PERSISTENCE, MEAN REVERSION AND NON-LINEARITIES IN THE US HOUSING PRICES OVER 1830-2013[*,**]

Luis A. Gil - Alana, University of Navarra, Pamplona, Spain

Rangan Gupta, University of Pretoria, Pretoria, South Africa

and

Fernando Perez de Gracia, University of Navarra, Pamplona, Spain

Abstract

The objective of this study is to provide a direct estimate of the degree of persistence of measures of nominal and real house prices for the US economy, covering the longest possible annual sample of data, namely 1830-2013. The estimation of the degree of persistence accommodates for non-linear (deterministic) trends using Chebyshev polynomials in time. In general, the results show a high degree of persistence in the series along with a component of non-linear behaviour. In general, if we assume uncorrelated errors, non-linearities are observed in both nominal and real prices but this hypothesis is rejected in favour of linear models for the log-transformation of the data. However, if autocorrelated errors are permitted, non-linearities are observed in all cases, and mean reversion is found in the case of the logged prices, though given the wide confidence intervals, the unit root null hypothesis cannot be rejected in these cases.

JEL classification: C22, R21, R31

Keywords: US house prices, long span annual data, long memory, non-linear trends

Corresponding author: Prof. Rangan Gupta
Department of Economics
University of Pretoria
Pretoria, South Africa
Phone: +27 12 420 3460
Email: Rangan.Gupta@up.ac.za

[*] The helpful comments of the editor and two reviewers are highly appreciated. Luis A. Gil-Alana gratefully acknowledges financial support from the Ministerio de Economía y Competitividad (ECO2014-55236). Fernando Perez de Gracia also acknowledges financial support from the Ministerio de Economía y Competitividad (ECO2014-55496).

[**] We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours.

1. Introduction

The recent world-wide financial crisis, emerging from the collapse of house prices, has necessitated careful investigation of the time-series properties of both nominal and real house prices. While, Leamer (2007) notes that the housing market predicted eight of the ten post World War II recessions, Balcilar *et al*. (2014), goes further and provides evidence of the role played by house prices in driving the Great Depression. In general, the widely held view is that house prices can forecast (in- and out-of-sample) economic growth and inflation (Forni *et al.*, 2003; Stock and Watson, 2003). Given this, the persistence property of house prices is of paramount importance, since depending on its degree of persistence, the effect of an exogenous shock on house prices may have either short-lived or prolonged impact on the economy in general (besides the direct effect on house prices itself).

Against this backdrop, the objective of this study is to provide a direct estimate of the degree of persistence of measures of nominal and real house prices for the US economy, covering the longest possible annual sample of data, namely 1830-2013. For our purpose, instead of relying on tests of unit roots, as commonly done in the literature (discussed in detail below), we take a long memory approach. Unlike, standard unit root tests, which can only indicate whether a series is stationary or not by looking at 0 or 1 for the orders of integration, and have low power especially in cases where the series is characterized by a fractional process (Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996; and more recently, Ben Nasr *et al*., 2014); the long memory approach provides us with an exact measure of the degree of persistence. This in turn, can provide us with a time span that it would take for the shock to die off, if at all.

However, long memory models are known to overestimate the degree of persistence of the series in the presence of structural breaks (Cheung, 1993; Diebold and

Inoue, 2001; and more recently, Ben Nasr *et al.*, 2014), which are very likely in our case as it covers a long sample of 184 years.[1] Given this, we supplement our long memory model to accommodate for non-linear (deterministic) trends as in Cuestas and Gil-Alana (2012), *i.e.*, through the use of Chebyshev polynomials, which, in turn, are cosine functions of time. This approach is preferred over the method proposed by Gil-Alana (2008), whereby the number of breaks and the break dates in the series are determined endogenously, obtained by minimising the residual sum of the squares at different break dates and different (possibly fractional) differencing parameters. The reasons are as follows: First, from a technical point of view, since we are using low-frequency data, structural breaks should ideally be modelled in a smooth rather than an abrupt fashion. This smooth transition is also important, since housing market activities are known to be sluggish in nature, given the lumpy nature of housing investments. Secondly, conventional wisdom argues that housing prices in the US rise more quickly and fully to market events that increase the equilibrium price than they do to market events that lower the equilibrium price (see Balcilar *et al*., forthcoming, and references cited therein). For example, the fall of housing prices during the recent financial crisis and Great Recession and beyond did not occur quickly enough to clear housing markets around the country, significantly slowing the recovery process. In other words, house prices are intrinsically non-linear, and are also characterized by slow adjustment mechanisms, which we model through the Chebyshev polynomials in time. This allows for a non-abrupt change in the time series, unlike standard methods of incorporating structural breaks as sharp/sudden changes using dummy variables. To the best of our knowledge, this is the first attempt to analyze house price persistence accounting for non-linear (deterministic) trends, which in turn, allows us

[1] Further details regarding the dates of structural breaks for the nominal and real house price indices have been discussed in the data segment of the paper.

to provide credible estimates of persistence by accounting for nonlinearity either because of structural breaks or regime-switching.

