PERSISTENCE AND CYCLICAL DYNAMICS OF U.S. AND U.K. HOUSE PRICES: EVIDENCE FROM OVER 150 YEARS OF DATA

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ABSTRACT

We propose a modeling approach for the historical series of real and nominal house prices in the United States and the United Kingdom that permits the simultaneous estimation of persistence at zero frequency (trend) and at frequency away from zero (cycle). We also consider the separate cases of a standard I(d) process, with a pole at the zero frequency, and a cyclical I(d) model that incorporates a singularity at a non-zero frequency. We use annual data from 1830 to 2016 for the United States and 1845 to 2016 for the United Kingdom. We find, in general, that the degree of fractional integration associated with the long run or zero frequency is less than one, but greater than 0.5, while the degree of fractional integration associated with the cyclical frequency is greater than zero and less than 0.5. Thus, the long-run component of house prices is nonstationary but mean reverting, while the cyclical component is stationary. This contrasts with the results of the standard model and much of the empirical literature, where the rejection of the unit root seldom occurs. Some policy implications of the results appear in the conclusion.

JEL Classification: C22, H21, H31.

Keywords: Long memory; house prices; fractional integration, cycles.

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Prof. Luis A. Gil-Alana gratefully acknowledges financial support from the Ministerio de Economía y Competitividad (ECO2017-85503R).

1. Introduction

This paper examines the long-run dynamics and the cyclical structure of the historical U.S. and U.K. house price data. House price dynamics play an important role in the macroeconomy, which drive complex economic relationships with major economic implications for the economy. A growing empirical literature stresses the relationships between housing markets and the business cycle. Unlike financial assets, houses play the dual role of a mechanism to store wealth and a durable consumption good. Changes in house prices can affect household's wealth and because of the important role that housing wealth has on aggregate consumption, declines in house prices lead to declines in economic activity (Iacoviello, 2002, 2005; Campbell and Cocco, 2007; André al., 2012).

The recent financial crisis underscores the key role of house prices as a major driver of macroeconomic activity. Shiller (2007) claims that the housing bubble that began in the mid-1990s is the major, if not the only, cause of the sub-prime mortgage crisis and the worldwide economic and financial crisis of 2007–2009. Balcilar et al. (2014) provide evidence on the role of house prices in causing the Great Depression. Leamer (2007) argues that for the United States "housing is the business cycle" or, more precisely, that house prices drive the U.S. business cycle. Empirical evidence on the leading nature of housing markets and house prices with respect to the business cycles in other countries also was recently developed by Alvarez et al. (2010) for the Euro area, Ferrara and Vigna (2010) for France, and Alvarez and Cabrero (2010) for Spain. Monetary policy authorities frequently attempt to derive signals contained in house price dynamics to inform them on the future direction of the economy, inherently believing in the predictive power of house prices.

The financial literature debates how monetary policy should respond to asset price fluctuations and, in particular, to house price fluctuations, believing that major deviations of house prices from their fundamentals pose a significant risk for the stability of the economy (Bordo and Jeanne, 2002; Bordo and Lowe, 2002; Cecchetti et al, 2002; Dufrenot and Malik, 2010). Leamer (2007) claims that eight out of the ten U.S. post-war recessions have been preceded by substantial housing problems. He also proposes a monetary policy based on data from the housing sector such as housing starts as opposed to the output gap. Bjørnland and Jacobsen (2010) suggest that central banks have successfully kept inflation in check, yet have failed to prevent house prices from bursting and exerting negative effects on the economy. Girouard and Blöndal (2001) argue that the deregulation and liberalization of the mortgage markets since the 1970s (e.g., the development of secondary mortgage markets, the introduction of new mortgage instruments, the elimination of regulation Q in the United States, and the abolition of credit controls or corset in the United Kingdom) made it easier for households to borrow for current consumption on the basis of their housing wealth. Moreover, the easing of borrowing constraints often accompanied sizeable withdrawal of housing equity. House prices also influence the profitability of the home building industry and, given the close association between profitability of housing construction and private residential investment, residential property prices can provide useful indicators of demand pressures in the economy.

Given the macroeconomic significance of house prices, it is important to understand their stochastic properties. Several studies test for the presence of a unit root and cannot reject this hypothesis in most cases (e.g., Meen 1999, 2002; Peterson, et al. 2002; and Muñoz 2004). More recently, however, Cook and Vougas (2009) and Chang, et al. (2016) show that using more sophisticated testing procedures, one can reverse the findings of a unit root. Cook and Vougas (2009), using the smooth-transition momentum-threshold autoregressive (ST-MTAR) test of Leybourne et al. (1998), confirm the stationarity of the U.K. housing market. Chang et al. (2016), using the sequential panel-selection method (SPSM) proposed by Chortareas and Kapetanios (2009) and Kapetanios, et al. (2003) that test with a Fourier function, conclude that house prices for the nine provinces of South Africa are stationary.

Determining whether a unit root exists in real house prices sheds light on the appropriateness of theoretical urban models that explain real house prices. If real income contains a unit root and the real house price is trend stationary, then the models such as the one by Capozza and Helsley (1989, 1990) that suggest an equilibrium relationship between the real house price and real income are puzzling. Researchers largely employ unit-root tests in the context of temporal diffusion mechanisms. The main contributions to this literature on "spillover" effects include Balcilar et al. (2013), Canarella et al. (2012), Pollakowski and Ray (1997), Peterson et al. (2002), Zhang, et al. (2015) for the United States, Meen (1999, 2002), Cook (2003), and Holly et al. (2010) for the United Kingdom, and, more recently, Gong et al. (2016), Lee and Chien (2011), Nanda and Yeh (2014), and Balcilar et al. (2013) for China. These tests, however, are now recognized as imposing restrictive assumptions on the behavior of the data, and are known to possess low power. They discriminate between stationary I(0) and nonstationary I(1) processes, but do not allow for the fractional alternatives of "long memory" models.

This paper uses fractional integration to infer the long memory and persistence behavior of house prices in the United States and the United Kingdom over a period spanning two centuries. Persistence measures the extent to which current short-term shocks lead to transitory or permanent future changes (Gil-Alana et al. 2014). Thus, modeling persistence of house prices provides an understanding of the stability of the housing markets. Further, the persistence of house prices transmits to other sectors of the economy and to macroeconomic variables. It is, thus, important to know whether this transmission exhibits transitory or permanent effects.

