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Do House Prices Hedge Inflation in the US? A Quantile Cointegration Approach

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Abstract: This study analyses the long-run relationship between U.S house prices and non-housing Consumer Price Index (CPI) over the monthly period 1953 to 2016 using a quantile cointegration analysis**.** Our findings show evidence of instability in standard cointegration models, suggesting possibility of structural breaks and nonlinearity in the relationship between house prices and non-housing CPI. This motivates the use of a time-varying approach, namely, a quantile cointegration analysis, which allows the cointegrating coefficient to vary over the conditional distribution of house prices and simultaneously test for the existence of cointegration at each quantile. Our results suggest that the U.S non-housing CPI and house price index series are cointegrated at lower quantiles only, with house prices over-hedging inflation at these quantiles.

Keywords: house prices, inflation, hedging, quantile cointegration

JEL Classifications: C22, C32, E31, R31

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1. Introduction

Price stability plays an important role in the economy, since price levels affect economic activities, financial sector and investment decisions (Chang, 2016). A rise in price levels can reduce the real value of holding money, and since the main objective for investors is to obtain a positive real rate of return on their investment portfolio (Rubens et al., 1989), they aim to increase the portfolio positions of inflation-hedging assets. The relationship between real estate returns and inflation has been a subject of interest particularly for investors since perceived inflation-hedging ability of real estate is often used to justify its inclusion in mixed-asset investment portfolios (Simpson et al, 2007).

The importance of the relationship between house prices and inflation is highlighted in that, in the United States and other countries, residential real estate is the principal asset held in most private portfolios (Hong et al, 2013). In the United States, two thirds of the nation's households are homeowners and homeowner equity constitutes approximately one third of all households (Tracey et al., 1999; Iacoviello, 2012). Corporate equity has recently surpassed homeowner equity to become the largest asset in the household sector but it is important to note that over half of all households do not hold corporate equity. In this context, homeowner equity constitutes the larger portion of most households' investment portfolio and its ability to protect the investor against price level changes has important implications for personal wealth and the economy as a whole (Anari and Kolari, 2002).

Empirical studies show mixed evidence on whether real estate provides a good inflation hedge.[1] Using residential property indexes for the period 1975 to 2008, Hong et al (2013) find that house prices are a relatively good hedge over the long term against inflation in the US and UK. Anari and Kolari (2002) using new and existing house prices and CPI excluding housing costs for the US from 1968 to 2000 also supports the evidence that house prices provide a stable inflation hedge in the long run. In contrast, Hoesli et al (2007), using UK data, conclude that real estate provides little hedging ability when the inflation rate is low, which actually disappears when inflation is high. Barber et al (1997) support the findings that the UK real estate provides weak hedge against changes in underlying

[1] See also Fama and Schwert, (1977); Fogler et al. (1985); Hartzell et al. (1987); Rubens et al. (1989).

inflation, and no hedge against shocks that change price levels. Furthermore, there is also evidence that real estate assets are not a good hedge against inflation both in the shorter- and longer-terms (Glascock et al, 2008). Mixed evidence can also be found in earlier studies of Fama and Schwert, (1977); Fogler et al. (1985); Hartzell et al. (1987); Rubens et al. (1989).[2]

In addition to the studies that consider the relationship between house prices and inflation, other studies focus on securitized real estate in the form of real estate investment trust (REITs) (Chang, 2016; Hong and Lee, 2013; Hardin III et al, 2012; Glascock et al, 2002; Park et al, 1990; Gyourko and Linneman, 1988). This literature shows that the role of REITs as inflation hedge is also ambiguous, with some evidence supporting REITs as a good inflation hedge, while others show evidence that they provide a perverse inflation hedge.

So clearly, there is mixed evidence on whether real estate provides a good inflation hedge, and this mixed evidence could possibly be because of the time-varying relationship between house prices and its predictors, including inflation, as suggested by Anari and Kolari (2002), Bork and Møller (2014), and Pierdzioch et al., (2016). In addition, this empirical relationship should be tested regularly based on updated data, given the dynamic nature of the housing market and the transformations it has gone and going through continuously post the recent financial crisis. Given this, the objective of the study is to explore within the context that cointegration coefficients may vary over time, the long-run impact of inflation on homeowner equity by analyzing the relationship between house prices and prices of non-housing goods and services, which is Consumer Price Index (CPI) excluding housing costs[3], across various quantiles of house prices using monthly data from 1953 to 2016. Note that, we decided to work with house prices instead of REITs, given the role played by the housing market in the recent financial crisis, and its influence on US business cycles (Leamer, 2007; Ghysels et al., 2013), thus making it of paramount importance to determine the predictors, in this case, inflation in driving the US housing market. In addition, the size of investment in owner-occupied homes are also larger compared to that of REITs (Iacoviello, 2012) Following Anari and Kolari (2002), non-housing

