PERSISTENCE AND CYCLICAL DYNAMICS OF US AND UK HOUSE PRICES: EVIDENCE FROM OVER 150 YEARS OF DATA

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ABSTRACT

This paper provides a new and unique look at the dynamics and persistence of historical house prices in the US and the UK using fractional integration techniques not previously applied to housing markets. Unlike previous research, we consider two components of persistence of house prices: the component associated with the long-run trend and the component associated with the cycle. We find evidence of cyclical and long-run persistence in the UK, housing markets. In contrast, we fail to find evidence of cyclical persistence for the US. For the sub-samples, which account for a structural break in each series, an important difference is the asynchronous pattern of the breaks, an indication of heterogeneity in the house price dynamics of the two countries and a sign that national rather than global events have played an important role. Although the house price movements of the last decade are dramatic, the greatest structural changes in the overall nominal and real price dynamics of the UK and the US appear to have taken place much earlier, in the late 1970s and early 1980s in the UK and in the mid-1950s and early 1970s in the US. An important result, common to the whole and sub-samples, is that long-run persistence plays a greater role than cyclical persistence in explaining the dynamics of house prices in both countries. These findings have substantial implications for policy decisions.

JEL Classification: C22, H21, H31.
Keywords: Persistence; house prices; fractional integration, cyclical behavior.

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1. Introduction

In recent years, considerable interest focuses on the housing markets, and a sizable literature recognizes that housing markets play a critical role in the economy, the business cycle, and the financial system. Evidence from recent economic history include Case et al. (2005), Carroll et al. (2011), Attanasio et al. (2011), Chen et al. (2018), Davis and Heathcote (2005), Leamer (2007), Funke and Paetz (2013), and many others.[1] The important role of housing markets in the business cycle became painfully clear during the collapse of the sub-prime mortgage market in late 2006 and the resulting severe recession and financial crisis of 2007-2009, the worst since World War II (Mian and Sufi, 2010). 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. Leamer (2007) offers a more provocative assertion, arguing that for the US, "housing is the business cycle" or, more precisely, that house prices drive the US business cycle.[2]

Arguably, the recent financial crisis, more than any other macroeconomic event, underscores the importance of understanding the dynamics of house prices, and, in particular, the role of persistence and the effect of shocks on house price dynamics. Numerous empirical studies have analyzed these issues using alternative time-series methods, including univariate and panel unit-root tests, and fractional-integration. This literature is not only relevant to our understanding of the dynamics of house prices, but also sheds some light on and at times questions the appropriateness of theoretical urban and housing models. For instance, Capozza and Helsley (1989, 1990) suggest that an equilibrium relationship exists between real house

[1] Evidence of the strong link between housing markets and the economy is not only provided by recent economic history, but also by the entire postwar era (Holly and Jones, 1997) and even predates the Industrial Revolution (Eichholtz, Straetmans and Theebe, 2012).

[2] Alvarez et al. (2010) for the Euro area, Ferrara and Vigna (2010) for France, and Alvarez and Cabrero (2010) for Spain provide empirical evidence on the leading nature of housing markets and house prices with respect to the business cycles.

prices and real income. If real income has a unit root and house prices are stationary, however, then the equilibrium relationship between real house price and real income does not seem plausible, given the time-series characteristic of the two data series.

Meen (1999) and Peterson et al. (2002) find that the UK house prices follow a unit-root process. Meen (2002) fails to reject the unit root in house prices in the UK and the US. Muñoz (2004) and Clark and Coggin (2011) fail to reject the unit-root hypothesis of house prices in the US. Arestis and González (2014) confirm the presence of a unit root in house prices of 18 OECD countries. In contrast, Cook and Vougas (2009) support the stationarity of UK housing prices but with structural change. More recently, Zhang et al. (2016) present evidence from a 120-year national dataset that US house prices are trend stationary.

Unit-root tests do not completely measure the degree of persistence of a series. Unit-root tests discriminate between stationary and nonstationary processes, but do not allow for fractional alternatives, where the nonstationarity property of the data may overlap their mean-reversion property, and where stationarity may not exclude persistence. The standard practice to achieve stationarity differences the data. It is possible that to achieve stationarity, however, only fractional differencing is required (Granger, 1980). In this case, the process is fractionally integrated, or $I(d)$. The fractional integration approach is more general than the standard method that only consider $I(0)$ and $I(1)$ processes, since it allows d to be any real number, including a fractional value. If $d = 0$, the process exhibits "short memory" and the values of the autocorrelations show a fast exponential decay. In contrast, if $d > 0$, the process displays "long memory" and the values of the autocorrelations show a slow hyperbolic decay. If $0 < d < 0.5$, the process is stationary, while $d \geq 0.5$ implies nonstationarity. Moreover, if $d < 1$, the process exhibits mean reversion, which implies that if $0.5 \leq d < 1$, the process is nonstationary, but mean reverting, while if $d \geq 1$the process is nonstationary, but not mean reverting. Examples of papers that model house prices as fractional integration processes include Barros et al. (2012, 2015), Gil-Alana et al. (2014), Gil-Alana et al. (2013), and Gupta et al. (2014). Two observations, however, are warranted regarding this empirical literature. First, none of these studies tests for the presence of structural breaks in the series. Second, all these studies test only for the presence of long-run persistence in house prices. That is, the failure to include all relevant stochastic characteristics may lead to a biased estimate of the long-run persistence.