The fractional integration methodology is relatively new, and includes as special cases the standard stationary I(0) and nonstationary (unit-root) I(1) cases. Thus, the I(d) model provides a richer degree of flexibility in the dynamic specification of the data and, depending on the value of d, determines stationarity with short memory (d = 0), stationarity with long memory ($0< d <0.5$), nonstationarity with mean reversion ($0.5 \leq d < 1$), or nonstationarity without mean-reversion ($d>=1$). These I(d) models belong to the wider class of long memory models, which exhibit strong degrees of association of observations widely separated in time. Thus, by employing fractionally integrated models, we infer the long memory and persistence of the historical U.S. and U.K. price series. The fractional integration parameter, d, indicates the degree of persistence related with the long-run behavior of the data. Researchers have extensively studied the problem of estimating and testing I(d) models (e.g., Yajima 1988, 1991; Dahlhaus 1989; Sowell, 1992; Beran, 1994, Robinson 1994, 1995a, 1995b, 2005; Phillips and Shimotsu, 2004; Shimotsu and Phillips 2005; Velasco 1999, 2003; and Abadir et al., 2007, among many others).

Empirical research on the long-run persistence of house prices using the fractional integration approach include Barros, et al. (2012, 2015), Gil-Alana, et al. (2014), Gil-Alana, et al. (2013), and Gupta, et al. (2014).

Barros, et al. (2012) examine state house prices in the United States using quarterly data from 1975:Q1 to 2009:Q2 and find strong evidence in favor of unit roots in only eight U.S. states (Alaska, Nebraska, New Hampshire, New Mexico, New York, North Carolina, Oregon, and Pennsylvania). In the remaining U.S. states, as well as for the entire United States, they reject the unit-root hypothesis. In most cases, however, the rejections favor alternatives with orders of integration exceeding one, implying highly persistent house prices.

Gil-Alana, et al. (2014) provide evidence on house prices from two important European cities: Paris and London. Monthly data on London house prices cover 1995:M1 to 2010:M3, while quarterly data on Paris house prices cover 1992:Q1 to 2009:Q4. The results indicate that both house price series incorporate much persistence. The orders of integration exceed one for the Paris apartments, for the London average price, and for the London housing index, signifying very persistent series. For one London index ("London sales"), however, the order of integration of less than one implies mean reversion, although convergence to its original average takes considerable time.

Barros, et al. (2015) analyze state and metropolitan house prices in the United States, focusing on the long-range dependence of price volatility (i.e., proxied by squared and absolute returns) based on the fractional integration approach. They use quarterly observations on state house price indices from each of the 50 U.S. states and the S&P/Case-Shiller house price index for 20 U.S. metropolitan areas. Using parametric and semiparametric long-memory methods, Barros, et al. (2015) observe that most of the estimates of the fractional differencing parameter in the squared and absolute returns values are positive and constrained between zero and 0.5, implying stationary long-memory behavior.

Gupta et al. (2014) analyze quarterly data on real house prices for eight European economies (Belgium, Finland, France, Germany, Ireland, Italy, Netherlands, and Spain) from 1971:Q1 until 2012:Q4 and find that the orders of fractional integration fall strictly above one in all cases, implying that the growth rate series (i.e. their first differences) display long memory behavior.

More recently, Balcilar et al. (2018) searched for periods of US housing price explosivity over 1830–2013. They make use of several robust techniques that allow them to identify such periods by determining when prices start to exhibit explosivity with respect to its past behaviour and when it recedes to long term stable prices. In this regard, one of the approaches that Balcilar et al., (2018) uses, is the Robinson's (1994) test statistic, besides Generalized supADF (GSADF) test procedure developed by Phillips et al. (2011). The test statistic of Robinson (1994) compares the null of a unit root process against the alternative of specified orders of fractional integration. The analysis date-stamps several periods of US house price explosivity, allowing the authors to contextualize its historic relevance.

A remarkable shortcoming exists, however, with the analysis of house prices in the extant literature, since few studies consider their cyclical structure and component. In addition to the stochastic trends, the cyclical structure of economic data is also important, which several studies document, especially for business cycles. Researchers propose nonlinear (e.g., Beaudry and Koop, 1993; Pesaran and Potter, 1997) and fractionally ARIMA (ARFIMA) (e.g., Candelon and Gil-Alana, 2004) models. Harvey (1985) and Gray et al. (1989, 1994) argue that cycles provide an additional component to the long-run trend and the seasonal structure of the data. This feature of house prices is not well captured by I(0), I(1), or even I(d) models. Typically, house prices exhibit a peak in the periodogram at zero, but also at non-zero frequencies, indicating cyclical dynamics. Testing for persistence while ignoring the cyclical structure of the data tends to overestimate long-run persistence. The available evidence suggests that periodicity of economic and financial data ranges from five to ten years and, in most cases, a periodicity of about six years is estimated (e.g., Baxter and King, 1999; Canova, 1998; and King and Rebelo, 1999).

Evidence of fractional integration at zero frequency and at frequencies away from zero exists in many financial and economic data, such as U.S. real output (Gil-Alana, 2005), U.K. stock market returns (Gil-Alana, 2005b), Shiller's data on dividends, earnings, interest rates, stock prices, and long-term government bond yields (Caporale, et al. 2012), U.S. hours worked (Caporale and Gil-Alana, 2014a), the U.S. stock market (Caporale and Gil-Alana, 2014b), the historical gold and silver prices (Gil-Alana and Gupta, 2015), the Eurobond rate (Caporale and Gil-Alana, 2016.), and the federal funds rate (Caporale and Gil-Alana, 2017), among others.

In this paper, we extend the existing literature on the dynamics of house prices by examining the relevance of persistence, the main stochastic property of house prices, at both the zero frequency and at a frequency away from zero. Persistence at frequency zero is long-run persistence (i.e., persistence related to the trend); and persistence at a frequency away from zero is cyclical persistence (i.e., persistence related with a cyclical pattern in the data).