The remainder of the paper is structured as follows: Section 2 reviews the literature on housing prices mean reversion. Section 3 briefly describes the methodology and justifies its application in the context of housing prices series. Section 4 presents the data and the main empirical results, while Section 5 contains some concluding comments.

2. Literature review on mean reversion in housing prices

Time series properties of house prices (*e.g.*, short-run persistence and strong serial correlation) have been investigated as early as Case and Shiller (1989, 1990).[2] In their pioneer work, Case and Shiller (1989, 1990), using data of Atlanta, Chicago, Dallas and San Francisco / Oakland, stated that housing market is not efficient based on evidence of short-run persistence and strong serial correlation. Other empirical studies that also obtained notable short-run persistence are that of Meese and Wallace (1994), Englund and Ionanides (1997), Røed Larsen and Weum (2008) and Gil-Alana *et al*. (2014). Moreover, like in Case and Shiller (1989), longer-horizon negative serial correlation in housing prices is also found by Cappozza and Seguin (1996), Meen (2002), Capozza *et al*. (2004), Gao et al. (2009) and Mikhed and Zemcik (2009) among others.

Early empirical studies suggest that housing prices experienced a faster mean reversion in larger than in smaller metropolitan areas and also that the serial correlation of housing prices is greater in metropolitan areas with higher real income and population (see, for example, Capozza *et al*., 2004). A recent study by Gil-Alana *et al*.

[2] Additional studies on this topic are that of Abraham and Hendershott (1996), Meese and Wallace (1994), Englund and Ionanides (1997), Malpezzi (1999), Meen (2002), Capozza *et al*. (2002; 2004), Gao *et al*. (2009), Mikhed and Zemcik (2009), Beracha and Skiba (2011), Lean and Smyth (2013), André et al. (2014), Gil-Alana, Barros and Peypoch (2014), Gil-Alana *et al*. (2014) and Gupta and Majumdar (2015) among others.

(2013) focusing on the South African house market, show that affordable and luxury house segments have experienced mean reversion dynamics in house prices, but very high persistence and lack of mean reversion was observed for the different categories of the middle-segment house prices.

Most of the previous empirical papers focus on metropolitan or regional housing prices and tend to use quarterly data. For example, Case and Shiller (1989, 1990) focus on data from 4 US cities; Meese and Wallace (1994) analysed 16 municipalities in the San Francisco area; Capozza *et al*. (2004) analysed data for 62 US metropolitan areas; Hwang and Quigley (2004) investigated data from Stockholm metropolitan area; Røed Larsen and Weum (2008) study housing prices in the city of Oslo; Gao *et al*. (2009) use data from 19 major cities in the US. Recently, Gil-Alana et al. (2013) proposed to take into account alternative house price segments such as affordable, luxury and middle-segments in the South African market.

Instead of focusing on metropolitan or regional housing prices, in this paper we analyze mean reversion using aggregate data for the US covering nearly two centuries. Specifically, we estimate the US housing price time series properties (*e.g*., short-run persistence and strong serial correlation) using a long memory model with non-linear trends.

3. Methodology

Let us suppose that y_t is the time series we observe. We can consider the following model,

$$y_t \;=\; \sum_{i=0}^{m} \theta_i \, P_{iT}(t) \;+\; x_t \,, \qquad t \;=\; 1,\, 2,\, \ldots\,, \tag{1}$$

with *m* indicating the order of the Chebyshev polynomial which are defined below, and x_t is a fractionally integrated process of order d (and denoted as I(d)) of the form

$$(1-L)^d x_t = u_t, \quad t = 0, \pm 1, ..., \tag{2}$$

with $x_t = 0$ for $t \leq 0$, and $d > 0$, where L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is $I(0)$.[3]

The Chebyshev polynomials $P_{i,T}(t)$ in (1) are defined by:

$$P_{0,T}(t) = 1,$$

$$P_{i,T}(t) = \sqrt{2}\cos\left(i\pi(t-0.5)/T\right), \quad t = 1, 2, ..., T; \quad i = 1, 2, ... \tag{3}$$

(see Hamming (1973) and Smyth (1998) for a detailed description of these polynomials). Bierens (1997) uses them in the context of unit root testing. According to Bierens (1997) and Tomasevic and Stanivuk (2009), it is possible to approximate highly non-linear trends with rather low degree polynomials. If $m = 0$ the model contains an intercept, if $m = 1$ a linear trend is also included, and if $m > 1$ the model becomes non-linear, and the higher m is the less linear the approximated deterministic component becomes.