Our paper provides a new and unique look at the dynamics and persistence of historical house prices in the US and the UK, using methods not previously applied to housing markets. We use yearly data on real and nominal house prices over a period from 1830 to 2016 for the US, and from 1845 to 2016 for the UK, which provides a much longer perspective on the behavior of house prices than commonly appears in the literature, where most empirical work uses data starting from the 1980s or later. We also differ, however, from previous fractional integration research as we extend the fractional integration methodology by taking into account two components of house price persistence (i.e., the component affecting the long run trend, and the component affecting the cyclical structure).[3] In spectral analysis, persistence related to the long-run trend is persistence at frequency zero, while persistence related to the cyclical pattern of the data is persistence at a frequency away from zero.

We hypothesize that persistence of house prices may play different roles in the long run and in the cycle and that modeling jointly these two closely related components of the house price provides a much broader and more comprehensive view of the housing market dynamics and persistence. Typically, house prices exhibit a peak in the periodogram at zero frequency, which indicates long-run persistence, but also at a frequency away from zero, indicating cyclical dynamics. Testing for persistence while ignoring the cyclical component of persistence tends to overestimate long-run persistence. The available evidence suggests that the periodicity of economic and financial data ranges from five to ten years and, in most cases, researchers

[3] Several studies document the relevance of the cyclical structure of many economic data. See Gray et al. (1989).

estimate a periodicity of about six years (e.g., Baxter and King, 1999; Canova, 1998; and King and Rebelo, 1999).

We consider three different fractional integration models -- a standard model, defined by a process with a pole in the spectrum at the zero frequency, a process with a pole at the non-zero frequency, and a composite model by incorporating poles at zero and non-zero frequencies in a single framework. Thus, the third model estimates jointly the two components of persistence in house prices. We estimate each of the three models using the parametric procedure of Robinson (1994). This approach has two distinctive features compared with other methods. First, it does not require normality, which is an assumption rarely satisfied by economic data, and, second, and most importantly, the tests exhibit standard null distributions.

Finally, we examine the possibility of a structural break in the data. This is a relevant issue, not only because of the historical breadth of the data, but also because fractional integration and structural breaks can easily be confused. We account for this issue by re-estimating the fractional models using two sub-samples, with the dates identified by the Bai and Perron (2003) methodology.

The outline of the paper is as follows. Section 2 describes the models and outlines the main aspects of the fractional integration methodology. Section 3 presents the data. Section 4 reports the full sample results, while Section 5 deals with the analysis of breaks. Policy implications appear in Section 6.

2. The models

Let d_L and d_C be, respectively, the long-run and cyclical orders of integration. We consider three fractional integration models. The first $I(d_L)$ model is the standard 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 conventional fractional integration model.

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

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.

Note that the specification in equation (1) includes the standard $I(1)$ case, which is employed in the literature for unit-root testing, when $d_L = 1$. 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,

$$f_x(\lambda) \to \infty \quad as \quad \lambda \to 0^+ \tag{3}$$

We observe this feature in many aggregated data. The spectrum, however, may display a pole or singularity at a non-zero frequency. In this case, the process may still display long memory, but the autocorrelations exhibit a cyclical structure that decay slowly. This is a property of the Gegenbauer processes (Gil-Alana, 2001), defined as

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

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. Note that if $r = 0$, the fractional polynomial in equation (4) becomes $(1-L)^{2d}$, which is the polynomial associated with the $I(d_L)$ model. Gray et al. (1989) show that x_t in equation (4) is stationary if $|\mu| < 1$ and $d <$ 0.50 or if $|\mu| = 1$ and $d < 0.25$, where $\mu = cos\, w_r$. These authors also show that we can express the polynomial in equation (4) in terms of the orthogonal Gegenbauer polynomials $C_{j,d}(\mu)$ such that for all $d \neq 0$,

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

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 $d = 1$, reduces to

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

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 in this model, the spectral density of x_t is given by:

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

Thus, the second model is the cyclical d_C model (Gil-Alana, 2001), which can be specified as follows:

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

where d_C refers to the cyclical order of integration.[4] As in the $I(d_L)$ model, the fractional order of integration can be any real number and u_t is assumed $I(0)$.

Finally, in the third model, $I(d_L, d_C)$ 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 frequency (long-run trend) along with another one corresponding to the cyclical frequency. The model is given by:

$$(1 - L)^{d_L}(1 - 2\mu + L^2)^{d_C} x_t = u_t, \quad t = 1, 2, \ldots, \tag{9}$$

Caporale and Gil-Alana (2016, 2014a, b, 2017) provide detailed technical explanations about estimation and testing procedures suggested by Robinson (1994).

3. Data

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[4] The parameter μ is defined as cos*w*, where $w = 2\pi/r$, *r* indicating the number of time periods per cycle.

We compile a dataset of annual time series for the US and the UK 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. Thus, the US sample contains 187 observations while the UK sample contains 172 observations.

The nominal house price index (i.e., Winans International Real Estate Index, WIREI) for the US comes from the Global Financial Database (https://www.globalfinancialdata.com/). We deflate this index by the Consumer Price Index (CPI) to derive the US real house price index. The CPI data come from the website of Robert Sahr (http://oregonstate.edu/cla/polisci/sahr/sahr). The nominal house price and the Consumer Price Index data for the UK come from the database *A Millennium of Macroeconomic Data* maintained by the Bank of England at: https://www.bankofengland.co.uk/statistics/research-datasets as part of the Three Centuries of Macroeconomic Data project. For a summary overview of the methodology and construction of this database, see Thomas and Dimsdale (2017).

As in the US case, we obtain the UK real house price index by deflating the nominal index by the CPI. An advantage of these historical samples 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 annual data on house prices in the US and the UK. From the perspective of fractional integration, however, they are relatively small samples. The US sample contains 187 observations while the UK sample contains 172 observations.