[2] For a detailed review of the international literature on housing acting as an inflation hedge, the readers are referred to Inglesi-Lotz and Gupta (2013).
[3] Housing costs historically range from 20% to 30% of the consumer price index (Anari and Kolari, 2002).

CPI is used instead of return series and inflation rate as in previous studies because of two important reasons. Firstly, return on housing cannot be accurately measured as they strongly depend on the underlying assumptions about imputed values of rent and services performed by the owner, house prices can therefore be used since they fully reflect total return on housing. Secondly, by using returns series, the time series is differenced and this is likely to lead to loss of long-run information contained in the time series.

Note that, since the quantile cointegration approach of Kuriyama (2016), which we follow in this paper allows us to test for the existence of cointegration and also estimate the cointegrating parameters, at each point of the conditional distribution of the dependent variable, it is inherently a time-varying approach to detecting and estimating long-run relationships (Xiao, 2009). This is because each point of the conditional distribution of the dependent variable captures the phase in which the dependent variable, in our case, the housing market is, with lower quantiles suggesting bear market, the median capturing the normal phase of the market, while the upper quantiles depicting the bull-phase of the market. Clearly, this approach is preferable over Markov-Switching methods (see, Jochmann and Koop (2015) for a detailed discussion of regime-switching cointegration), as we do not explicitly need to pre-specify and test for the number of regimes in the housing market. Of course, there are pure time-varying parameter cointegration approaches of Park and Hahn (1999), and Bierens and Martins (2010). We, however, decided to work with the quantile cointegration test, since unlike the time-varying cointegration, the former test allows us to detect cointegration at specific parts of the conditional distribution, and hence specific points of housing market phases. Time-varying cointegration tests for whether there is overall time-varying cointegration to fixed-parameter based cointegration, and thus is of little value to the question we are asking, which is to determine cointegration at specific market phases. In addition, in time varying cointegration, testing for parameter restriction is not necessarily straight-forward and requires understanding of cointegrating spaces (Martins, forthcoming). An alternative approach could have been the interrupted cointegration method of Martins and Gabriel (2014), which would have allowed us to detect cointegration at specific points in time, but this again would have required us to use extraneous information to

categorize the market phase the housing prices were in. So overall, for our purpose of detecting time varying inflation hedging at specific phases of the housing market, the quantile cointegration approach is the most-suited, with it being also preferable over recursive or rolling test of cointegration as pursued in Anari and Kolari (2002) in relation to housing and inflation. This is because results in such approaches are sensitive to the size of the estimation window (sub-samples) with no clear-cut statistical approach in determining the length of the window to be used (Nyakabawo et al., 2015).

To the best of our knowledge, this is the first attempt to test for inflation hedging characteristic of house prices using a quantile cointegration method. Prior to that, we take the following standard steps: First we test the variables for unit root using standard unit root tests as a starting point for cointegration analysis. Since house price series and inflation are characterized by the presence of potential structural breaks (Canarella et al., 2012; Caporin and Gupta, forthcoming) which can significantly reduce the power of unit root tests, we apply the Zivot and Andrews (1992) unit root test which allows for an endogenous structural break. Furthermore, we employ Lumsdaine and Papell (1997) and Lee and Strazicich (2003) unit root test which allows for two shifts in the deterministic trend at two distinct unknown dates, with the main difference between the two being that the latter test allows for breaks under both the null and alternative hypotheses. To accommodate the possibility of a non-linear dynamics of house prices and inflation (Canarella et al., 2012; Álvarez-Díaz, 2016), we perform Kapetanios et al., (2003) nonlinear unit root test. All the tests suggested that both house prices and non-hoisng CPI are I(1) processes, so we proceeded to testing for cointegration using various standard cointegration tests (for example, Engle and Granger (1987), Phillips and Ouliaris (1990), Park (1992) and Johansen (1988, 1991)). However, these tests provided mixed evidence in favour of cointegration, which was not surprising given that we detected instability in the cointegrating vector using Hansen's (1992) parameter instability test. This statistical result in turn, justified the implementation of the quantile cointegration methodology proposed by Kuriyama (2016), which test for the existence of a long-run relationship across the conditional quantiles of the dependent variable, which is house price. The remainder of the paper is organized as follows: Section II presents the theoretical model that defines our econometric testing framework, while Section III

outlines the basics of the quantile cointegration approach. Section IV discusses the data and empirical results, with Section V concluding the paper.