Cuestas and Gil-Alana (2012) propose a simple method that is basically a slight modification of Robinson (1994). They consider the set-up in (1) and (2) testing the null hypothesis:

$$H_o : d = d_o, \tag{4}$$

for any real vector value d_o. Under H_o, and using the two equations,

$$y_t^* = \sum_{i=0}^{m} \theta_i P_{iT}^*(t) + u_t, \quad t = 1, 2, ..., \tag{5}$$

where

$$y_t^* = (1-L)^{d_o} y_t, \quad P_{iT}^*(t) = (1-L)^{d_o} P_{iT}(t),$$

[3] An I(0) process is defined as a covariance stationary process with a spectral density function that is positive and finite at the long-run or zero frequency.

and given the linear structure of the above relationship and the *I(0)* nature of the error term u_t, the coefficients in (5) can be estimated by standard ordinary least square/generalized least square (OLS/GLS). A Lagrange Multiplier (LM) test of H_o (4) in (1) and (2) is then

$$\hat{R} = \frac{T}{\hat{\sigma}^4} \hat{a}' \hat{A}^{-1} \hat{a}, \tag{6}$$

where *T* is the sample size, and

$$\hat{a} = \frac{-2\pi}{T} \sum_{j}^{T-1} \psi(\lambda_j)\, g(\lambda_j; \hat{\tau})^{-1} I_{\hat{u}}(\lambda_j),$$

$$\hat{A} = \frac{2}{T}\left(\sum_{j}^{T-1} \psi(\lambda_j)\psi(\lambda_j)' - \sum_{j}^{T-1} \psi(\lambda_j)\hat{\varepsilon}(\lambda_j)' \left(\sum_{j}^{T-1} \hat{\varepsilon}(\lambda_j)\hat{\varepsilon}(\lambda_j)' \right) \sum_{j}^{T-1} \hat{\varepsilon}(\lambda_j)\psi(\lambda_j)' \right)$$

with $\psi(\lambda_j) = \log\left| 2 \sin \frac{\lambda_j}{2} \right|$ and $\hat{\varepsilon}(\lambda_j) = \frac{\partial}{\partial \tau} \log g(\lambda_j; \tau)\Big|_{\tau = \hat{\tau}}$,

and $\lambda_j = 2\pi j/T$. $I(\lambda_j)$ is the periodogram of $\hat{u}_t = (1 - L)^{d_o} y_t - \sum_{i=0}^{m} \hat{\theta}_i P_{iT}^*(t)$, with

$$\hat{\theta} = \left(\sum_{t=1}^{T} P_T^*(t) P_T^*(t)' \right)^{-1} \left(\sum_{t=1}^{T} P_T^*(t)\, y_t^* \right),$$

and $P_T^*(t)$ as the (*mx1*) vector of transformed Chebyshev polynomials and $\hat{\tau}$ = $\arg\min_{\tau \in T^*} \sigma^2(\tau)$, with T^* as a suitable subset of the R^q Euclidean space. Finally, the function g above is a known function coming from the spectral density of u_t:

$$f(\lambda; \tau) = \frac{\sigma^2}{2\pi} g(\lambda; \tau), \qquad -\pi < \lambda \leq \pi.$$

Note that these tests are purely parametric and, therefore, they require specific modelling assumptions for the short-memory specification of u_t. Thus, if u_t is white noise, $g \equiv 1$, and if u_t is an AR process of the form $\phi(L)u_t = \varepsilon_t$, $g = |\phi(e^{i\lambda})|^{-2}$, with $\sigma^2 = V(\varepsilon_t)$, so that the AR coefficients are a function of τ.

Under very mild regularity conditions,[4] it can be shown that as in Robinson (1994):

$$\hat{R} \quad \rightarrow_d \quad \chi^2_M \qquad as \quad T \rightarrow \infty, \qquad (7)$$

and, based on Gaussiantiy of u_t, it can also be shown the Pitman efficiency theory of the test against local departures from the null. That means that if we direct the test against local alternatives of form:

$$H_a : \ d \ = \ d_o \ + \ \delta T^{-1/2},$$

where δ is a non-null parameter vector, $\hat{R} \rightarrow_d \chi^2_M(\Lambda) \ as \ T \rightarrow \infty$, indicating a non-central chi-squared distribution with non-centrality parameter which is optimal under Gaussiantiy of u_t. Note that the method just presented is a testing procedure and therefore we do not directly estimate the fractional differencing parameter vector but simply present confidence intervals based on the non-rejections for a given set of values. Nevertheless, in the empirical application carried out in the following section we display estimates of d, which are based on the values that minimize the absolute value of the test statistic. This approach is found to be appropriate by means of Monte Carlo simulations.[5]

4. Data and empirical results

The data examined correspond to measures of nominal and inflation-adjusted, i.e., real house prices for the aggregate US economy covering the period of 1830-2013. The data are sourced from Winans International, and the index measures the nominal and real values of price of new homes going back to 1830. We work with both raw and the

[4] These conditions only include moments up to a second order.
[5] See Cuestas and Gil-Alana (2012).

natural logarithms of the nominal and real versions of the Winans international US real estate index.[6]