Figure 1 plots the US and UK real and nominal price series in their log-transformed form as well as the first differences of the log-transformed data. Several observations come from the descriptive analysis of the data. First, real and nominal house prices increased in both the UK and the US over the sample periods. Between 1845 and 2016, UK house prices rose at an average annual rate of growth of 3.8 percent in nominal terms and 1.1 percent in real terms. By comparison, between 1830 and 2016, US house prices rose at an average annual rate of growth of 3.5 percent in nominal terms and 1.7 percent in real terms. Second, the growth of nominal and real US and UK house prices has experienced different rates over time. UK house prices in real and nominal terms remained relatively stable from 1845 to 1898. Between 1899 and 1941, however, UK house prices fell on average by 1.2 percent per year in real terms, although they increased by 1.1 percent per year in nominal terms. After World War II, UK house prices began a positive trend, with particularly high growth rates in the 1990s until the Great Recession. During the Great Recession (2007-2009), UK house prices declined on average by 6.3 percent per year in real terms and 4.5 percent per year in nominal terms, and did not recover at the end of the Great Recession, reaching new lows in 2012.

By comparison, US house prices in nominal terms remained relatively stable until the 1950s. US house prices in real terms increased by 1.6 per year until World War I, contracted during the war, and recovered during the interwar period. During the Great Depression (1929-1939), US house prices fell by 1.6 percent per year in real terms and by 3.5 percent in nominal terms. Following World War II, US house prices first surged then remained remarkably stable until the early 1990s. During the past two decades, US house prices increased substantially before falling steeply during the Great Recession and beginning to recover only five years after the end of the Great Recession.

Since 2012, the increase in house prices in the US rose more dramatically that in the UK. 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.[5]

[5] 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 UK log-transformed nominal price.

4. Empirical results for the whole sample

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

Table 1 reports the whole sample estimates of the degree of fractional integration $d = d_L$ in the first model, $I(d_L)$, which considers only the long-run component of persistence of the series. We assume that the disturbances are uncorrelated (white noise) (top panel of Table 1) and autocorrelated (bottom panel of Table 1). In the latter case, we use a non-parametric approach proposed by Bloomfield (1973) that approximates highly parameterized ARMA processes with a few number of parameters and that accommodates extremely well in the context of fractional integration (Gil-Alana, 2004; Velasco and Robinson, 2000). For each series, we consider the three standard cases examined in the literature: (*i*) no deterministic terms (i.e., $\beta_0 = \beta_1 = 0$), (*ii*) an intercept and no trend (β_0 unknown, and $\beta_1 = 0$), and (*iii*) a constant with a linear time trend (β_0 and β_1 unknown). We obtain estimates of d_L by using the Whittle function in the frequency domain (Dahlhaus, 1989). Together with the estimates, we also report the 95-percent confidence bands of the non-rejection values of d_L, using the parametric procedures outlined in Robinson (1994). See, also, Gil-Alana and Robinson (1997). We mark in bold in Table 1 the selected cases according to the significance of the alternative deterministic terms. Note that Robinson's (1994) parametric approach does not require preliminary differencing. Thus, it allows us to test any real value d_L encompassing both stationary and nonstationary hypotheses.

The results of the estimation of the $I(d_L)$ model use the log-transformed house prices. In Table 1, under the assumption of no autocorrelation, the empirical results suggest that the house-price dynamics in the US and UK differ substantially. We observe that the time trend does not achieve statistical significance for the UK nominal and real house prices nor for the US real house price. For the nominal house price in the US, however, the time trend achieves significance.

We also observe that the estimates of d_L are much higher for the two UK house prices than for the US prices. For the UK, the estimated values of d_L equal 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 US house prices, 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 permit autocorrelated disturbances the differences are somewhat reduced. The time trend becomes statistically significant in all four cases. The estimates of d_L are substantially reduced: 1.21 and 0.92 for the nominal and real UK series, and 0.88 and 0.67 for the corresponding US series. We cannot reject the unit-root hypotheses for the two US house prices and for the real UK price. For the UK nominal price, however, we still reject the unit-root hypothesis in favor of $d_L > 1$.

Given that the disparities in the results in Table 1 depend on whether we permit autocorrelation or not, we further estimate d_L using a semiparametric approach, where we make no assumption on the structure of the error term. Table 2 displays the estimates of d_L based on the "local" Whittle semiparametric method (Robinson, 1995). The estimation requires the selection of the bandwidth parameter. The Table presents results for selected bandwidth values (m = 11, 12, …, 16), reported at the top.[6] Bold type identifies evidence of unit roots. The 95-percent confidence bands for the unit-root hypothesis are reported at the bottom of the Table. The semiparametric estimates of d_L are generally robust across the bandwidth parameters, but lower than the corresponding parametric estimates. For the UK house prices, we find no evidence of mean reversion. For any reported value of the bandwidth parameter, we reject the

[6] 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.

unit-root hypothesis for the UK nominal house price in favor of the alternative of $d_L > 1$, but cannot reject the unit-root hypothesis for the UK real house prices for any reported value of the bandwidth parameter. By contrast, we reject the unit-root null hypothesis for the US real house price for any reported value of the bandwidth parameter and, except for the first value of the bandwidth parameter, also for the nominal US house price. The estimates of d_L for the US house prices are below 1 and we find mean reversion for almost any reported value of the bandwidth parameter. In general, we detect much less consistency between the parametric and semiparametric estimates. This may indicate that the model is incorrectly specified. In particular, the UK estimates, more than the US estimates, may include an upward bias, since the model does not include the cyclical component.