2. Theoretical Framework

Economic theory identifies housing expenditure as possessing both investment and consumption effects. Survey findings of Case and Shiller (1988), and Case et al., (2012) tend to show that 44% to 64% of responding households purchase houses for investment benefits, while only 10% considered potential investment benefits as unimportant.

Since houses are considered as both investment and consumption goods, it is important to understand their relationship with inflation. There exist two transmission channels through which higher prices of goods and services can be transmitted to higher house prices (Anari and Kolari, 2002). Through the consumer good channel, inflation causes an increase in construction costs through higher costs of not only building materials, but also construction wages. These higher construction costs of new houses will result in higher new house prices. This further affects replacement costs of existing houses which also increase since they are close substitutes for new houses.

The second channel is through a house being an investment good. House prices in the investment context are equivalent to the present value of actual or imputed net rents. Without taking into account taxes on income and capital gains, the present value model can be defined as:

$$HP = PV = \sum_{k=1}^{n} \frac{E_t(R_{t+k})}{(1+r)^k} \quad (1)$$

where PV denotes present value (equivalent to house price or HP), n is the life span of the house, $E_t(R_{t+k})$ is the net annual rent in period $t + k$ that is expected in period t, and r is the discount rate. Anari and Kolari (2002) further define net annual rent as gross rent less depreciation and other charges, and depreciation charges accumulated at the end of the lifespan of the house are used to develop another house on the land. Flow of net rent is therefore permanent, meaning that $n \to \infty$.

When rent and discounting are presented in real terms, it means that the present value is also in real terms. Imposing the assumption that annual rent is constant, Equation 1 can be represented as:

$$HP = PV = \frac{R}{r} \tag{2}$$

Fisher (1930) proposes that a 1% increase in expected inflation will increase interest rates by 1% because of constant real rate of interest. Applying this proposition to Equation (2) means that it can be expressed in nominal terms, to show the link between nominal house prices and goods and services prices adjusted for housing costs. Since landlords aim to maintain purchasing power of rental income in real terms, expected inflation is incorporated in rent agreements by taking into account consumer price index. Therefore Equation (2) can be expressed as:

$$HP_t = PV_t = \frac{R\left[\frac{E_t\left(NH_{CPI_{t+1}}\right)}{NH_{CPI_b}}\right]}{r} \tag{3}$$

where $E_t\ (NH_{CPI_{t+1}})$ is the expected nonhousing price index of goods and services for period $t\ +1$ based on all available information in period t, and NH_CPI_b is the nonhousing price index in the base period. Assuming that R and r are constants and that $NH\_CPI_b\ = 1$, and taking the log of both sides of Equation (3), we obtain

$$ln\, HP_t\ =\ \alpha\ +\ \beta\ ln\, E_t\ (NH\_CPI_t\ ) \tag{4}$$

where the coefficient of the goods price index $\beta\ = 1$, and the constant term $\alpha\ = ln\, R\ - ln\, r$. Equation (4) is consistent with the Fisher effect as it proposes that in the absence of taxes, there is inflation elasticity of unity for house prices with respect to goods and services prices adjusted for housing costs (Anari and Kolari, 2002).

But, accounting for taxes complicates the relationship between house prices and inflation. Taxes applying to landlords include income tax on rents and capital gains from selling property, and deductions for depreciation and maintenance costs from rental income are included. However, by living in a home for two of the previous five years, homeowner can be exempt from capital gains tax and are permitted to subtract mortgage interest payments from their income but not depreciation and

maintenance expenses (Anari and Kolari, 2002). But, there are data limitations in analysing the impact of taxes and exemptions on housing prices or returns.

Darby (1975) and Carrington and Crouch (1987) suggest that the effects of all these taxes and exemptions are reflected in the β coefficient. They further suggest that if $NIR_t, RIR_t,$ and INR_t represent nominal interest rate, real interest and inflation rate respectively, and T is the tax rate, then the Fisher relationship can be written as

$$NIR_t = (1-T)^{-1}RIR_t^e + (1-T)^{-1}INR_t^e \tag{5}$$

According to Crowder and Wohar (1999) and Anari and Kolari (2001), the tax version of the Fisher relationship will hold for the relationship between asset price and CPI indexes, such that the β coefficient in Equation (4) can be written as $\beta = (1-T)^{-1}$.