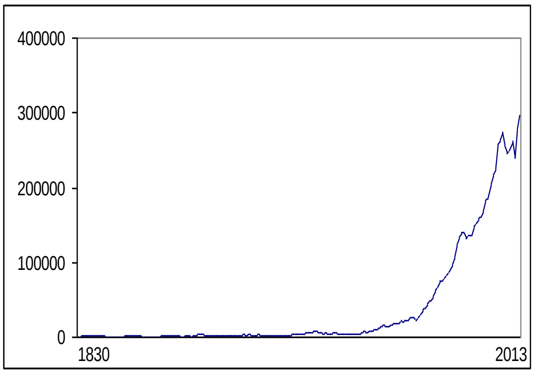
Figure 1 shows the original (untransformed raw) time series (nominal and real house prices), the first differences and the correlogram of the first differenced data. While Figure 2 displays the logged time series, the growth rates and the correlogram of the growth rates. As we can see, the correlograms of the first differenced data present significant values in both series in both cases of non-logged and logged data, suggesting that fractional integration may be a plausible approach in the modeling of these series. Further, to motivate the use of the non-linear deterministic trends, we carried out direct tests of multiple structural breaks using the Bai and Perron (2003) tests, as well as the Brock *et al*., (1996; BDS) test of non-linearity in the non-logged and logged values of the nominal and real house price indices. Based on the Bai and Perron (2003) tests of structural breaks applied to the regressions of nominal and real house prices on a constant only, with a maximum number of breaks set to 5 and an end point trimming of 15% of the observations; we detected 2 breaks each for both nominal and real raw data at the same points: 1960 and 1987. For the logged nominal and real series, we found 4 breaks each for both, at exactly the same dates: 1879, 1920, 1955 and 1982. Note that, even if there exists additional structural breaks within the 15% trimming areas, for instance the subprime crisis, they would be captured by the non-linear deterministic trends. While, the BDS test overwhelmingly rejected the null hypothesis (with the null having a *p*-value of 0.00 under dimensions 2 to 6) that the filtered series are *i.i.d*, with filtering being done using the first differences of the untransformed and logged nominal

[6] EViews and FORTRAN are used to conduct all the empirical analyses, and the codes are available upon request from the authors.

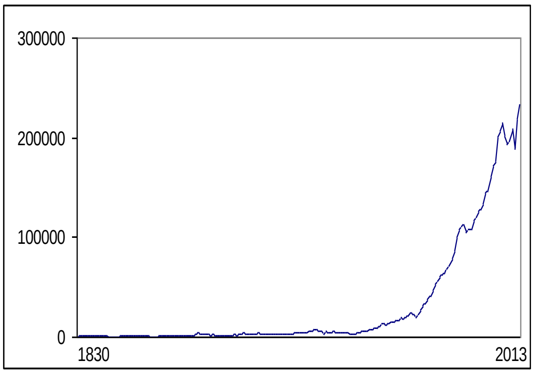
and real house prices. Consequently, the results from these two sets of tests suggest that there are likely to be non-linear structure in the data.[6]

Figure 1: Original time series, first differences and correlogram of first differences

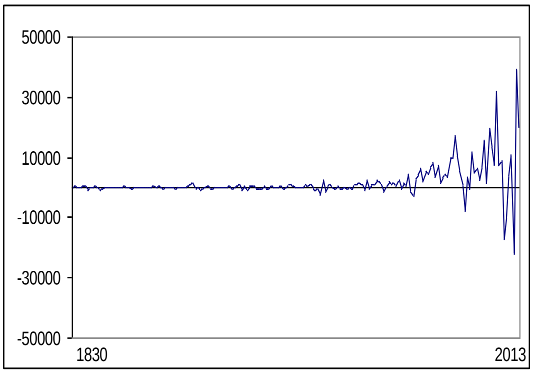
Nominal house pr.



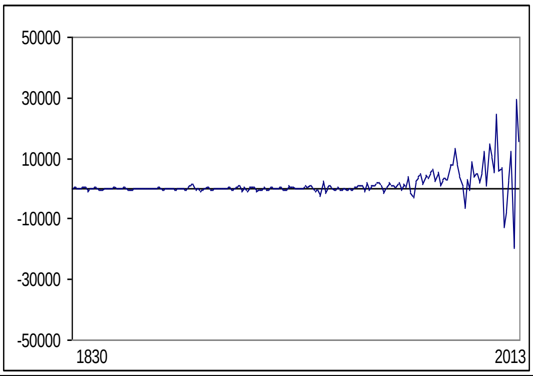
Real house pr.



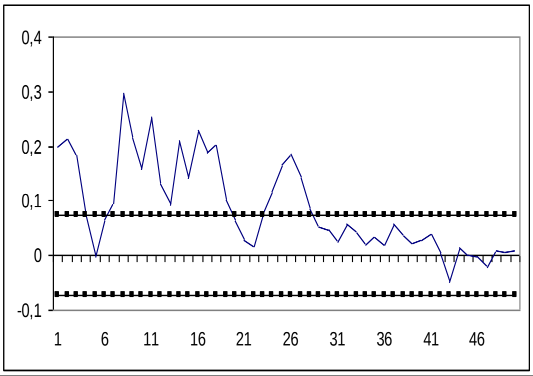
First differences nominal pr.