Thus, the evidence based exclusively on the $I(d_L)$ model indicates some degree of heterogeneity between the US and the UK house price dynamics, although the results vary substantially depending on the methodology employed. The UK house prices are either unit-root processes or display orders of integration significantly above one. In contrast, the US house prices are unit-root process in one case and mean-reverting nonstationary processes in all other cases.

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

Table 3 report the whole sample estimates of the second model, the $I(d_C)$ model, which considers only the cyclical component of persistence. The high values of the d_L estimates in the $I(d_L)$ model leads us to estimate the $I(d_C)$ model using first differences of the logarithm of house prices (Panels A and C) and the mean-subtracted first differences (Panels B and D). As in the $I(d_L)$ model, we assume that the error term is *I*(0), and consider, once more, the two cases of no autocorrelation (Panels A and B) and autocorrelation (Bloomfield-type) (Panels C and D). Little variation in the results exists across the two alternative assumptions on the error structure. Substantial differences in the cyclical component of persistence between the UK and the US house prices do exist. We observe that the cyclical component is much lower than the long-run component in both the UK and the US from Tables 1 and 2. For the UK, the estimates of d_C are positive and less than 0.5, indicating that the cyclical component of persistence in UK house prices is stationary but has "long-memory" behavior. In contrast, the US estimates of d_C are positive but not significantly different from zero, indicating that the cyclical component of persistence is stationary and displays "short-memory" behavior. Moreover, in the case of the UK, the cyclical component of persistence is much higher for nominal prices than for real prices. In the US case, instead, we see no significant differences.

[Insert Table 3]

We also observe in Table 3 that the housing cycle presents more variability in the US than in the UK. The estimated periodicity (the value of j) ranges between 5 and 6 years for the UK and between 5 and 8 years for the US, which is consistent with the empirical literature on business cycles. These results are robust to changes in the assumptions of the error term and the treatment of the data.

4.3 Results from the $I(d_L, d_C)$ model

Finally, we examine the model given by equation (9), which is more general than the previous two specifications in the sense that it includes two fractional integration parameters, one at the zero (long-run) frequency and the other at the cyclical frequency. Table 4 focuses on white-noise errors (Panels A and B), as well as the autocorrelated (Bloomfield) case (Panels C and D).

[Insert Table 4 about here]

The estimated periodicity (the value of j) ranges between 5 and 6 years for the UK and the US, the US estimate is slightly smaller than the US estimate obtained by the $I(d_C)$ model, but is still consistent with the empirical literature on business cycles. We find striking differences between the house price dynamics of the US and the UK as well as substantial similarities. For both the US and UK house prices, the estimates of d_L substantially exceeds the estimate of d_C in all cases, implying that the long-run component plays a more important role than the cyclical component in explaining house price dynamics in the two countries. In both countries, the long-run component is less than one and greater than 0.5, suggesting that long-run house prices are nonstationary, but mean reverting. The long-run component of the UK is much higher than that of the US, especially when we include the assumption of autocorrelation in the residuals, implying that UK house prices take longer to revert to the initial equilibrium. Significant differences between the UK and the US also exist in the estimates of the cyclical component of persistence of house prices. For the UK, the estimates for the nominal series are positive and less than 0.5, indicating that the cyclical component of persistence in the UK nominal house prices is stationary, but has "long memory." In contrast, for the UK real home price and for the US nominal and real home prices, the estimates are positive but not significantly different from zero, indicating that the cyclical component of persistence is stationary, but has "short memory." For the UK, the cyclical component is much higher for the nominal price than for the real price. For US, instead, no significant difference exists. Thus, the cyclical component is only relevant for the UK nominal house price; for the US nominal and real house prices and for the UK real house price, the $I(d_L)$ model sufficiently describes the persistence in the data.

An obvious but important caveat to these results is, however, in order. The analysis of historical datasets, such as the ones used in this work, is particularly vulnerable to the problem of structural change, which may limit the relevance of our conclusions. Housing markets in the

US and the UK have experienced remarkable political and economic reforms, such as financial deregulation and liberalization, and technological advances, such as mortgage securitization. Our estimates in Section 4 have ignored this problem and, consequently, may include bias due to the presence of structural breaks in the data. We attempt to deal with this issue in the next section.

5. Structural breaks and sub-sample results

This section addresses the issue of structural breaks in the data. As earlier argued, this is a relevant issue not only because of the historical breadth of the data, but also because fractional integration and structural breaks are intimately related to and easily confused with each other (Gourieroux and Jasiak, 2001; Diebold and Inoue, 2001; Granger and Hyung, 2004; Sibbertsen, 2004; Smith, 2005; Gil-Alana, 2008, among others). The empirical literature provides evidence that structural changes can affect house price dynamics. Cook and Vougas (2009) find structural change in UK house prices and show that contrary to standard unit-root tests smooth-transition threshold autoregressive tests reject the presence of a unit root in UK house prices. Canarella et al. (2012), in turn, find structural breaks in house prices in the US.

Thus, to complete our analysis, we adopt the approach developed by Bai and Perron (2003) that estimates endogenously a number of potential breaks in the data along with their respective break dates. After identifying break dates, we re-estimate the fractional parameters in each sub-sample defined by the break dates.[7] Another caveat, however, is in order. The estimation of multiple sub-samples corresponding to more than one break is constrained by the sample-size problem. Allowing for more break dates would produce sub-samples with a small number of observations, invalidating the analysis based on fractional integration. Thus, we present the results that define a dominant (i.e., main break), but do not exclude the possibility of other non-dominant breaks. Still, even allowing only one break, we cannot eliminate the

[7] We also apply the methodology developed by Gil-Alana (2008). Interestingly, the results are exactly the same.

sample-size problem. In particular, the sample size in the second sub-samples may lead to unreliable estimates and other estimation problems.