3. Methodology

Let $z_t = (y_t, x_t)'$ be (k+1)x1 process, where y_t is a scalar. We further assume that z_t is an $I(1)$ process and the elements of x_t are not cointegrated. Consider the following model:

$$y_t = \alpha' d_t + \beta' x_t + u_t, \quad t = 1,2,\dots,T, \tag{6}$$

$$z_t = z_{t-1} + v_t, \tag{7}$$

where d_t is the vector of deterministic components like constant and a linear trend. If the error terms u_t and v_t are (0) , then y_t and x_t are cointegrated.

Xiao and Phillips (2002) suggest a cumulated sum (CUMSUM) statistic for testing the null of cointegration. The authors argue that if y_t and x_t are cointegrated, then the residual process $\hat{u}_t$ of regression (6) should be stable and reflect only equilibrium errors. Thus, the null of cointegration can be tested directly by looking at the fluctuation of the residual process $\hat{u}_t$ through the following statistic:

$$\underbrace{max}_{\tau=1,2,\ldots,T} \frac{1}{\sqrt{T}} \sum_{t=1}^{\tau} |\hat{u}_t|. \tag{8}$$

It is the well-known (Park and Phillips (1988); Phillips and Hansen (1990)) that under the null of cointegration, the least squares estimator of the cointegration vector, $\hat{\beta}_{LS}$, is super-consistent (T-consistent). Unfortunately, the asymptotic distribution of $\hat{\beta}_{LS}$ is miscentered and depends on nuisance parameters. As a consequence, the statistic (8) cannot be used directly for valid inference.

Xiao and Phillips (2002) show that the conventional CUMSUM statistic can be applied to test the null of cointegration. To construct a CUMSUM statistic with a limiting distribution free from nuisance parameters, Xiao and Phillips (2002) construct fully modified (FM) residuals in the spirit of the fully modified least squares (FMLS) method of Phillips and Hansen (1990).

Kuriyama (2016) extends the CUSUM type fully modified analysis of Xiao and Phillips (2002) to the case of conditional quantiles. Specifically, the proposed statistic examines the equilibrium relationships across different quantiles of the distribution of the response variables. To introduce the statistic for quantile cointegration, Kuriyama (2016) introduces the quantile analog of eq. (6):

$$y_t = \alpha'(\tau)d_t + \beta'(\tau)x_t + u_t(\tau) = \theta'(\tau)z_t + u_t(\tau), \quad t = 1,2,\ldots,T, \tag{9}$$

where $\theta(\tau) = (\alpha'(\tau), \beta'(\tau))'$.

This suggests that $\hat{u}_t = y_t - \hat{\theta}'(\tau)z_t$ and the estimator $\hat{\theta}(\tau)$ of the parameters of interest $\theta(\tau)$ is the solution to:

$$\min_{\theta} \sum_{t=1}^{T} \rho_\tau\big(y_t - z_t{}'\theta(\tau)\big), \tag{10}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$, the check function (Koenker and Basset, 1978). Kuriyama (2016) shows that although $\hat{\beta}(\tau)$ is consistent, its asymptotic distribution shares the same undesirable properties with the least squares estimator of the cointegration vector β, $\hat{\beta}_{LS}$. Specifically the asymptotic distribution of $\hat{\beta}(\tau)$ contains nuisance parameters and second order bias terms. These effects make $\hat{\beta}(\tau)$ a poor candidate for inference. The author following Xiao and Phillips (2002)

adopts the FM corrections initially suggested by Phillips and Hansen (1990). The resulting FM estimator $\hat{\beta}^{+}(\tau)$ of $\beta(\tau)$ takes the following form:

$$\hat{\beta}^{+}(\tau) = \hat{\beta}(\tau) - \left[f\left(\widehat{F^{-1}(\tau)}\right)\sum_{t=1}^{T} x_t^d x_t^{d\prime}\right]^{-1}\left[\sum_{t=1}^{T} x_t^d\, \hat{\Omega}_{\psi x}\hat{\Omega}_{xx}^{-1}\Delta x_t + \hat{\Delta}_{x\psi}^{+}\right], \tag{11}$$

