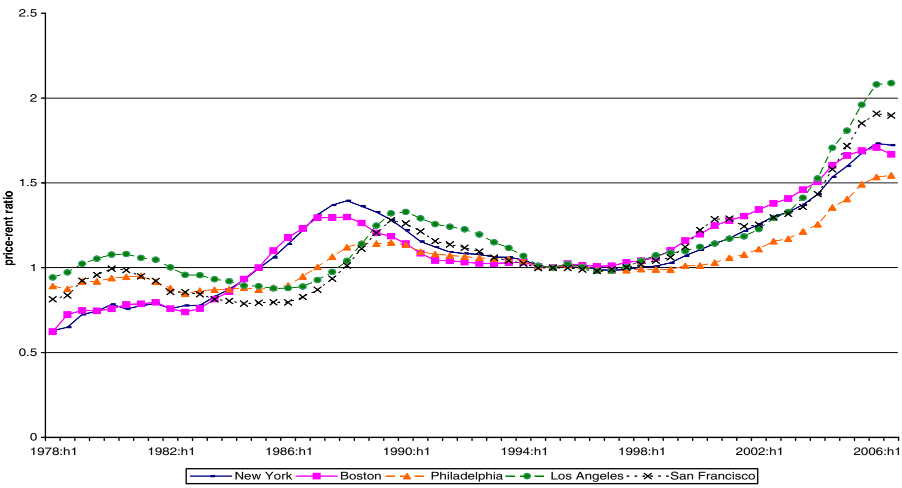


**Fig. 1** Price–rent ratios using indexes, Part 1/4

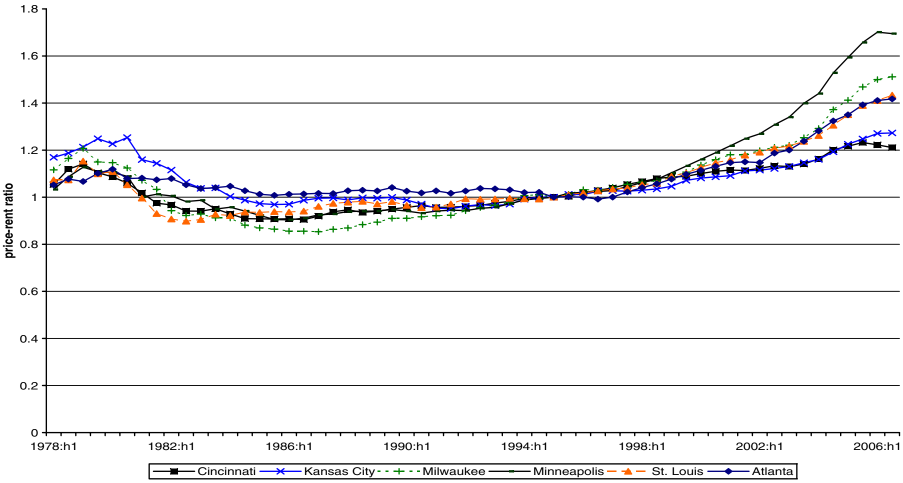


**Fig. 2** Price–rent ratios using indexes, Part 2/4

regions. The results of our tests using this dataset are very similar to those obtained using our main dataset and are omitted for brevity.[8]

## 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 Eq. 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 10-year data window.

### Unit Roots

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

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

where $i = 1, \ldots, N$ is the cross-sectional dimension of the data and $t = 1, \ldots, T$ is the number of observed periods. $\mu_i$ is a fixed effect, $\omega_i t$ is an individual trend and $\rho_i$ is an autoregressive coefficient. $\epsilon_{it}$ 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.

[8] A working paper with a complete set of results is available upon request.