An interesting finding of this analysis is that while the house price swings of the last decade are dramatic, the greatest structural changes in the overall nominal and real price dynamics of the UK and the US appear to occur much earlier and seem to match both macroeconomic shocks (for the UK) and specific political legislative outcomes (for the US). Most importantly, the breaks are asynchronous, lending further credence to the view that the housing markets in the UK and the US are not homogeneous in the sense that they do not share the same dynamics.

For the UK, the break dates occur at 1976 and 1983 for the real and nominal house prices, respectively. These dates roughly associate with important national macroeconomic events, such as the Secondary Banking crisis of 1973-1975, the deep recession of the early 1980s, and the large escalation in interest rate and inflation in the late 1970 and early 1980s. The UK break dates are consistent with some of the extant research. For example, Miles (2015) finds that, while large price swings exist in the 2000s, the 1980s exhibit sharp episodes of boom and bust. Zhang et al. (2017) using the Bai and Perron (2003) methodology identify statistically significant structural breaks at 1973, 1987 and 1997.

For the US, the break dates occur at 1955 and 1972 for the real and nominal house prices, respectively. These dates roughly associate with the major post-World War II developments in the US housing policy, which include the National Housing Act of 1949,[8] which expanded the federal role in mortgage insurance, the 1955 Amendment to the National Housing Act of 1949, the Housing and Urban Development Act of 1965, which produced major

[8] The National Housing Act was the US government's response to the severe shortage of housing in the post-World War II America, when almost 11 million men and women came home from the armed services. The Act is best remembered for its declaration that every American deserves a "decent home and a suitable living environment," which helped millions of American realize the "dream" of homeownership. The Levitt brothers approach to building homes put the American dream within grasp of the middle class family. By the end of the 1950s, no less than 15 million homes were under construction nationwide.

revision of the US federal housing policy and instituted several major expansions in federal housing programs as part of Johnson's "Great Society" programs, and the Housing and Urban Development Act of 1968 which created the Government National Mortgage Association (commonly referred to as GinnieMae). Interestingly, we do not find a dominant break associated with the Great Moderation, which literature documents as a substantial reduction of volatility in major US macroeconomic time series since the 1980s.

In this section, we present the sub-sample results using the same three fractional integration models that we considered for the whole sample. Each sub-sample is uniquely defined by the corresponding break date, and this results in a different sample sizes for each sub-sample. Our analysis of the sub-samples, however, is incomplete, since the limited length of the data does not permit estimation of the second sub-sample in the third model.

5.1 Sub-sample results from the long-run $I(d_L)$ model

Table 5 reports the results of the estimation of the long-run $I(d_L)$ model for the two sub-samples and the three specifications of the deterministic component, under the two cases of uncorrelated (top panel) and autocorrelated errors (bottom panel).

[Insert Table 5 about here]

Under the assumption of white-noise disturbances, we observe that the trend is not required for the first sub-sample, and is only required for the US data in the second sub-sample. The estimates, however, are similar independently of the inclusion or exclusion of the trend. The orders of fractional integration are significantly higher than 1 for the UK data in both the first and the second sub-samples. The unit-root hypothesis is accepted for the US data in the first sub-sample; in the second sub-sample, however, the orders of fractional integration exceed 1 for the nominal series and do not differ from 1 for the real series. Thus, the results generally mirror the whole sample estimates, and we find no evidence of mean reversion in any case.

In contrast, under the assumption of autocorrelated (Bloomfield) disturbances, the trend is significant in several cases, especially in the second sub-samples. We observe a reduction of the estimate of d_L when we move from the first sub-sample to the second, with the exception of the US nominal series. We cannot reject the unit-root hypothesis in any case, except for US real prices in the second sub-sample. Nevertheless, we do not observe significant differences in the orders of integration across the sub-samples, regardless of the assumptions about the disturbances.

5.2 Sub-sample results from the cyclical $I(d_C)$ model

Table 6 reports the sub-sample results for the cyclical $I(d_C)$ model. The length of the cycles lies between 4 and 6 years in all cases, which is consistent with the whole sample estimates. Evidence of substantial differences in the estimates of d_C exists, however, between the whole sample and the two sub-samples. In panel A, the estimates lie between zero and 0.5 in the first sub-sample for the UK nominal series and the US real series, suggesting cyclical mean reversion. In the second sub-sample, only the estimate for the US real series is significant and less than 0.5. In Panel B, all estimates are significant in the first sub-sample, suggesting high cyclical persistence and mean reversion. In the second sub-sample, the estimates of both the real series are greater than zero but are not significant. This lack of significance, however, may reflect the smaller size of the second sample, which likely produces large confidence intervals. Overall, however, the results of the estimates of the cyclical component in the two sub-samples are not consistent with the corresponding results of the whole sample.

[Insert Table 6 about here]

5.3 Sub-sample results from the from the $I(d_L, d_C)$ model

Finally, Table 7 display the results for the $I(d_L, d_C)$ model, which includes both orders of integration, zero and the cyclical one, once more, for the two cases of uncorrelated errors (Panels A and B) and autocorrelated (Bloomfield) errors (Panels C and D). In this case, however, we only report the estimates for the first sub-samples, since the number of observations in the second sub-samples was not sufficient to guarantee significant results. Panels A and B of Table 7 assume white-noise disturbances. The number of periods per cycle varies from 4 to 7 year in the UK data, and from 4 to 5 in the US data. In Panel A, the estimates of d_L exceed 1 in all series except the US nominal data, and the estimate of d_C is significantly positive and less than 0.5 only for the UK nominal series, and insignificant for the remaining series. In panel B, in contrast, all the estimates of d_L exhibit mean reversion, but only the US real data exhibit nonstationarity.