where x_t^d denotes demeaned or detrended regressors, and $f\left(\widehat{F^{-1}(\tau)}\right)$ is a nonparametric consistent estimator of the density function $f\left(F^{-1}(\tau)\right)$. $\hat{\Omega}_{\psi x}$ and $\hat{\Omega}_{xx}$ are semiparametric kernel estimators of the long run covariance matrices: $\Omega_{\psi x} = \Omega_{x\psi}' = \sum_{t=-\infty}^{\infty} E\left(\upsilon_t \psi_\tau(u_0(\tau))\right)$, and $\Omega_{xx} = \sum_{t=-\infty}^{\infty} E(\upsilon_t \upsilon_0{}')$, where $\psi_\tau(u(\tau)) = \tau - I(u < 0)$. Analogously, $\hat{\Delta}_{x\psi}^{+}$ is semiparametric kernel estimators of the modified one-sided long run covariance matrix $\Delta_{x\psi}^{+} = \Delta_{x\psi} - \Omega_{\psi x}\Omega_{xx}^{-1}\Delta_{xx}$, where $\Delta_{x\psi} = \sum_{t=0}^{\infty} E\left(\upsilon_t \psi_\tau(u_0(\tau))\right)$, $\Delta_{xx} = \sum_{t=0}^{\infty} E(\upsilon_t \upsilon_0{}')$. Kuriyama (2016) shows that the fully modified estimator $\hat{\beta}^{+}(\tau)$ follows asymptotically a mixed normal distribution:

$$T\left(\hat{\beta}^{+}(\tau) - \beta(\tau)\right) \Rightarrow MN\left(0, \frac{\omega_{\psi.x}^2}{f\left(F^{-1}(\tau)\right)}\left[\int B_{xd} B'_{xd}\right]^{-1}\right), \tag{12}$$

where $B_{xd} = B_x - (\int B_x d')(\int B_d{}')^{-1} B_d$ is a demeaned or detrended Brownian motion (for more details see Kuriyama (2016)), B_x is a Brownian motion with covariance matrix Ω_{xx}, $\omega_{\psi.x}^2 = \omega_\psi^2 - \Omega_{\psi x}\Omega_{xx}^{-1}\Omega_{x\psi}$, and ω_ψ^2 the long run variance of $\psi_\tau(u(\tau))$. Again, all long run variances are estimated nonparametrically using kernel methods. Next, the author uses the residuals $\hat{u}^{+}(\tau) = y_t^{+} - \hat{\theta}^{+\prime}(\tau) z_t$, from the fully modified regression to build the CUSUM test statistic in the spirit of eq. 8, as follows:

$$CS_T(\tau) = \max_{n=1,\ldots,T} \frac{1}{\hat{\omega}_{\psi.x}\sqrt{T}} \left|\sum_{t=1}^{n} \psi_\tau(\hat{u}_t^{+}(\tau))\right|, \tag{13}$$

where $\hat{\theta}^{+}(\tau) = \hat{\theta}(\tau) - \left[f\left(\widehat{F^{-1}(\tau)}\right)\sum_{t=1}^{T} z_t z_t{}'\right]^{-1}\left[\sum_{t=1}^{T} z_t\, \hat{\Omega}_{\psi x}\hat{\Omega}_{xx}^{-1}\Delta x_t + \bar{\hat{\Delta}}_{x\psi}^{+}\right]$,

$\bar{\hat{\Delta}}_{x\psi}^{+} = \left(0, \hat{\Delta}_{x\psi}^{+}{}'\right)'$, and $y_t^{+} = y_t - \hat{\Omega}_{\psi x}\hat{\Omega}_{xx}^{-1}\Delta x_t$. Kuriyama (2016) shows that under certain assumptions and for a certain quantile τ, the asymptotic represantaion of the $CS_T(\tau)$ statistic is as follows:

$$CS_T(\tau) \Rightarrow \underbrace{sup}_{0 \le r \le 1} |W(r)|, \tag{14}$$

Where $W(r) = W_1 - [\int dW_1 S'][\int SS']^{-1} \int_0^r S$, $S = (B_d', W_2')$, and W_1 and W_2 are one and k-dimensional independent standard Brownian motions. Critical values of the $CS_T(\tau)$ statistic can be obtained by Monte Carlo simulation (see Table 1, Xiao and Phillips (2002), among others).