We consider three different model specifications: a) a standard I(d) process with a pole in the spectrum solely at the zero frequency; b) a cyclical I(d) model with a single pole at the non-zero frequency, and c) a general model that incorporates the long-run and cyclical frequencies in a single framework by incorporating two fractional integration parameters with two poles, one at the zero (long-run) frequency and the other at the non-zero (cyclical) frequency. For the zero (long-run) frequency, we use both parametric and semiparametric methods, whereas for the non-zero (cyclical) frequency, we employ a version of the parametric testing procedure of Robinson (1994).

The results of our analysis suggest that convincing evidence exists for two distinct poles, at the zero (long-run) and non-zero (cyclical) frequencies with pronounced differences in house price dynamics. The results show that the long-run component is clearly non-stationary, but mean reverting, with an order of integration greater than 0.5 and less than one. On the other hand, the cyclical component is stationary with short memory, although we cannot rule out fractional orders of integration. These findings have substantial implications for policy decisions. Shocks affecting the long-run component will persist for a long time, while those affecting the cyclical component will not. Thus, policymakers should adopt stronger policies with respect to long-run movement to create an environment whereby the economy can return to its original level.

A word of caution is warranted, however. Long spans of data probably include structural breaks, due to both domestic and external shocks, such as wars, economic crises, and changes in institutional arrangements. Clearly, for our sample periods, structural breaks could exist. This is particularly relevant in housing markets, where structural changes have occurred since the 1950s. The empirical literature provides evidence that structural changes can affect house price dynamics. Cook and Vougas (2009) find structural change in U.K. house prices and show that contrary to standard unit-root tests smooth transition-momentum threshold autoregressive tests (ST-MTAR) reject the presence of a unit root in U.K. house prices. Canarella, et al. (2012) find structural breaks in house prices in the United States. In this context, researchers can easily confuse the fractional integration approach and long-memory processes with regime switching processes. Moreover, fractional integration may disguise structural breaks. A large literature is developing on long memory and structural breaks (e.g., Bos et al., 1999; Diebold and Inoue, 2001; Granger and Hyung, 2004; Gil-Alana, 2008 and André al., 2014). Discriminating between the two processes may prove difficult, since fractional integration and structural breaks are intimately related to and easily confused with each other (Diebold and Inoue, 2001). For this reason, we limit the analysis to the fractional integration dynamics of house prices and leave the interconnected question of structural breaks open for future research.

The outline of the paper is as follows. Section 2 describes the models employed and the methodology used. Section 3 presents the data and the main empirical results. Section 4 concludes.

2. The models

We consider three fractional integration models. First, we consider the standard I(d) model of the form advocated, for example, in Gil-Alana and Robinson (1997). The model incorporates two equations. The first accommodates the deterministic terms, while the second expresses the standard case of the I(d) model:

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad (1 - L)^{d_L} x_t = u_t, \qquad t = 1, 2, \ldots, \quad (1)$$

where y_t is the observed time series; β_0 and β_1 are the coefficients corresponding, respectively, to the intercept and linear time trend, L is the lag operator ($Lx_t = x_{t-1}$), and x_t is I(d_L), where d_L refers to the zero (long-run) frequency order of integration. That is, the d_L-differenced series may display no autocorrelation (i.e., white noise) or autocorrelated (of its weak form) throughout, for example, the exponential spectral model of Bloomfield (1973).

Different processes emerge depending on the value of d_L. Thus, if $d_L = 0$ in equation (1), $x_t = u_t$, and the process is a short memory, I(0) process with autocorrelations that decay exponentially fast. On the other hand, if $d_L > 0$ the process possesses long memory, because of the high degree of association between observations that are far distant in time from each other. If $d_L < 1$, the process is mean reverting with shocks disappearing in the long run. Note that the specification in equation (1) includes the standard I(1) case, which is widely employed in the literature for testing unit roots, when $d_L = 1$.[1] In such cases, shocks are permanent. The fact that x_t is I(d_L) implies that we can express its spectral density function as follows:

$$f_x(\lambda) = \frac{\sigma^2}{2\pi}\left|1 - e^{i\lambda}\right|^{-2d_L}, \qquad -\pi \le \lambda < \pi. \tag{2}$$

Thus,

$$f(\lambda) \to \infty, \quad as \;\; \lambda \to 0^+. \tag{3}$$

We observe this feature in many aggregated data.[2] The spectrum, however, may display a pole or singularity at a non-zero frequency. This case produces a cyclical pattern. Thus, we extend the second equation in equation (1) and consider the cyclical I(d_c) model as follows:

$$(1 - 2\mu L + L^2)^{d_c} x_t = u_t, \quad t = 1,2,\ldots, \tag{4}$$

where d_c refers to the cyclical order of integration. It can be as before a real number and once more u_t is I(0). Gray et. al. (1989, 1994) show that x_t in equation (4) is stationary if $|\mu| < 1$ and $d_C < 0.50$ or if $|\mu| = 1$ and $d_C < 0.25$. These authors also show that we can express the polynomial in equation (4) in terms of the Gegenbauer polynomial $C_{j,dc}(\mu)$ such that for all $d_C \neq 0$,

$$(1 - 2\mu L + L^2)^{-d_c} = \sum_{j=0}^{\infty} C_{j,dc}(\mu) L^j, \tag{5}$$

where $$C_{j,dc}(\mu) = \sum_{k=0}^{[j/2]} \frac{(-1)^k (d_c)_{j-k} (2\mu)^{j-2k}}{k!(j-2k)!}; \qquad (d_c)_j = \frac{\Gamma(d_c + j)}{\Gamma(d_c)},$$

[1] See Dickey and Fuller (1979), Phillips and Perron (1988), Elliot et al. (1996), Ng and Perron (2001), and so on.