Panels C and D of Table 7 assumes autocorrelated (Bloomfield) disturbances. The error structure does not appear to affect the periodicity of the series, as the years per cycle varies from 4 to 6 in the UK and from 4 to 5 in the US. In Panel C, the estimates of d_L exceed 1 in the UK data and are less than 1 in the US data, implying nonstationarity and non-mean reversion for the UK data and nonstationarity and mean reversion for the US data. The estimate of d_c is significantly positive and less than 0.5 only for the UK nominal series. In Panel D, all the estimates of d_L fall below 1, suggesting mean reversion, but only the estimate for the US nominal series falls below 0.5. As in panel A, the estimate of d_C is significantly positive and less than 0.5 only for the UK nominal data.

[Insert Table 7 about here]

In conclusion, the results for the first sub-sample generally mirror those of the whole samples. We cannot conclude, however, that we observe significant differences when we account for structural breaks because we lack evidence from the second-sub-samples.

6. Conclusions

In the past decade, the US and UK housing markets have experienced significant housing price booms, followed by sharp declines. The temptation exists because the apparent similarities, namely the existence of sub-prime lending and the use of mortgage backed securities, to conclude that the US and UK markets mirror each other and share the same experience. From a historical viewpoint, the differences between the two markets are just as important as their similarities. Most literature on housing markets generally accepts the idea that house prices are nonstationary. In this literature, however, house prices are specified in a stochastic model that assumes only the presence of a pole at the zero frequency. Such models only describe the long-run persistence of house prices. In this paper, we suggest that such models may be misspecified, since they fail to account for the cyclical component of persistence in house prices. In this paper, we provide a new and unique look at the dynamic and persistence structure of historical house prices in the US and the UK, using fractional integration techniques not previously applied to housing markets. We suggest that the US and the UK historical house prices may conform to a stochastic process that includes two poles in the spectrum: one at the zero frequency, corresponding to the long-run dependency 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 US and 1845 to 2016 for the UK, which provides a much longer perspective on the behavior of house prices than commonly implemented in the literature, where most empirical work uses data starting from the 1980s or later. We consider three fractional-integration models: a) a standard $I(d_L)$ model with a pole at the zero frequency, which captures only the long-run component of persistence; b) a cyclical $I(d_C)$ model that incorporates a pole at a non-zero frequency and captures only the cyclical component of persistence; and c) the composite $I(d_L, d_C)$ model that incorporates both poles and captures simultaneously the component associated with the long-run trend and the component associated with the cycle.

We find that each country exhibits rich house-price dynamics, at the level of the whole sample and sub-samples, with the break dates estimated using the Bai and Perron (2003) methodology. The sub-sample analysis is necessary not only because of the historical breadth of the data, but also because fractional integration and structural breaks are intertwined issues. Interestingly, although the house-price swings of the last decade are dramatic, the greatest structural changes in the overall nominal and real price dynamics of the UK and the US appear to occur much earlier, in the late 1970s and early 1980s in the UK, and in the mid-1950s and early 1970s in the US. This asynchronous pattern of the breaks indicates heterogeneity in house-price dynamics of the two countries and a sign that national rather than global events played an important role. Sub-sample estimation, however, presents some unique challenges in a fractionally integrated setting, resulting from the small sample size problem. In particular, the sub-sample analysis is only partial in the third model as the sample size after the break is not large enough to produce meaningful estimates. We find, however, that structural breaks affect the estimates of the long-run and cyclical components.

For the whole sample, we find convincing evidence that in the UK housing markets, nominal house prices incorporate two distinct poles in house-price dynamics, at the zero (long-run trend) and non-zero (cyclical) frequencies. In contrast, we fail to find evidence of cyclical persistence for the US and the real house price in the UK. In contrast, the cyclical model provides evidence that significant cyclical persistence exists in the first sub-sample for both the UK and the US.

An important result, common to the whole sample and the sub-samples, is that the long-run component of persistence plays a greater role than the cyclical component in explaining the dynamics of house prices in both countries. In no instance, however, are shocks permanent. 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 house-price movements to create an environment whereby housing markets can readily revert to their original trends.

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Table 1: Estimates of d_L for the whole sample using a parametric approach

i) White noise			
Series	No terms	An intercept	A linear time trend
UK nominal prices	1.13 (1.05, 1.22)	**1.60 (1.46, 1.82)**	1.61 (1.46, 1.82)
UK real prices	1.02 (0.93, 1.15)	**1.61 (1.41, 1.87)**	1.61 (1.41, 1.88)
US nominal prices	1.03 (0.93, 1.15)	1.03 (0.92, 1.18)	**1.04 (0.91, 1.19)**
US real prices	1.02 (0.93, 1.15)	**0.98 (0.84, 1.15)**	0.98 (0.84, 1.15)
ii) Autocorrelation (Bloomfield)			
Series	No terms	An intercept	A linear time trend
UK nominal prices	1.17 (1.06, 1.34)	1.14 (1.10, 1.36)	**1.21 (1.11, 1.37)**
UK real prices	0.96 (0.80, 1.18)	0.93 (0.82, 1.15)	**0.92 (0.78, 1.17)**
US nominal	1.00 (0.83, 1.22)	0.89 (0.78, 1.10)	**0.88 (0.72, 1.11)**
US 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. In parenthesis, the 95 percent band of non-rejection values of *d*. For the confidence bands, we use Robinson (1994).