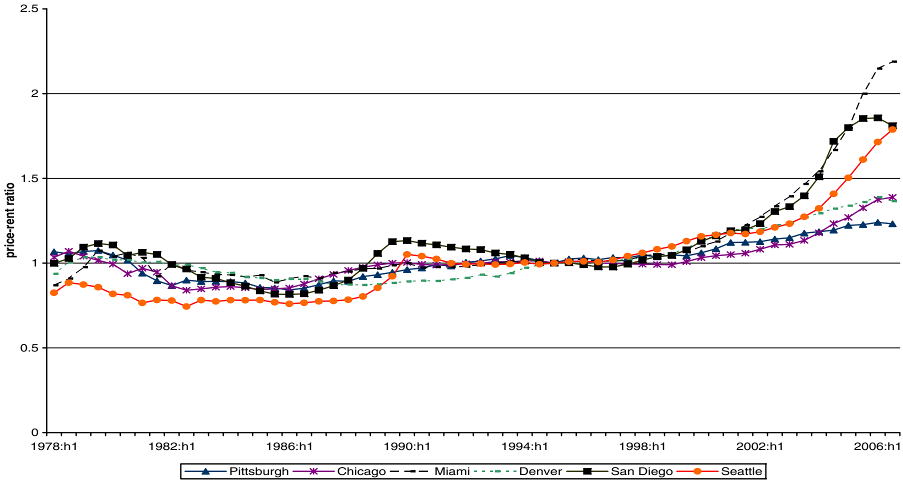


**Fig. 3** Price–rent ratios using indexes, Part 3/4

There is an additional dimension here not present in univariate time series. $\rho_i$ can be the same across cross-sections (i.e. $\rho_i = \rho$) or it can differ. Tests in Levin et al. (2002), Breitung (2000), 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

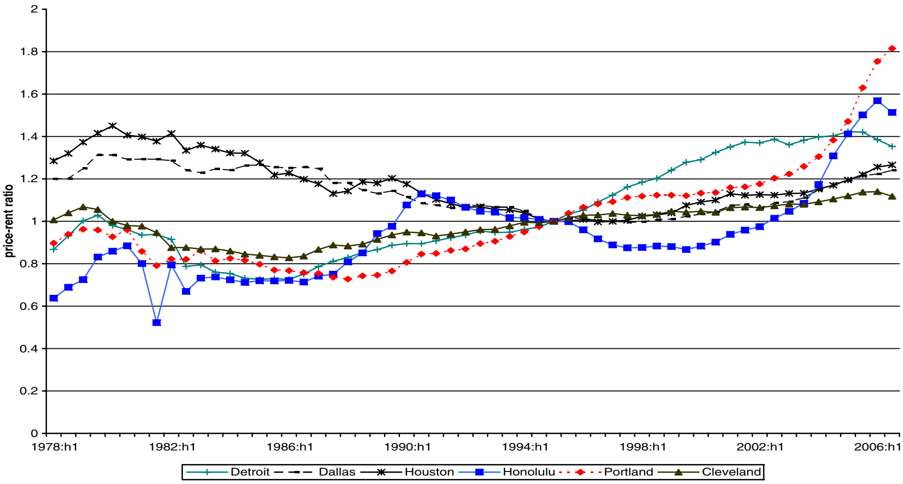


**Fig. 4** Price–rent ratios using indexes, Part 4/4

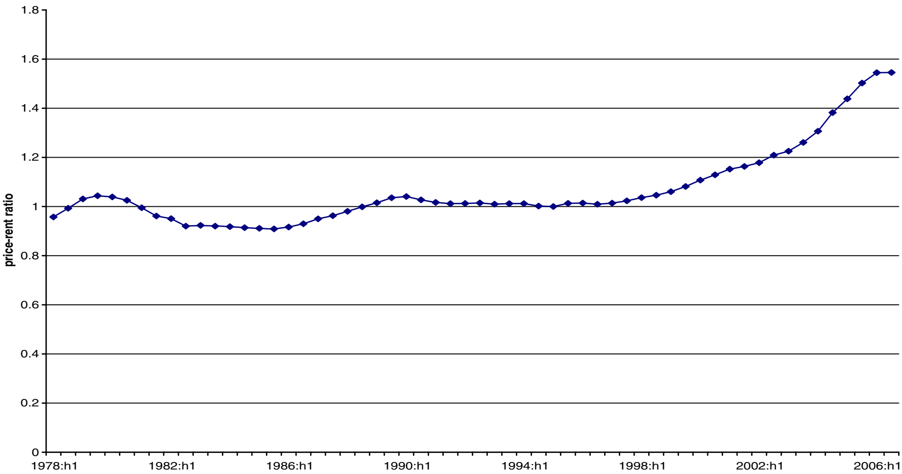


**Fig. 5** Average price–rent ratios using indexes

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), 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):