[2] See Robinson (1978), Granger (1980), and more recently by Parke (1999), Oppenheim and Viano (2004), Zaffaroni (2004) and Haldrup and Vera-Valdes (2017).

where Γ(x) means the Gamma function, and a truncation is required below equation (4) to make equation (1) operational. Thus, the process in equation (4) becomes:

$$x_t \;=\; \sum_{j=0}^{t-1} C_{j,d_c}(\mu)\, u_{t-j}, \qquad t \;=\; 1,\, 2,\, \ldots.,$$

and when d_C = 1, we have

$$x_t \;=\; 2\mu\, x_{t-1} \;-\; x_{t-2} \;+\; u_t, \qquad t \;=\; 1, 2, \ldots., \tag{6}$$

which is a cyclical I(1) process of the form proposed earlier by Ahtola and Tiao (1987), Bierens (2001), and others to test for unit-root cycles in AR(2) models. Note that using this specification, the spectral density of x_t is given by:

$$f_x(\lambda) \;=\; \frac{\sigma^2}{2\pi}\left|1 \;-\; 2\,\mu e^{i\lambda} \;+\; e^{2i\lambda}\right|^{-2d_L}, \qquad -\pi \;\le\; \lambda \;<\; \pi, \tag{7}$$

Finally, we consider the third specification, which incorporates the two structures dealing with the degree of persistence in a single framework. That is, we include a structure producing a singularity at the zero (long-run) frequency along with another one corresponding to the cyclical frequency. The model is given by:

$$(1 \;-\; L)^{d_L}\; (1 \;-\; 2\mu L + L^2)^{d_c}\, x_t \;=\; u_t, \quad t \;= 1, 2, \ldots, \tag{8}$$

allowing for both deterministic terms in x_t, and potential weak autocorrelation in u_t. Researchers have already employed this model in the analysis of macro data by Caporale and Gil-Alana (2014a,b, 2017), Ferrara and Guegan (2001), Sadek and Khotanzad (2004), and others in the context of the k-factor Gegenbauer processes.

We estimate and test all three specifications of the fractional model by means of the Whittle function in the frequency domain (Dahlhaus, 1989, 1995). We also use the general testing procedure suggested by Robinson (1994) that tests these hypotheses, which can entail one or more integer or fractional roots of arbitrary order anywhere on the unit circle in the complex plane.

3. Data

We compile a dataset of annual time series for the United States and the United Kingdom spanning 1830-2016 and 1845-2016, respectively, which includes nominal and real house prices, with real values obtained by deflating the nominal house prices with the consumer price index. All variables for the United States come from the Global Financial Database. The data for the United Kingdom come from the database called the A millennium of macroeconomic data, maintained by the Bank of England at: https://www.bankofengland.co.uk/statistics/research-datasets. We transform the original data into logarithms. An advantage of this long sample is the ability to examine how the housing markets of these two countries evolve over time, covering almost their entire modern economic history. These series are the longest available data on house prices in the United States and the United Kingdom.

Figures 1 and 2 display the actual and log-transformed data, respectively. The historical development of the U.S. nominal prices does not differ in any significant manner from that of the U.K. nominal prices. Both series display no trend until the early 1950s, suggesting possible stationary behavior. Since then, a strong upward trend emerges in all four series, suggesting possible non-stationary behavior. The evolution of the U.S. real house price appears more volatile than that of the U.K. real house price series. The real estate bubble, where house prices peaked in early 2006, started to decline in 2006 and 2007, and reached new lows in 2012, appears pronounced in both countries, suggesting the possibility of structural breaks in the series.

[Insert Figures 1 to 5 about here]

Figure 3 displays the first differences of the log-transformed data. The U.K. prices appear to experience longer swings than the U.S. prices. Figures 4 and 5 display the periodograms (evaluated at the discrete Fourier frequencies $\lambda_j = 2\pi j/T,\ j = 1, 2, ..., T/2$), respectively, for the log-transformed data and their first differences.

The periodogram is an asymptotic unbiased estimate of the spectral density function. If the data are I(1) or I(d), d>0, with a peak at the zero frequency, the spectral density function is unbounded at the origin. In such case, we should expect the highest value in the periodogram at the smallest frequency. The periodograms of the log-transformed data show the highest values in the close vicinity of the zero frequency, while the periodograms of the first differences on the log-transformed data display the highest values at a non-zero frequency, providing evidence of cyclical patterns, with the exception of the U.K. log-transformed nominal price.

4. Empirical results

4.1 Results from the long-run I(d_L) model

Table 1 reports the estimates of the degree of fractional integration *d* = d_L in the model given by equation (1). We consider the three standard cases of (i) no deterministic terms (i.e., $\beta_0 = \beta_1 = 0$ *a priori*), (ii) an intercept and no trend (β_0 unknown, and $\beta_1 = 0$ *a priori*), and (iii) a constant with a linear time trend (β_0 and β_1 unknown). These values emerge through a grid-search with the tests of Robinson (1994) and choosing the values of d_L that produces the lowest statistics.[3] Together with the estimates, we also present the 95-percent confidence band of the non-rejection values of d_L, using Robinson's (1994) parametric tests. Since this method is parametric, we report in Table 1 the results assuming that x_t is a white-noise process and that it follows the autocorrelated model of Bloomfield (1973), which is a non-parametric approach of modeling the I(0) error term.

[3] These values were practically identical to those obtained by using the Whittle function in the frequency domain (Dahlhaus, 1989) and based on the first differenced data, then adding one to the obtained results.

The Bloomfield model accommodates nicely in the context of fractional integration (Gil-Alana, 2004; Velasco and Robinson, 2000).

We observe in Table 1 that under the assumption of no autocorrelation, the time trend is statistically insignificant for the two U.K. series and also for the U.S. real house price. For the nominal house price in the United States, however, the time trend is required. We also observe that the estimates of d_L are much higher for the U.K. house price than for the U.S. price. Thus, for the United Kingdom, the estimated values of d_L are 1.60 and 1.61, respectively, for the nominal and real prices, implying that we can decisively reject the unit-root null hypothesis in favor of $d_L > 1$ as the confidence bands in these cases all exceed one. We cannot reject, however, the unit-root null hypothesis for the U.S. house price, where the estimated values of d_L are 1.04 and 0.98, respectively, for the nominal and real prices.

[Insert Tables 1 and 2 about here]

When we allow for autocorrelated disturbances by means of the exponential spectral model of Bloomfield (1973), the time trend becomes statistically significant in all four cases. The estimates of d_L are now smaller, and we cannot reject the unit-root hypotheses for the two U.S. house prices and for the real U.K. price. For the U.K. nominal price, however, the estimated value of d_L remains significantly above one.