Table 2: Estimates of d_L for the whole sample using a semiparametric approach

Series	11	12	13	14	15	16
UK nominal prices	1.418	1.339	1.292	1.331	1.352	1.397
UK real prices	**0.925**	**0.937**	**0.890**	**0.892**	**0.907**	**0.926**
US nominal prices	**0.755**	0.668	0.632	0.659	0.679	0.708
US real prices	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 (4) assuming white noise errors (Panels A and B) and autocorrelated (Bloomfield) errors (Panels C and D)**

Panel A		
Series	J	d_C
UK nominal prices	6	0.42*
UK real prices	5	0.14*
US nominal prices	6	0.05
US real prices	7	0.01
Panel B		
Series	J	d_C
UK nominal prices	6	0.43*
UK real prices	5	0.14*
US nominal prices	8	0.04
US real prices	7	0.01
Panel C		
Series	J	d_C
UK nominal	6	0.41*
UK real	5	0.14*
US nominal	6	0.05
US real	6	0.05
Panel D		
Series	j	d_C
UK nominal	6	0.43*
UK real	5	0.14*
US nominal	5	0.02
US real	7	0.01

*: Significance at the 95% level.

Table 4: Estimated coefficients in (9) assuming white noise errors (Panels A and B) and autocorrelated (Bloomfield) errors (Panels C and D)

Panel A			
Series	d_L	j	d_C
UK nominal	0.79	6	0.14^{*}
UK real	0.86	4	0.03
US nominal	0.79	5	0.07
US real	0.80	5	0.09
Panel B			
Series	d_L	j	d_C
UK nominal	0.60	5	0.10^{*}
UK real	0.65	4	0.01
US nominal	0.60	4	0.02
US real	0.60	4	0.03
Panel C			
Series	d_L	j	d_C
UK nominal	0.68	4	0.40^{*}
UK real	0.86	4	0.03
US nominal	0.51	6	0.10
US real	0.52	5	0.09
Panel D			
Series	d_L	j	d_C
UK nominal	0.68	4	0.38^{*}
UK real	0.80	5	0.04
US nominal	0.51	5	0.09
US real	0.50	5	0.08

*: Significance at the 95% level.

Table 5: Estimates of d_L for each sub-sample using a parametric method

i) White noise						
	First sub-sample			Second sub-sample		
Series	No terms	Intercept	Trend	No terms	Intercept	Trend
UK nom. prices	1.08 (0.99, 1.22)	**1.60** **(1.45, 1.85)**	1.61 (1.46, 1.87)	0.93 (0.66, 1.26)	**1.73** **(1.41, 2.13)**	1.65 (1.33, 2.06)
UK real prices	0.98 (0.89, 1.10)	**1.66** **(1.41, 1.98)**	1.64 (1.41, 1.94)	0.90 (0.67, 1.20)	**1.60** **(1.22, 2.14)**	1.64 (1.41, 2.23)
US nom. prices	1.01 (0.91, 1.15)	**1.00** **(0.86, 1.19)**	1.00 (0.86, 1.19)	0.94 (0.75, 1.21)	1.32 (1.09, 1.56)	**1.22** **(1.07, 1.42)**
US real prices	1.02 (0.91, 1.16)	**0.98** **(0.78, 1.19)**	0.98 (0.81, 1.19)	0.95 (0.79, 1.18)	0.72 (0.56, 1.27)	**0.86** **(0.58, 1.25)**
ii) Autocorrelation (Bloomfield)						
	First sub-sample			Second sub-sample		
Series	No terms	Intercept	Trend	No terms	Intercept	Trend
UK nom. prices	1.03 (0.88, 1.25)	1.18 (1.07, 1.35)	**1.20** **(1.06, 1.38)**	0.56 (0.19, 1.36)	0.66 (0.27, 1.93)	**0.68** **(-0.26,1.72)**
UK real prices	1.02 (0.82, 1.25)	**0.89** **(0.68, 1.20)**	0.89 (0.68, 1.20)	0.67 (0.13, 1.34)	0.61 (0.40, 1.07)	**0.19** **(-0.42,1.10)**
US nom. prices	0.99 (0.80, 1.25)	0.74 (0.46, 1.07)	**0.72** **(0.48, 1.07)**	0.80 (0.29, 1.26)	1.42 (0.34, 1.96)	**1.26** **(0.91, 1.84)**
US real prices	0.98 (0.77, 1.29)	0.61 (0.43, 1.14)	**0.63** **(0.34, 1.10)**	0.85 (0.55, 1.25)	0.49 (0.37, 0.63)	**0.22** **(-0.01,0.75)**

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 6: Estimated coefficients in (4) for each subsample

i) Original data				
Series	First sub-sample		Second sub-sample	
	j	d_C	j	d_C
UK nominal	6	0.48*	5	-0.09
UK real	5	-0.18	5	-0.22
US nominal	5	-0.19	4	0.31
US real	4	0.32*	4	0.41*
ii) Mean subtracted data				
Series	First subsample		Second subsample	
	j	d_C	j	d_C
UK nominal	6	0.54*	6	0.02
UK real	6	0.47*	5	0.30
US nominal	6	0.53*	6	-0.08
US real	6	0.48*	6	0.31

*: Significance at the 95% level

Table 7: Estimated coefficients in (9) assuming white noise errors (Panels A and B) and autocorrelated (Bloomfield) errors (Panels C and D) with the first sub-samples