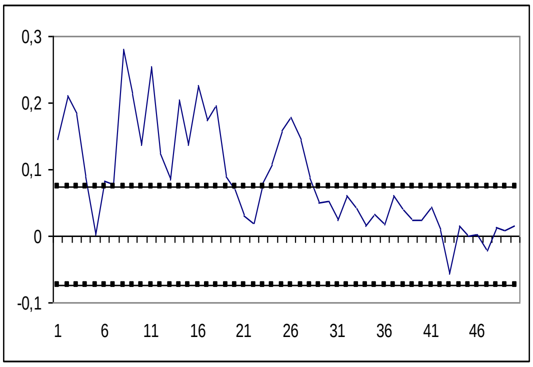
First differences real pr.



Correlogram first differences nominal pr.



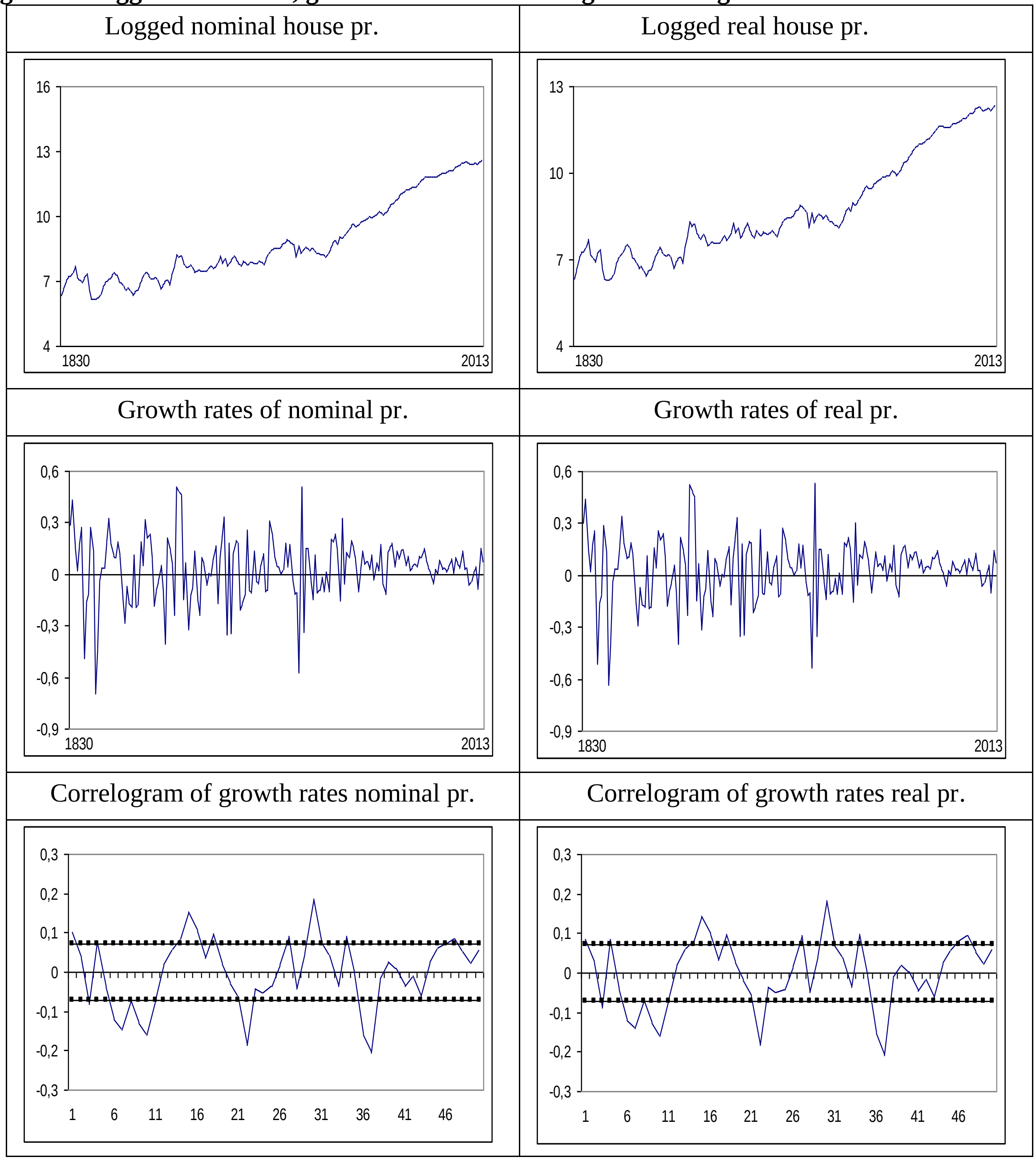
Correlogram first differences real pr.