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

where $\varepsilon_{it}$ 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:

$$H_0 : \ \alpha_i = 0, \tag{11}$$

$$H_1 : \ \begin{cases} \alpha_i = 0 \text{ for } i = 1, 2, \ldots, N_1 \\ \alpha_i < 0 \text{ for } i = N_1 + 1, N_1 + 2, \ldots, N. \end{cases} \tag{12}$$

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 $\alpha_i$'s in the individual ADF regressions (denoted as $t_{iT_i}(p_i)$) and then compute their average:

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

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

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

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 individual constant with a linear trend. As indicated in our specification Eq. 10, we opt for the most general case with the number of lags set to unity in each case. A complementary approach to the IPS test is used in Maddala and Wu (1999) and Choi (2001). They define a test based on functions of the $p$-value associated with the ADF test in individual regressions. As the results based on these tests are similar to the IPS test results, we do not report them here.

The IPS test is valid under the assumption of no cross-section dependence in the data. In other words, the residuals in the ADF regression equation Eq. 10 are not correlated. This may be a very strong assumption and Pesaran (2007) demonstrates that its violation often leads to undesirable finite sample properties of the IPS test. Therefore, we use the general diagnostic test for cross section dependence in panels proposed by Pesaran (2004) to find whether the dependence is present in the data. The test statistic

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} \mathrm{Corr}(\hat{\epsilon}_i, \hat{\epsilon}_j)\right) \Rightarrow N(0, 1), \tag{15}$$

where $\hat{\epsilon}_i, i = 1, \ldots, N$ is a $(T \times 1)$ vector of estimated residuals from equation Eq. 10. This test exhibits much less size distortions then the standard Lagrange multiplier test based on squared correlation coefficients. Our test results are reported in Table 1 and clearly indicate strong dependence in our data in levels for both prices and rents.

**Table 1** Diagnostic tests for cross section dependence in panels

| Price-level $CD$ | Price-diff. $CD$ | Rent-level $CD$ | Rent-diff. $CD$ |
|---|---|---|---|
| 75.12* | −0.69 | 29.13* | −0.64 |

Sample: 23 MSA, 1978:01-2006:02 semi-annual data. ADF regression: intercept, trend, and the first lag of the dependent variable. Under the null of no cross section dependence: $CD \Rightarrow N(0, 1)$

*Significant at the 1 % level

Pesaran (2007) suggests a way of constructing a test robust to the presence of cross-section dependence in a panel. The test uses a cross-sectionally augmented Dickey–Fuller regression (CADF):

$$\Delta y_{it} = \mu_i + \omega_i\, t + \alpha_i y_{i,t-1} + \upsilon_i \bar{y}_{t-1} + \sum_{j=1}^{p_i} \lambda_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p_i} \varpi_{ij} \Delta \bar{y}_{i,t-j} + \varepsilon_{it}, \quad (16)$$

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

$$\bar{t}^{\dagger} = \frac{1}{N} \sum_{i=1}^{N} \tilde{t}_i(N, T). \quad (17)$$

Critical values for this statistic are available in Pesaran (2007).

We use Gauss code to conduct our empirical analysis. The IPS test is implemented using Nonstationary Panel Time Series Module 1.3 for Gauss (NPT 1.3) written by Chihwa Kao. We programmed the CADF and CIPS tests ourselves.[9] We report our results for the CADF t-tests in Table 2. The MSA are in alphabetical order and we calculate $\tilde{t}_i(T, N)$ for prices, rents, and price–rent ratios. As expected, the t-CADF statistic rejects much less often than the standard t-ADF (not reported). Only two price–rent ratios are deemed stationary for the whole sample period. Table 3 gives a summary of all conducted panel data unit root tests. The tests indicate that using the whole sample period in both cases, prices and rents are integrated of order one and the price–rentprice–rent ratio is non-stationary. $P/r$ inverse (results not reported here) is not stationary either. Results based on the IPS test, while quantitatively different, are qualitatively the same as the results based on the CIPS test. Given that prices and rents series have the same order of integration, the natural next step is testing for cointegration in panel data. The cointegration test can indicate whether it is appropriate to formulate a dynamic model of the dependence of house prices on rents in terms of first differences or whether we should formulate an error-correction model.