Table 2 displays the estimates of d_L based on the "local" Whittle semiparametric method, where we do not impose a functional form on the process. The estimation, however, requires the selection of a bandwidth. Table 2 presents results for a selected group of bandwidths, reported at the top.[4] Bold type identifies evidence of unit roots. The confidence bands are reported at the bottom. The semiparametric estimates of d_L are

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[4] The choice of the bandwidth (m) shows the trade-off between bias and variance: the asymptotic variance and the bias decrease and increase, respectively, with m.

generally robust across the bandwidth numbers. We observe that for any reported bandwidth, we reject the unit-root hypothesis for the U.K. nominal house price in favor of the alternative of d_L >1. We cannot reject the unit-root null hypothesis for the real U.K. house price for any reported bandwidth and for the nominal U.S. house price for the first bandwidth. We detect evidence of non-stationarity associated with mean reversion in the cases of the U.S. nominal and real house prices for almost any reported bandwidth. This contrasts with the parametric estimates of d_L, which, in turn, may suggest misspecification. In particular, the estimates in equation (1) may be biased, since the model does not include the cyclical component.

As a conclusion to this preliminary work (and based exclusively on one differencing parameter at the zero, long-run frequency), the results indicate high levels of persistence, especially for the U.K. prices, though it seems that they are sensitive to the methodology used.

4.2 *Results from the cyclical I(d_C) model*

Next, given that d_L showed high values in all cases, we take first differences of the log price and perform the model given by equation (4), assuming that $\mu = 2\cos w_r$, where $w_r = 2\pi r/T$ with $r = T/j$, where j indicates the number of periods per cycle and r the frequency with a singularity or pole in the spectrum. As before, we assume that u_t is I(0). We consider once more the two possibilities of no correlation, white noise (Table 3) and the autocorrelated model of Bloomfield (Table 4). In the two cases, we present the results for the original data and the mean-subtracted series. Generally, the estimates of d_c are positive and less than 0.5 in the four series. Evidence of significant positive values occurs only for the U.K. data when we assume white-noise errors. Employing the exponential spectral model of Bloomfield (1973) for the I(0) error term u_t in equation (4) produces estimates of d_c fairly similar to those reported in Table 3 for the white-noise errors.

[Insert Tables 3 and 4 about here]

We also observe in these two tables that the estimated value of j ranges between 5 and 8, which is consistent with the empirical literature on business cycles where cycles in economics exhibit a periodicity constrained between four and twelve years (e.g., Baxter and King, 1999; Canova, 1998; and King and Rebelo, 1999).

4.3 Results from the I(d_L , d_C)

Finally, we examine the model given by equation (8), which is more general than the previous two specifications in the sense that it includes two differencing parameters, one at the zero (long-run) frequency and the other at the cyclical frequency. Table 5 focuses on white-noise errors while Table 6 refers to the autocorrelated (Bloomfield) case.

[Insert Tables 5 and 6 about here]

Tables 5 and 6 report that the values of j, once more, ranges between four and six years in all cases. Focusing on the estimates of the differencing parameters, we observe that d_L substantially exceeds d_C in all cases, especially under no autocorrelation for the error term. For the cyclical component, the estimates of d_C substantially exceed zero in the case of the log of nominal U.K. data, but close to zero in the remaining cases, implying that the cyclical component only become relevant for the log of the U.K. nominal price. In all the other cases, the single I(d_L) model sufficiently describes the persistence in the data.

5. Conclusions

Most literature on house prices generally accepts that house prices are nonstationary. In this literature, house prices are specified in a stochastic model that presents only one pole at the zero frequency. Such models only describe the long-run dependency of house prices. In this paper, we suggest that such models may be misspecified, since they can fail to account for the cyclical components of house prices. We suggest that U.S. and U.K. historical house prices may conform to a stochastic process that includes two poles or singularities in the spectrum: one at the zero frequency, corresponding to the long-run behavior of the series, and another away from the zero frequency, corresponding to the cyclical dependency of the series.

We use annual data from 1830 to 2016 for the United States and 1845 to 2016 for the United Kingdom and consider three cases: a) a standard $I(d_L)$ model with a pole at the zero frequency; b) a cyclical $I(d_C)$ model that incorporates a singularity at a non-zero frequency; and c) the composite $\mathbf{I}(d_L, d_C)$ model that incorporates two singularities: one at frequency zero and one at a frequency away from zero. We find, in general, that the degree of fractional integration associated with the zero (long-run) frequency is less than 1, while the degree of fractional integration associated with the cyclical frequency is greater than zero and less than 0.5. The first result questions the random-walk property of house prices and suggests that house prices in the long run revert after a shock to their equilibrium values. The second result, while confirming the link between house prices and the business cycle, appears to question the real business cycle view of nonstationarity of the business cycle (Nelson and Plosser, 1982). When modeling these two frequencies together, however, we find that the zero frequency component dominates the cyclical component, and only for the nominal U.K. prices does the cyclical component become significant, whereas in the remaining cases, we find that the order of integration of the cyclical frequency is close to zero. Still, the long-run component of house prices remains mean reverting. Thus, contrary to the vast majority of papers in the house-price literature, shocks to house prices do not generate permanent effects.