Notes: The thick lines in the bottom plots refer to the 95% confidence band for the null hypothesis of no autocorrelation; pr. stands for prices.

[6] Further details of these tests are available upon request from the authors.

Figure 2: Logged time series, growth rates and correlogram of the growth rates



Notes: The thick lines in the bottom plots refer to the 95% confidence band for the null hypothesis of no autocorrelation; pr. stands for prices.

In Table 1, we display the estimated values of d and their corresponding 95% non-rejection intervals in the model captured byequations (1) and (2), for the cases of m = 0, 1, 2 and 3 and white noise errors. The first observation is that non-linearities (m = 3) are detected in the two unlogged series, while linear process (m = 1) are observed in case of the two logged series. Thus, it seems that by taking log-transformations, we may remove the non-linearity of the data. Focusing on the fractional differencing parameter, d is equal to 1.14 for the nominal prices and 1.11 for the real ones, and in both cases the deterministic terms are statistically significant up to m = 3 (see Table 2). Moreover, in these two cases, the unit root null hypothesis (d = 1) is rejected in favour of higher degrees of differentiation. However, the estimated orders of integration are 1.05 and 1.04 respectively for the logged nominal and real prices. Thus, the unit root null cannot be rejected, and only an intercept and a linear trend are required to describe the deterministic part of the processes. (See Table 2).

Table 1: Estimates of d and 95% confidence intervals with white noise errors

	m = 0	m = 1	m = 2	m = 3
Nominal pr.	1.18 (1.11, 1.27)	1.18 (1.12, 1.26)	1.17 (1.10, 1.25)	**1.14** **(1.06, 1.23)**
Real pr.	1.15 (1.09, 1.23)	1.16 (1.12, 1.24)	1.15 (1.08, 1.22)	**1.11** **(1.03, 1.20)**
Log nominal pr.	1.03 (0.92, 1.19)	**1.05** **(0.94, 1.20)**	1.03 (0.90, 1.19)	1.00 (0.85, 1.19)
Log real pr.	1.02 (0.91, 1.17)	**1.04** **(0.93, 1.18)**	1.01 (0.89, 1.17)	0.99 (0.83, 1.17)

Notes: In bold, the significant cases at the 5% level.

Table 2: Estimated coefficients of the selected models in Table 1

	m = 0	m = 1	m = 2	m = 3
Nominal pr.	34787.35 (2.483)	-32051.29 (-1.717)	33107.57 (1.940)	-25258.08 (-2.108)
Real pr.	33234.54 (2.661)	-29873.26 (-1.969)	27245.13 (2.006)	-20476.60 (-2.366)
Log nominal pr.	8.6745 (6.153)	-1.6587 (-1.679)	---	---
Log real pr.	8.5489 (6.454)	-1.5673 (-1.690)	---	---

Notes: In parentheses, the corresponding t-values.

Tables 3 and 4 are similar to Tables 1 and 2 above but imposes autocorrelated errors. However, instead of using standard autoregressive (AR) process here, we use a non-parametric approach due to Bloomfield (1973). This model produces autocorrelations that decay exponentially as in the AR case. Another advantage of this approach is that this method is stationary for all its coefficients, as opposed to what happens in the AR model. In Bloomfield (1973) the model is exclusively presented in terms of its spectral density function, which is given by:

$$f(\lambda;\tau) \;=\; \frac{\sigma^2}{2\pi}\;\exp\left(2\sum_{r=1}^{k}\tau_r\cos(\lambda r)\right), \qquad (8)$$

where k indicates the number of parameters required to describe the short run dynamics of the series. Bloomfield (1973) showed that the logarithm of an estimated spectral density function of an ARMA(p, q) process is often found to be a fairly well-behaved function and can thus be approximated by a truncated Fourier series. He showed that (3) approximates it well, where p and q are of small values, which is usually the case in economics. Moreover, this model fits very well in the context of Robinson's (1994) parametric tests.[7]

Table 3: Estimates of d and 95% confidence intervals with autocorrelated errors

	m = 0	m = 1	m = 2	m = 3
Nominal pr.	1.27 (1.16, 1.49)	1.26 (1.17, 1.40)	1.25 (1.14, 1.38)	**1.19** **(1.04, 1.35)**
Real pr.	1.28 (1.17, 1.49)	1.27 (1.18, 1.40)	1.26 (1.15, 1.41)	**1.20** **(1.08, 1.36)**
Log nominal pr.	0.89 (0.78, 1.10)	0.92 (0.76, 1.13)	0.81 (0.60, 1.10)	**0.55** **(0.27, 1.02)**
Log real pr.	0.87 (0.76, 1.11)	0.91 (0.76, 1.14)	0.80 (0.61, 1.09)	**0.54** **(0.23, 1.01)**

Notes: In bold, the significant cases at the 5% level.