[9]Our code was cross-checked with the Gauss procedures kindly provided by professor Pesaran and his research assistant Takashi Yamagata. They yielded identical results.

**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 |

Sample: 23 MSA, 1978:01-2006:02, semi-annual data, levels only. 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. 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 *). MSA are in alphabetical order

## 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 $m = 2, ..., M$ explanatory variables and Pedroni

**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 |

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. 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. 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

*Significance at the 1% level for both tests

(2004) covers the case for just one regressor. The hypothesized cointegrating regression is

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

Again, $T$ is the time dimension and $N$ the cross-sectional dimension. The slope coefficient $\psi_i$ and the fixed-effects parameter $\mu_i$ are allowed to vary across individual panel members. Also included is an individual time trend with a coefficient $\omega_i$. 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 $\gamma_i$ is the autoregressive coefficient of the residual $\hat{\zeta}_i$ extracted from estimating the regression equation Eq. 18. The alternative hypothesis is $H_1 : \gamma_i = \gamma < 1$ for all $i$'s, i.e. it assumes a common value for $\gamma_i$'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 of a unit root in residuals from the panel data regression may be due to heterogenous autoregressive coefficients rather than due to the presence of a unit root. Pedroni (2004) also conducts some Monte Carlo experiments that show that the finite sample properties of the group ADF t-statistic dominate the properties of the other two group tests and hence we employ this one in our analysis.

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

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

[11] Wagner, M. and J. Hlouskova (2007). The Performance of Panel Cointegration Methods: Results from a Large Scale Simulation Study. Institute for Advanced Studies Vienna, Working Paper.

## Bubble Indicator

Here we combine the previously described methodology of testing for unit roots and cointegration in panel data and further analyze the relationship between house prices and rents in levels. We propose an indicator summarizing the implications of the present value model. The theory suggests that there is a bubble if either (i) the price-level is non-stationary while the rent-level is stationary, or (ii) both series are of first order of integration but they are not cointegrated. In both cases, the relationship between the two variables breaks down and there is a bubble on the house market. The latter case prevails using the whole sample period. However, we would also like to be able to assess how the likelihood of a bubble changes over time. We define overlapping 10-year intervals covering our sample period. In accordance with the theory, we define a bubble indicator to be 0 for stationary prices and one for non-stationary prices and stationary rents. For cases in between, one would ideally use a cointegration test. However, this is potentially problematic since the

**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 |

Sample: 23 MSA, 1978:01–2006:02, semi-anual data, 10-year data windows end in a given year. 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. 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. 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

***Significance at the 1% level, **significance at the 5% level, and *significance at the 10% level for both tests

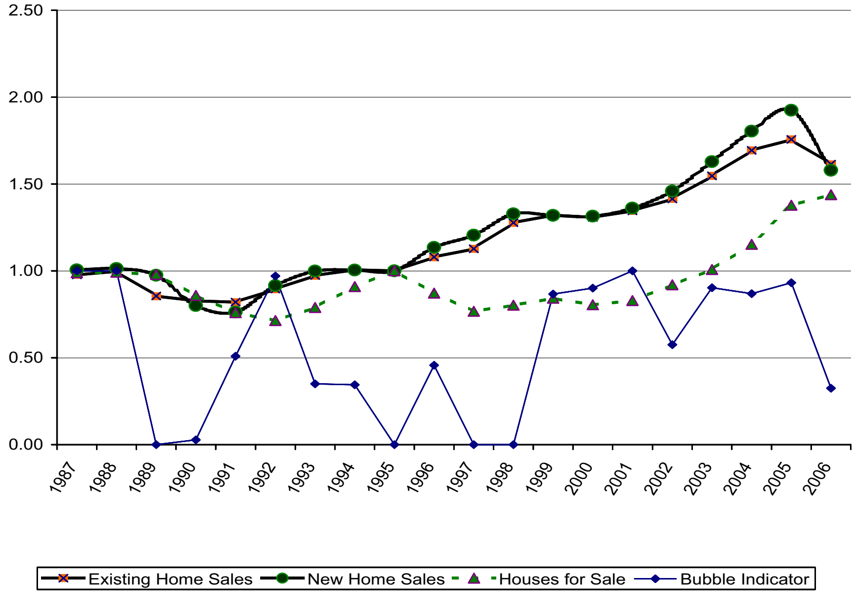


**Fig. 6** A bubble indicator, existing homes sales, new home sales, and houses for sale

test is often not well defined in a given sub-sample due to a different order of integration of the two series and it is cumbersome to check (one has to conduct unit root tests for higher order differences in many cases). Therefore we propose to replace the cointegration test with a test for the stationarity of the price–rent ratio, which has an intuitive appeal. We equate the bubble indicator to the $p$-value of the CIPS test for $P/r$ if it is not already 1 or 0.