Note that, we preferred the Kuriyama (2016) methodology over that developed earlier by Xiao (2009), since in the latter case, detection of cointegration is contingent on the correct choice of leads and lags in the model, as it is based on the Dynamic Ordinary Least Squares (DOLS)-type approach of Saikkonen (1991). The CUSUM test statistic developed by Kuriyama (2016) corrects for endogeneity by using fully-modified residuals.

4. Empirical Analysis

For the empirical estimation, we use monthly US data covering the monthly time period from 1953:M1 to 2016:M2 for non-housing CPI and nominal house price index. The data span ensures that we cover the longest possible known economic expansions and recessions, as well as housing market innovations that may imply different responses during different periods (Nyakabawo et al., 2015). Non-housing CPI is obtained from the United States Department of Labor, Bureau of Labor Statistics, and the nominal house price index is obtained from the data segment of the website of Professor Robert J. Shiller: http://www.econ.yale.edu/~shiller/data.htm. We process the data by first seasonally adjusting it, and then transform it into logarithms denoted as $LNHCPI$ and $LNHPI$ for non-housing CPI and house price index, respectively. Figure 1 shows the comovement between the housing price index and the non-housing CPI.

We perform standard unit root tests to determine whether the non-housing CPI and house price index series are stationary and results are reported in Table 1.[4] According to results in Table 1, the

[4] For all the unit root and cointegration tests, the choice of lag-length was based on the Schwarz Information Criterion. However, alternative choice of lag-length based on other criteria, like the Akaike Information Criterion and the Hannan-Quinn Criterion, yielded qualitatively the same results. Complete details of these results are available upon request from the authors.

Augmented Dickey and Fuller (ADF, 1981), Elliott et al.'s (1996) Dickey-Fuller Generalized Least Squares (DF-GLS), Phillips and Perron (PP, 1988) (PP), and Ng and Perron (2001) tests fail to reject the null hypothesis of non-stationarity for the non-housing CPI and house price index series at conventional levels of significance. The tests further indicate that the first differences of non-housing CPI and house price index series reject the null of a unit root. Therefore, the unit root test results indicate that the non-housing CPI and house price index series of the U.S both conform to $I(1)$ processes.

However, a major shortcoming with the standard unit root tests is that they do not allow for the possibility of structural breaks. Perron (1989) shows that the power to reject a false unit root null hypothesis decreases and therefore a structural break can be ignored. While Perron (1989) treats the structural break as being exogenous, we follow Zivot and Andrews (1992) by implementing a unit root test to determine a break point endogenously, allowing for a break in both trend and intercept. Results of Zivot and Andrews (1992) unit root test are reported in Table 2A and show that we cannot reject null hypothesis implying that both series contain unit root. It is also expected that there is a loss of power when two or more breaks are not accommodated when employing a test that only accommodates a one-time structural break. Therefore, we also implement Lumsdaine and Papell's (1997) unit root test that allows for two breaks in the trend at two distinct unknown dates. Table 2B reports the results of the Lumsdaine and Papell (1997) test allowing for breaks in both intercept and trend. According to the results, we cannot reject the null hypothesis, implying that non-housing CPI and house price index contain unit root with two breaks. In this regard, we further apply the powerful Lee and Strazicich (2003) LM unit root tests, which takes into account two structural breaks and the alternative hypothesis unambiguously implies the series to be trend stationary. Results are reported in Table 2C, and indicate that we cannot reject null hypothesis of unit root again.[5]

[5] We also applied the Residual Augmented Least Squares–Lagrange Multiplier (RALS–LM) unit root test with structural breaks in the mean and trend as recently proposed by Meng et al., (forthcoming); however, our results still indicated that both the house price index and the non-housing CPI index are I(1) processes. Complete details of these results are available upon request from the authors.

To accommodate the possibility of a non-linear dynamics of house price and non-housing CPI, we perform Kapetanios et al., (KSS, 2003) nonlinear unit root test on the de-meaned and detrended data, which shows further evidence of non-stationarity in these two variables, as reported in Table 2D.

Therefore, based on the unit roots tests which incorporate the possibility of one or two structural breaks and nonlinearity, the null hypothesis of unit root cannot be rejected, and hence, we can move ahead to the test of cointegration having met its pre-requisite of both variables being *I(1)*.