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Figure 1: Original data

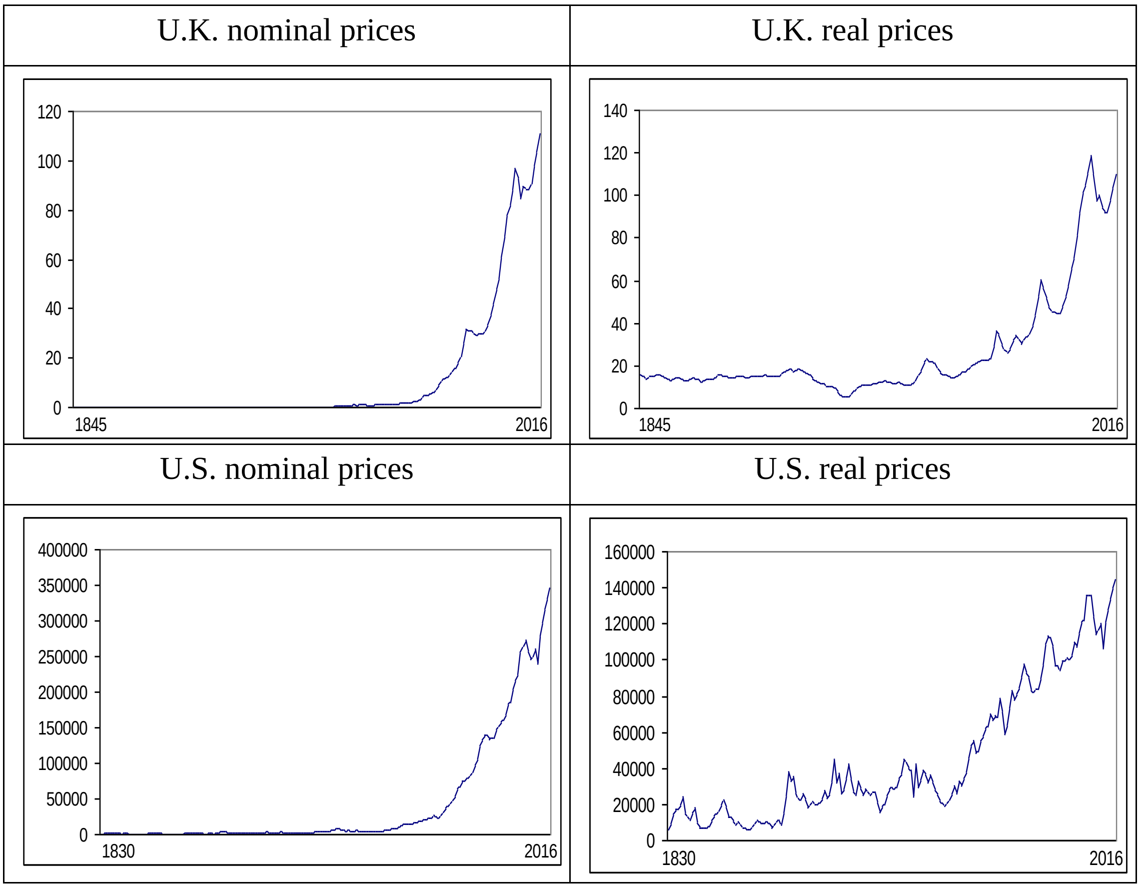


Figure 2: Log-transformed data

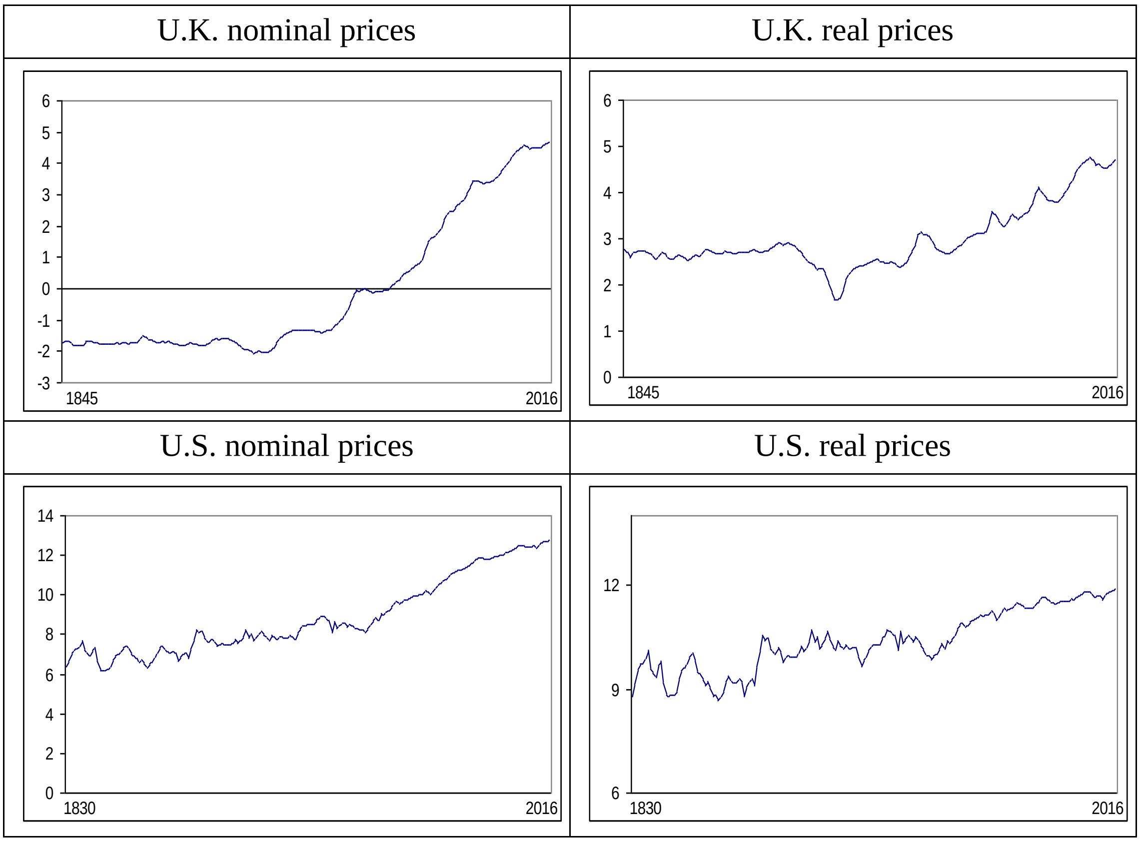
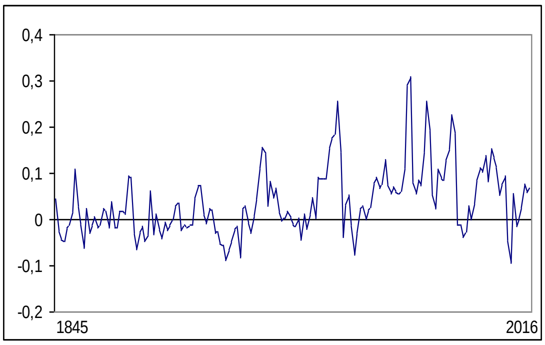
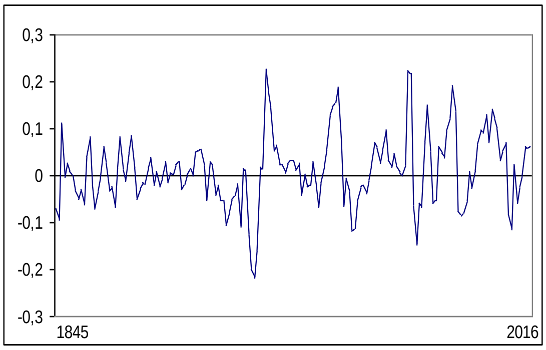