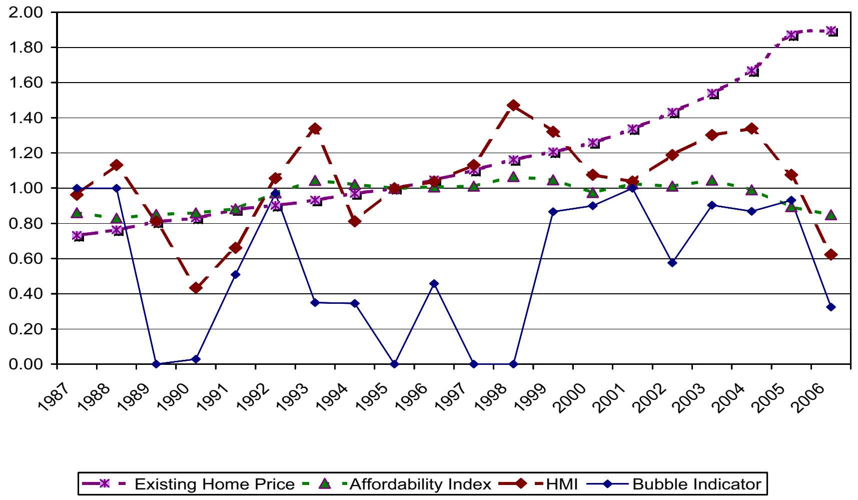


**Fig. 7** A bubble indicator, an existing home price, an affordability index, and HMI

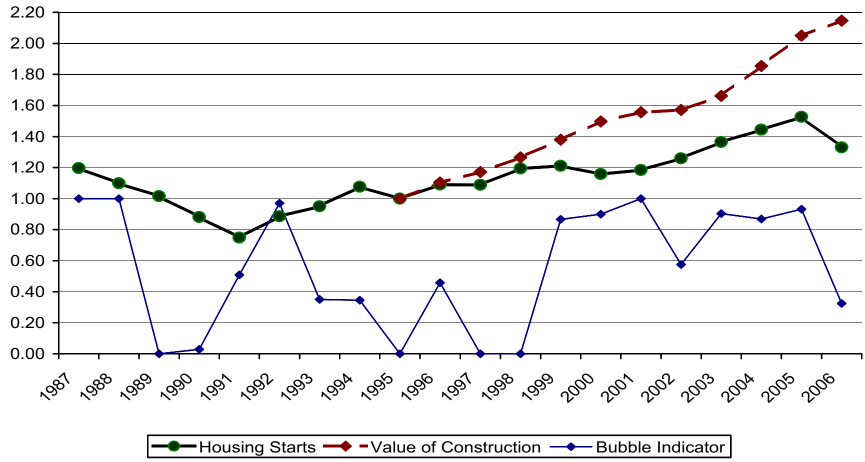


**Fig. 8** A bubble indicator, housing starts, and a value of construction

We calculate the Pedroni tests and the CIPS unit root tests, which respectively allow for the possibility of different autocorrelation coefficients in the residuals of the cointegrating regression and in a given time series. We present our results in Table 4. Looking at the CIPS unit root tests, we can see that house prices were non-stationary and rents stationary from 1987 to 1988 when we use ten prior years of data in each year. This results in the indicator being 1. In 1990, the rents become non-stationary but the price–rent ratio is stationary, resulting in a bubble indicator of 0.03, below the 5% level of significance. Overall, the periods when the indicator is higher correspond to rising average price–rent ratios in Fig. 5 prior to 1990 and prior to 2000. The indicator decreases by the end of a sample, which reflects a potential stagnation of the housing market.