We start off the cointegration analysis with the standard Engle and Granger (1987) cointegration test (reported in Table 3A) which tests the null hypothesis that series are not cointegrated.[6] Based on the results, we reject the null hypothesis of no cointegration indicating that non-housing CPI and the house price index series are cointegrated.[7] The Phillips and Ouliaris (1990) test (Table 3B) tests the null hypothesis that series are not cointegrated. We do not reject the null hypothesis of no cointegration suggesting that the non-housing CPI and house price index series are not cointegrated. Further analysis using Park (1992) added variable test (Table 3C), leads us to reject the null hypothesis of cointegration at one percent level suggesting that series are not cointegrated. We also perform the Johansen (1988; 1991) cointegration tests to determine whether non-housing CPI and house price index cointegrate with each other. The result reported in Table 3D reports show evidence of no cointegration between non-housing CPI and house price index, implying that the two series do not maintain a long-run relationship in log-levels. So, based on the cointegration results, the Engle and Granger (1987) test imply possible cointegration between non-housing CPI and house price index, while the Phillips and Ouliaris (1990), Park (1992), and Johansen (1988; 1991) cointegration test results show evidence of no cointegration between the two series. Therefore, these conflicting

[6] In cases where cointegration hold, for instance in the case of the Engle and Granger (1987) and Kuriyama (2016) tests, we normalize the cointegrating vector on the house price index, since we are interested in the inflation-hedging property of house price. But, standard Granger causality tests (available upon request from the authors) also indicated that house prices are caused by non-housing CPI, but not the other way round, hence, we can treat non-housing CPI as the exogenous variables and normalize the cointegrating vector on the house price index. Note however, for the single-equation based cointegration tests, our results were unaffected irrespective of which variable was used as the dependent variable. Again complete details of these results are available upon request from the authors.

[7] The inflation hedging coefficient in this case was 1.20 (p-value=0.00), suggesting that house prices act as an overhedge of inflation. This result was statistically vindicated when we found that this coefficient is significantly different from 1, with the coefficient restriction of equal to 1 being rejected at one percent level of significance. Complete details of these results are available upon request from the authors.

conclusions caused us to apply the parameter stability test of Hansen (1992) based on the Fully Modified Ordinary Least Squares (FM-OLS) estimation of the cointegrating vector. As shown in Table 3E, the null of parameter stability is overwhelmingly rejected, which implies that the long-run relationship between the two variables of concern are unstable. This result differs from the findings of Anari and Kolari (2002), who find evidence of a stable long-run relationship between these data series, though over a different sample period (1968:M1-2000:M6), which does not of course include the recent financial crisis. The existence of instability was further vindicated when we applied the powerful WDmax test of 1 to M globally determined breaks proposed by Bai and Perron (2003) to the FM-OLS estimated regression, and obtain five breaks at: 1968:M2, 1977:M7, 1986:M12, 1997:M4, and 2006M:10.

The mixed evidence on the cointegration relationship between non-housing CPI and house price index and that of parameter instability motivates us to apply the Kuriyama's (2016) quantile cointegration analysis which examines the equilibrium relationships across different quantiles of the distribution of the response variable, namely the house price in our case. The methodology allows the long-run relationship among time series which contains unit root to be non-uniform across the various conditional quantiles of the dependent variable. Test results are reported in Table 4. For each quantile the intercept term (α), fully modified coefficient estimate (β) and the CUSUM test statistic ($CS_T(\tau)$) are reported. We also report the *t*-test statistics for testing whether β is significantly different from zero and one. While the former allows us to test whether, the relationship between house price and non-housing CPI is significant, the latter tells us if housing under-hedges, serves as a perfect hedge or over-hedges inflation. The results provide evidence that non-housing CPI and house price index are cointegrated at the lower quantiles of 0.05 to 0.20 at 5 percent significance level. However, there is no evidence of a cointegration relationship over the quantile range of 0.30 to 0.90 even at the 10 percent level of significance. The response of house price to non-housing CPI is always positive and statistically significant over the entire conditional distribution of house price. In addition, β is also statistically greater than one over the entire conditional distribution, suggesting that house prices over-hedges inflation. But given that the cointegration exists only over the quantile range of 0.05 to 0.20,

we need to restrict our discussion of the overhedging characteristic of house prices to only these quantiles, over which one percent increases in inflation, leads to between 1.11 to 1.16 percent increases in nominal housing returns. As pointed out by Anari and Kolari (2002), the fact that the coefficients are greater than one is indicative of the fact that they may be incorporating the impact of tax (see also, Darby (1975), Carrington and Crouch (1987), and Crowder and Wohar (1999)). The fact that majority of the conditional mean based cointegration fail to pick up cointegration is possibly due to the fact that cointegration does not hold over the majority of the conditional distribution of house prices. But at the same time, our results highlight the importance of using the quantile-based approach, since if we would have just relied on the conditional-mean based tests, we would have wrongly concluded that house price does not hedge inflation, when in fact it overhedges inflation, but only at certain lower quantiles.[8] Understandably, overhedging suggests that the real value of the investment in housing is retained in the presence of inflation, as it ensures a positive real rate of return.