Figure 3: First differences on the log-transformed data

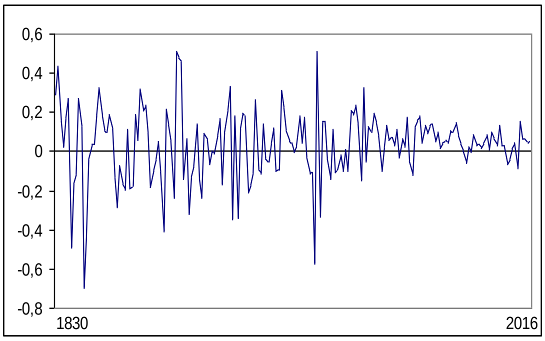
U.K. nominal prices



U.K. real prices



U.S. nominal prices



U.S. real prices

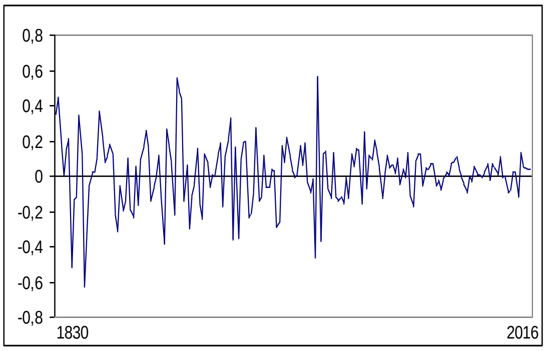
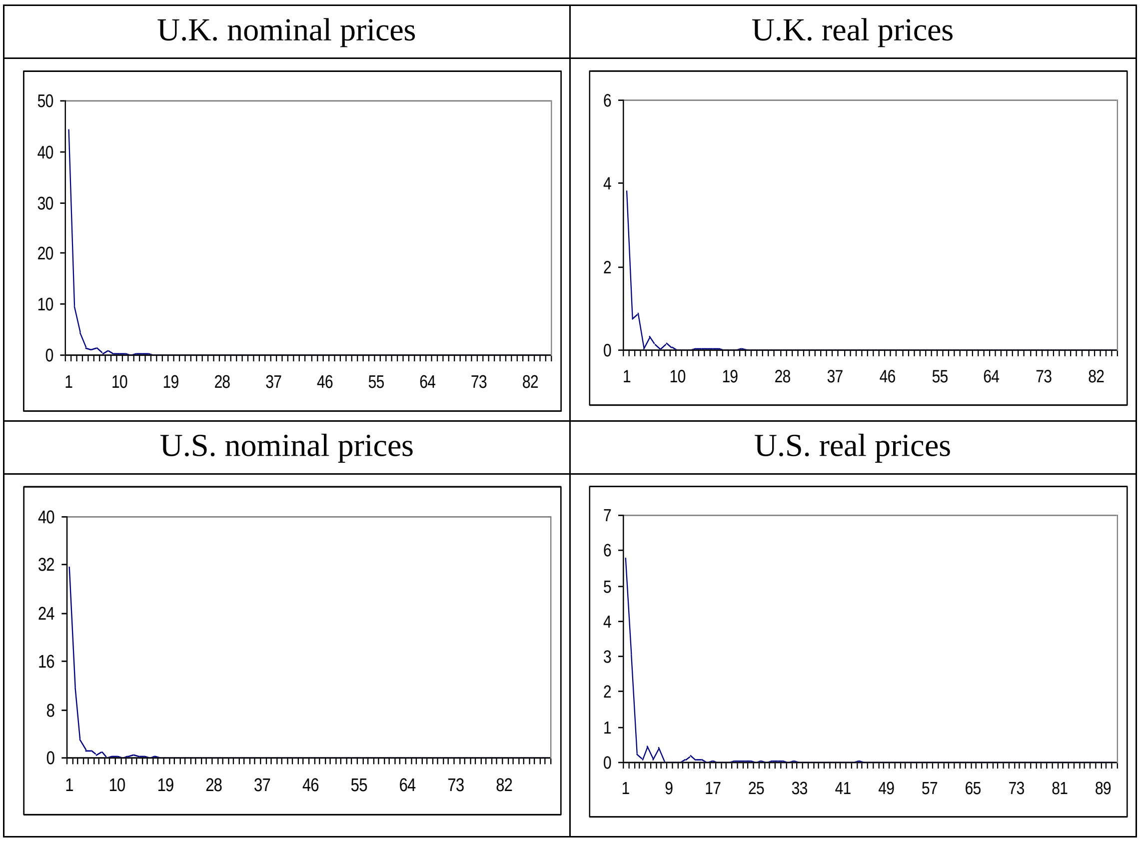
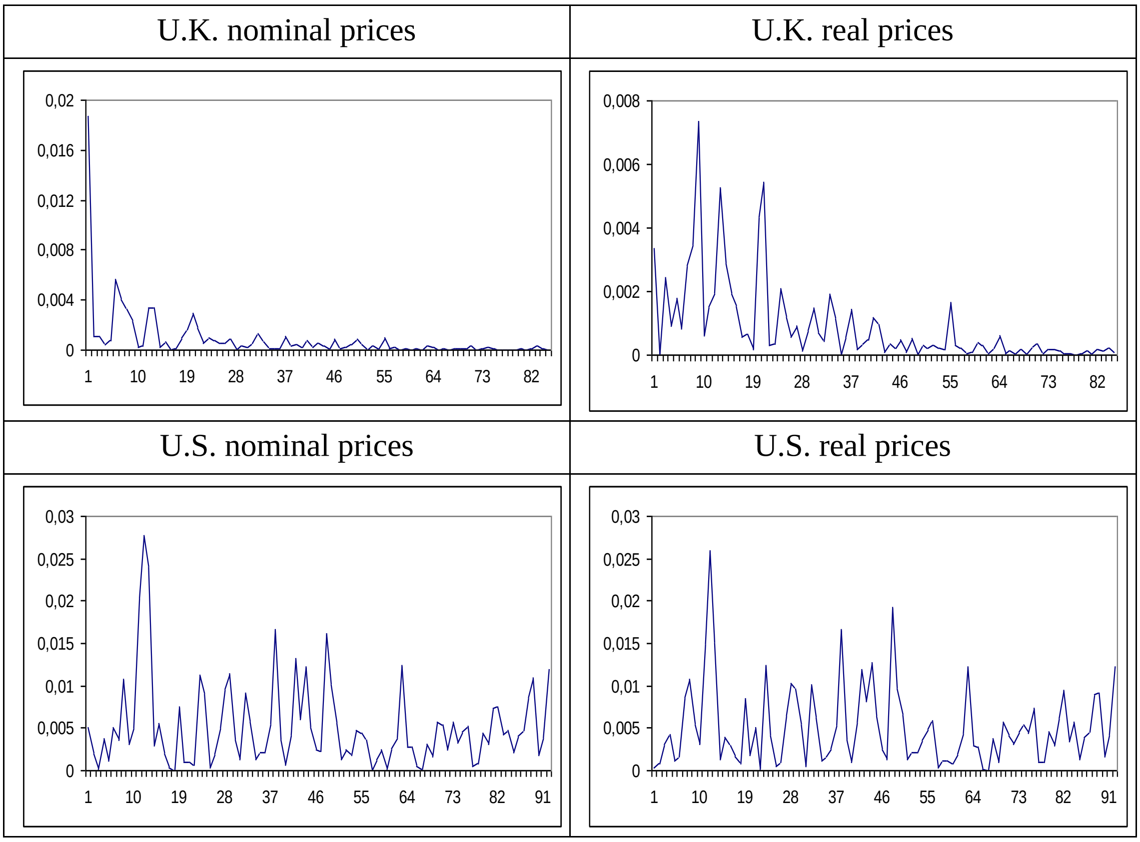