While the number of observations for our bubble indicator is fairly small for a thorough time series analysis, we at least provide an illustrative comparison to major house market indicators. First, we use existing home sales, sale price of existing homes, and the housing affordability index from the National Association of Realtors. Second, we use new home sales sold and for sale, total construction spending, and total housing units started from the Census Bureau, Department of Commerce. Finally, we use the Housing Market Index (HMI) from the National Association of Home Builders. A survey of these indicators is given in Baumohl (2005).

We split the indicators into three groups and depict their values together with our indicator in graphs Figs. 6, 7 and 8 (all indicators are normalized to 1

**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 |

in 1995). Interestingly, all of the indicators show a cooling of the housing market at the end of 2006. Figure 6 shows the correspondence of the indicator with existing home sales and new home sales, which is consistent with correlations in Table 5. Figure 7 demonstrates visually the positive correlations from Table 5 for existing home prices and HMI. Not surprisingly, the correlation between the indicator and the affordability index is negative. Interestingly, there is a strong positive correlation of the bubble indicator with housing starts and the value of construction (see Table 5 and Fig. 8).

**Predictability of House Prices and Rents**

The aggregate average price-to-rent ratio and its inverse are non-stationary. This prevents us from using the standard regression methodology and brings us to statistical predictability formulated in terms of Granger causality. First differences for both house prices and rents are stationary according to our panel data tests for unit roots. Therefore, we are in a position to test for causality between the two. Testing for causality gives an indication of whether changes in prices predict rents and vice versa. Similarly to recently developed panel data unit root and causality tests, there exists an analogous test for Granger causality in panel data with a short time-series dimension. This test is described in Hurlin (2004) and applied in Hurlin and Venet (2004).

Let $y_i$ and $x_j$ be two stationary variables. Consider the following linear model:

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

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

$$H_0 : \ \delta_i = 0, \quad \forall i = 1, ..., N, \tag{20}$$

**Table 6** Hurlin tests for HNC 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 where $\delta_i = (\delta_i^{(1)}, ..., \delta_i^{(L)})'$. The alternative hypothesis encompasses the possibility that there are $N_1$ individual units with no causality and is defined as:

$$H_1 : \delta_i = 0, \; \forall i = 1, ..., N_1, \\ \delta_i \neq 0, \; \forall i = N_1 + 1, ..., N, \tag{21}$$

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 $i = 1, \ldots, N$. Hurlin (2004) shows that the approximated standardized statistic

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

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

We first verify that there is no cross-sectional dependence in the residuals from regression Eq. 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 pricing model and it implies that one cannot use an error correction model for house prices with rents as the fundamental factor. We proceed a step further with our analysis and formulate a simple procedure that can help to determine the extent to which there is a (statistical) discrepancy between house prices and their fundamentals. At each point in time, we investigate a panel of house prices and rents for the last 10 years. If the prices are non-stationary but rents are not, we view that as an indication of a bubble. If prices are stationary, the bubble indicator is zero. In all other situations it is equal to the $p$-value of the panel data unit root test for the price–rent ratio. Our bubble indicator coincides

[12] The 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.

fairly well with the pattern of price–rent ratios and several housing market indicators. However, it has the advantage of being able to determine formally whether the price–rent ratio is "too high." Price–rent ratios are suggestive of rational bubbles in several periods but mainly in the late 1980s and in the late 1990s up to 2005.

Non-stationarity of the price-to-rent and rent-to-price ratios is documented for both the aggregate series and in our panels. In such a case, standard regression techniques cannot be used to investigate the predictive properties of the price-to-rent ratios for the growth rates of house prices or rents. However, since prices and rents are both $I(1)$, we can test for panel Granger causality. In spite of the fact that it can take over three decades for house prices to revert to a fundamental value corresponding to earnings, the first differences of house prices have predictive power with respect to rents and vice versa.

There are several possible extensions of our study, mainly considering different measures of property prices or variables providing information about fundamentals. On the price side, one can for instance attempt to use a quality adjusted index or correct for an upward bias present in the repeated-sales index used in this paper. On the side of fundamentals, yet another measure for rents can be employed, such as the owners' equivalent rent series. Also, income and interest rates can be included as explanatory variables. However, all these improvements come at a cost in the terms of reduced cross-sectional and/or time dimension of the data, a more complex structural theoretical framework, and a greater computational burden.

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