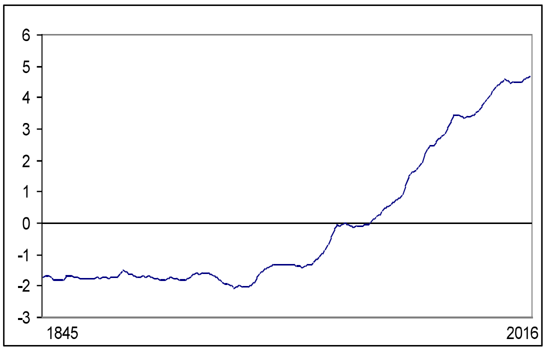
Panel A: Original data			
	d_L	j	d_C
UK nominal	1.29	7	0.22*
UK real	1.16	4	-0.03
US nominal	0.59	5	-0.07
US real	1.13	5	-0.04
Panel B: Mean subtracted data			
	d_L	j	d_C
UK nominal	0.78	5	0.24*
UK real	0.82	4	0.03
US nominal	0.50	4	0.00
US real	0.48	4	-0.03
Panel C: Original data			
	d_L	j	d_C
UK nominal	1.28	4	0.33*
UK real	1.04	4	-0.03
US nominal	0.66	6	0.06
US real	0.71	4	-0.04
Panel D: Mean subtracted data			
	d_L	j	d_C
UK nominal	0.58	4	0.19*
UK real	0.66	5	-0.01
US nominal	0.47	5	0.04
US real	0.61	4	-0.08

*: Significance at the 95% level

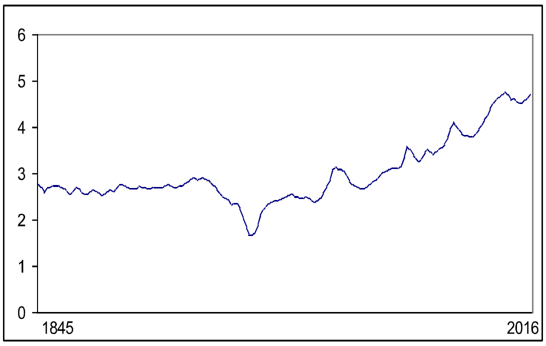
Figure 1

(a) **Log-transformed data**

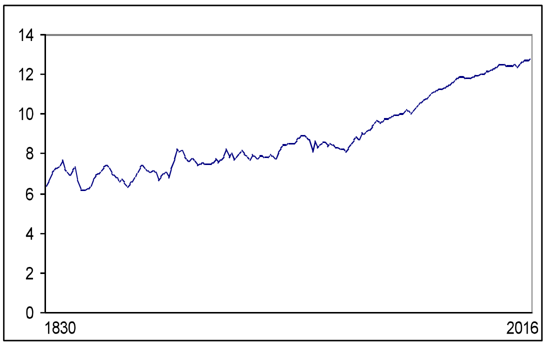
UK nominal prices



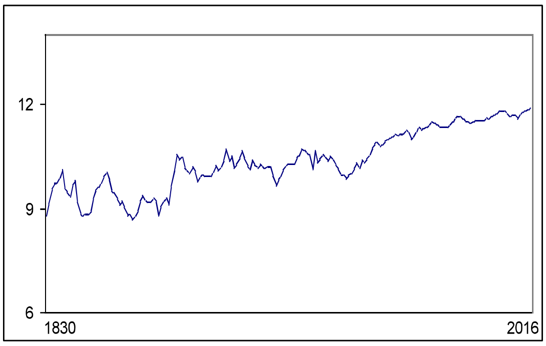
UK real prices



US nominal prices

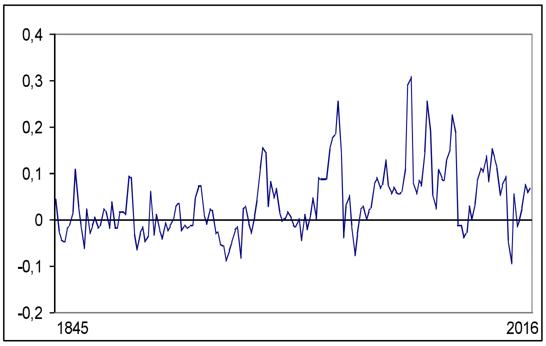


US real prices

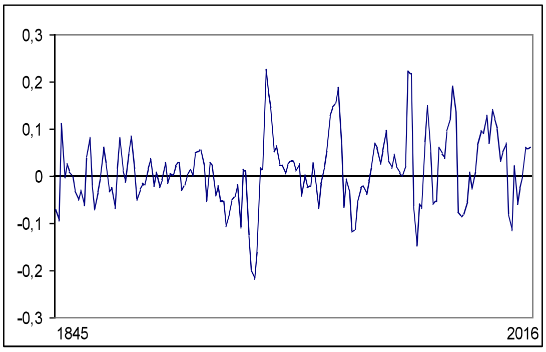


(b) **First differences on the log-transformed data**

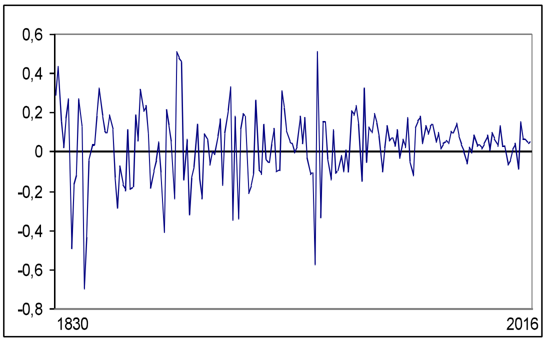
UK nominal prices



UK real prices



US nominal prices



US real prices