[7] See Gil-Alana (2004) for further details.

Table 4: Estimated coefficients of the selected models in Table 3

	m = 0	m = 1	m = 2	m = 3
Nominal pr.	21352.05 (2.237)	-21579.44 (-2.382)	30438.49 (2.334)	-23592.16 (-1.778)
Real pr.	15597.10 (2.208)	-16075.65 (-2.342)	23532.86 (2.255)	-18096.05 (-1.971)
Log nominal pr.	8.88165 (46.551)	-1.7277 (-15.561)	0.5269 (6.119)	-0.3321 (-4.719)
Log real pr.	8.7690 (49.431)	-1.6292 (-15.614)	0.4828 (5.923)	-0.3322 (-4.965)

Notes: In parentheses, the corresponding t-values.

Using the Bloomfield model for the I(0) error term, the results in terms of the estimation of d are presented in Table 3. Table 4 displays the estimated coefficients of the selected models. It is observed now that non-linear trends are required in all of the four series, and we also observe substantial differences depending on whether the series are log transformed or not. Thus, in the original series, the differencing parameter is equal to 1.19 for the nominal price index, and 1.20 for the real one. As in the previous case of white noise disturbances, the unit root null is rejected in favour of d > 1. However, a very different picture is obtained in the log-transformed case. Here, the estimated differencing parameter is equal 0.55 for the log-nominal price index and 0.54 for the real one. But the confidence intervals are so wide that the null of unit root cannot be rejected for either of the two series.

5. Concluding comments

In this paper, we provide a direct estimate of the degree of persistence of measures of nominal and real house prices for the US economy, covering a long annual span (1830-2013) data set, using long memory procedures, and incorporating non-linear deterministic trends, to account for both structural breaks and regime-switching. This is a clear deviation from previous empirical studies on housing prices that have analysed the persistence property of house prices in US regional and aggregate housing markets (see, for example, Case and Shiller, 1989, 1990; Abraham and Hendershott, 1996; Meese and Wallace, 1994; Capozza and Seguin, 1996; Englund and Ionanides, 1997; Englund *et al*., 1999 and Malpezzi, 1999 and recently Gil-Alana *et al*., 2014 among others).

The main results of the paper can be summarized as follows: In general, high orders of integration are observed in all cases, with it being higher for the non-logged data. We note that the unit root null hypothesis (i.e. d = 1) is rejected in favour of higher degrees of differentiation (d > 1) for the nominal and real prices in the two cases of white noise and correlated errors; however, this hypothesis (d = 1) cannot be rejected if the logged values are used. In fact, under the assumption of autocorrelated errors, the estimated value of d is significantly low in both nominal and real log-prices (0.55 and 0.54 respectively), but the confidence intervals are so wide that the unit root null cannot be rejected. Overall, our results suggest that US house prices have historically been highly persistent, with the results continuing to hold even after controlling for structural breaks and inherent nonlinearity in the data generating process of real and nominal values of house prices. The result implies that the effect of an exogenous shock on house prices may have prolonged impact on the economy in general, given the well-established leading indicator role of both nominal and real house prices.

References

Abraham, J.M., Hendershott, P.H., 1996. Bubbles in metropolitan housing markets. Journal of Housing Research, 7, 191-207.

André, C., Gil-Alana, L. A., Gupta, R., 2014. Testing for persistence in housing price-to-income and price-to-rent ratios in 16 OECD countries. Applied Economics, 46, 2127-2138.

Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18, 1-22.

Balcilar, M., Gupta, R., Miller, M.S., 2014. Housing and the great depression. Applied Economics, 46, 2966-2981.

Balcilar M., Gupta R., Miller M.S., forthcoming. The out-of-sample forecasting performance of non-linear models of regional housing prices in the US. Applied Financial Economics.

Ben Nasr, A., Ajmi, A.N., Gupta, R., 2014. Modeling the volatility of the Dow Jones Islamic market world index using a fractionally integrated time varying GARCH (FITVGARCH) model. Applied Financial Economics, 24, 993-1004.

Beracha, E., Skiba, H., 2011. Momentum in residential real estate. Journal of Real Estate Finance and Economics, 43, 299-320.

Bierens, H.J., 1997. Testing the unit root with drift hypothesis against nonlinear trend stationarity with an application to the US price level and interest rate. Journal of Econometrics, 81, 29-64.

Bloomfield, P., 1973. An exponential model in the spectrum of a scalar time series. Biometrika 60, 217-226.

Brock, W., Dechert, D., Scheinkman, J., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econometric Reviews, 15, 197-235.

Capozza, D., Hendershott, P., Mack, C., Mayer, C., 2002. Determinants of real house price dynamics. NBER Working Paper 9262, October.

Capozza, D.R., Hendershott, P.H., Mack, C., 2004. An anatomy of price dynamics in illiquid markets: Analysis and evidence from local housing markets. Real Estate Economics, 32, 1-32.