Figure 4: Periodogram of the log-transformed data



The horizontal axis refers to the discrete Fourier frequencies $\lambda_j = 2\pi j/T,\ j = 1, 2, ..., T/2$

Figure 5: Periodogram of the first differences on the log-transformed data



The horizontal axis refers to the discrete Fourier frequencies $\lambda_j = 2\pi j/T,\ j = 1, 2, ..., T/2$

Table 1: Estimates of d_L using a parametric approach

i) No autocorrelation			
Series	No terms	An intercept	A linear time trend
Log U.K. nominal	1.13 (1.05, 1.22)	**1.60 (1.46, 1.82)**	1.61 (1.46, 1.82)
Log U.K. real	1.02 (0.93, 1.15)	**1.61 (1.41, 1.87)**	1.61 (1.41, 1.88)
Log U.S. nominal	1.03 (0.93, 1.15)	1.03 (0.92, 1.18)	**1.04 (0.91, 1.19)**
Log U.S. real	1.02 (0.93, 1.15)	**0.98 (0.84, 1.15)**	0.98 (0.84, 1.15)
i) With autocorrelation (Bloomfield)			
Series	No terms	An intercept	A linear time trend
Log U.K. nominal	1.17 (1.06, 1.34)	1.14 (1.10, 1.36)	**1.21 (1.11, 1.37)**
Log U.K. real	0.96 (0.80, 1.18)	0.93 (0.82, 1.15)	**0.92 (0.78, 1.17)**
Log U.S. nominal	1.00 (0.83, 1.22)	0.89 (0.78, 1.10)	**0.88 (0.72, 1.11)**
Log U.S. real	0.98 (0.82, 1.21)	0.70 (0.58, 1.02)	**0.67 (0.44, 1.02)**

In bold the selected models according to the deterministic terms using the t-values of the corresponding estimated coefficients. For the confidence bands we use Robinson (1994).

Table 2: Estimates of d_L using a semiparametric approach

	11	12	13	14	15	16
Log U.K. nominal	1.418	1.339	1.292	1.331	1.352	1.397
Log U.K. real	**0.925**	**0.937**	**0.890**	**0.892**	**0.907**	**0.926**
Log U.S. nominal	**0.755**	0.668	0.632	0.659	0.679	0.708
Log U.S. real	0.500	0.500	0.500	0.522	0.577	0.502
Lower 5% I(1)	0.752	0.762	0.771	0.780	0.794	0.800
Upper 5% I(1)	1.247	1.237	1.228	1.219	1.212	1.205

In bold, evidence of unit roots at the 95% level.

Table 3: Estimated coefficients in (3) assuming white noise errors

i) Original data		
	j	d_C
Log U.K. nominal	6	0.42*
Log U.K. real	5	0.14*
Log U.S. nominal	6	0.05
Log U.S. real	7	0.01
ii) Mean-subtracted data		
	j	d_C
Log U.K. nominal	6	0.43*
Log U.K. real	5	0.14*
Log U.S. nominal	8	0.04
Log U.S. real	7	0.01

*: Significance at the 95% level.

Table 4: Estimated coefficients in (4) assuming autocorrelated (Bloomfield) errors

i) Original data		
	j	d_C
Log U.K. nominal	6	0.41*
Log U.K. real	5	0.14*
Log U.S. nominal	6	0.05
Log U.S. real	6	0.05
ii) Mean-subtracted data		
	j	d_C
Log U.K. nominal	6	0.43*
Log U.K. real	5	0.14*
Log U.S. nominal	5	0.02
Log U.S. real	7	0.01

*: Significance at the 95% level

Table 5: Estimated coefficients in (7) assuming white noise errors

i) Original data			
	d_L	j	d_C
Log U.K. nominal	0.79	6	0.14*
Log U.K. real	0.86	4	0.03
Log U.S. nominal	0.79	5	0.07
Log U.S. real	0.80	5	0.09
ii) Mean subtracted data			
	d_L	j	d_C
Log U.K. nominal	0.60	5	0.10*
Log U.K. real	0.65	4	0.01
Log U.S. nominal	0.60	4	0.02
Log U.S. real	0.60	4	0.03

*: Significance at the 95% level

Table 6: Estimated coefficients in (7) assuming autocorrelated (Bloomfield) errors

i) Original data			
	d_L	j	d_C
Log U.K. nominal	0.68	4	0.40*
Log U.K. real	0.86	4	0.03
Log U.S. nominal	0.51	6	0.10
Log U.S. real	0.52	5	0.09
ii) Mean subtracted data			
	d_L	j	d_C
Log U.K. nominal	0.68	4	0.38*
Log U.K. real	0.80	5	0.04
Log U.S. nominal	0.51	5	0.09
Log U.S. real	0.50	5	0.08

*: Significance at the 95% level