Capozza, D.R., Seguin, P.J., 1996. Expectations, efficiency and euphoria in the housing market. Regional Science and Urban Economics, 26, 369-386.

Case, K.E., Shiller, R.J., 1989. The efficiency of the market for single-family homes. American Economic Review, 79, 125-137.

Case, K.E., Shiller, R.J., 1990. Forecasting prices and excess returns in the housing market. Journal of the American Real Estate and Urban Economics Association, 18, 253-273.

Cheung, Y-W., 1993. Tests for fractional integration: A Monte Carlo investigation. Journal of Time Series Analysis, 14, 331-345.

Cuestas, J.C., Gil-Alana, L.A., 2012. A non-linear approach with long range dependence based on Chebyshev polynomials. Working Papers 2012-2013. The University of Sheffield, Department of Economics.

Diebold, F.X., Inoue, A., 2001. Long memory and regime switching. Journal of Econometrics, 105,131-159.

Diebold, F.S., Rudebusch, G., 1991. On the power of Dickey-Fuller tests against fractional alternatives. Economic Letters, 35, 155-160.

Englund, P., Gordon, T.M., Quigley, J.M., 1999. The valuation of real capital: A random walk down Kungsgatan. Journal of Housing Economics, 8, 205-216.

Englund, P., Ioannides, Y.M., 1997. House price dynamics: An international empirical perspective. Journal of Housing Economics, 6, 119-136.

Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2003. Do financial variables help forecasting inflation and real activity in the euro area? Journal of Monetary Economics, 50, 1243-1255.

Gao, A., Lin, Z., Na, C.F., 2009. Housing market dynamics: Evidence of mean reversion and downward rigidity. Journal of Housing Economics, 18, 256-266.

Gil-Alana, L.A., 2004. The use of Bloomfield (1973) model as an approximation to ARMA processes in the context of fractional integration, Mathematical and Computer Modelling 39, 429-436.

Gil-Alana, L.A., 2008, Fractional integration and structural breaks at unknown periods of time. Journal of Time Series Analysis, 29, 163-185.

Gil-Alana, L. A., Barros, C., Peypoch, N., 2014. Long memory and fractional integration in the housing price series of London and Paris, Applied Economics, 46, 3377-3388.

Gil-Alana, L.A., Aye, G., Gupta, R. (2013). Testing for persistence in South African house prices. Journal of Real Estate Literature, 21(2), 293-314..

Gupta, Rangan; Majumdar, Anandamayee, 2015. Forecasting US real house price returns over 1831–2013: evidence from copula models, Applied Economics, 47, 5204-5213.

Hamming, R.W., 1973. Numerical Methods for Scientists and Engineers, Dover.

Hassler, U. and J. Wolters, 1994, On the power of unit root tests against fractional alternatives, Economics Letters, 45, 1-5.

Hwang, M., Quigley, J., 2004. Selectivity, quality adjustment and mean reversion in the measurement of house values. Journal of Real Estate Finance and Economics, 28, 161 - 178.

Leamer, E.E., 2007. Housing is the business cycle. *NBER Working Paper* No. 13428, Retrieved from http://www.nber.org/papers/w13428.

Lean, H. H., Smyth, R., 2013. Do Malaysian house prices follow a random walk? Evidence from univariate and panel LM unit root tests with one and two structural breaks, Applied Economics, 45, 2611-2627.

Lee, D. and Schmidt, P., 1996. On the power of the KPSS test of stationarity against fractionally integrated alternatives. Journal of Econometrics, 73, 285-302.

Malpezzi, S., 1999. A simple error correction model of house prices. Journal of Housing Economics, 8, 27-62.

Meen, G., 2002. The time-series behavior of house prices: A transatlantic divide. Journal of Housing Economics, 11, 1-23.

Meese, R., Wallace, N., 1994. Testing the present value relation for housing prices: Should I leave my house in San Francisco? Journal of Urban Economics, 35, 245-266.

Mikhed, V., Zemcik, P., 2009. Do house prices reflect fundamentals? Aggregate and panel data evidence. Journal of Housing Economics, 18, 140-149.

Robinson, P.M., 1994. Efficient tests of nonstationary hypotheses. Journal of the American Statistical Association, 89, 1420-1437.

Røed Larsen, E., Weum, S., 2008. Testing the efficiency of the Norwegian housing market, Journal of Urban Economics, 64, 510-517.

Sing, T., Tsai, I., Chen, M., 2006. Price dynamics in public and private housing markets in Singapore. Journal of Housing Economics, 15, 305-320.

Smyth, G.K., 1998. Polynomial Aproximation, John Wiley & Sons, Ltd, Chichester, 1998.

Stock, J.H., Watson, M.W. (2003). Forecasting output and inflation: The role of asset prices. Journal of Economic Literature, 41, 788-829.

Tomasevic, N.M., Stanivuk, T., 2009. Regression Analysis and aproximation by means of Chebyshev Polynomial. Informatologia 42, 166-172.