5. Conclusion

In this paper, we analyse whether house prices provide a good hedge against inflation in the US by investigating the long run relationship between non-housing CPI and houses prices using quantile cointegration analysis. Monthly data covering the period 1953:M1 to 2016:M2 is used. Before proceeding with the quantile cointegration analysis, standard unit root tests were performed, and our

[8] We also tested for quantile cointegration using Xiao's (2009) methodology and detected evidence of quantile cointegration and over-hedging, but we prefer the Kuriyama (2016) approach for reasons already discussed in the methodology segment. Similar results in terms of overhedging were also obtained under the quantile Autoregressive Distributed Lag (QARDL) approach of Cho et al., (2015). Note that, Anari and Kolari (2002) had used an ARDL model, which in turn, is also a conditional mean-based model with existence or non-existence of cointegration being often sensitive to the appropriate choice of lag-lengths like many of the cointegration tests discussed in the main text. But, for the sake completeness and comparability, we also applied the test to our dataset, but failed to detect cointegration at conventional levels of significance, which should not be surprising given the evidence of parameter instability discussed in the main text. Complete details of all these results are available upon request from the authors.

results conclude that both non-housing CPI and house price index are $I(1)$ series. Allowing for the possibility of structural breaks, we perform unit root test with both one and two structural breaks and find evidence that we cannot reject the null hypothesis of unit root. Evidence from non-linear unit root test also concludes that the series are non-stationary. Next, when we conduct standard cointegration tests, we find mixed evidence of a cointegration relationship between non-housing CPI and house price index, which motivates us to perform a stability test on the cointegrating vector. Results from the stability test conclude that the cointegration relationship is unstable, therefore we use a time-varying approach by applying Kuriyama's (2016) quantile cointegration which test for the existences of a long-run relationship across the conditional quantiles of the dependent variable, thus capturing various phases of the US housing market. Empirical results using quantile cointegration suggest that the U.S non-housing CPI and house price index series are cointegrated at lower quantiles, but show evidence of no long-run relationship at the middle and upper quantiles. Our results also imply that at lower levels, house prices over-hedge against inflation. But given that there is no long-run relationship at moderate to high levels, our results are possibly indicative of bubbles that exists in an overheated housing market, captured by housing prices deviating from a fundamental, namely non-housing CPI in our case. As part of future research, it would be interesting to extend our analysis to REITs.

References

Abraham, J.M. and Hendershott, P.H. (1996). Bubbles in metropolitan housing markets. *Journal of Housing Research.* 7, 191–207.

Álvarez-Díaz, M., and Gupta, R. (2016). Forecasting US Consumer Price Index: Does Nonlinearity Matter? *Applied Economics*, 48(46), 4462-4475.

Anari, A. and Kolari, J.W. (2001). Stock Prices and Inflation. *Journal of Financial Research,* 24, 587-602.

Anari, A. and Kolari, J.W. (2002). House Prices and Inflation. *Real Estate Economics,* 30(1), 67-84.

Bai, J., and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1-22. Barber, C., Robertson, D., and Scott, A. (1997). Property and inflation: The hedging characteristics of U.K. real estate. *Journal of Real Estate Finance and Economics,* 15, 59–76.

Bierens, H. J., and Martins, L.F. (2010). Time varying cointegration. *Econometric Theory*, 26, 1453–1490.

Bond, M.T. and M.J. Seiler. (1998). Real Estate Returns and Inflation: An Added Variable Approach. *Journal of Real Estate Research* 15: 327–338.

Bork, L and Møller, S.V. Forecasting house prices in the 50 states using Dynamic Model Averaging and Dynamic Model Selection. *International Journal of Forecasting*. 31 (2015), 63–78.

Canarella, G., Miller, S.M., and Pollard, S. (2012). Unit Roots and Structural Change: An Application to US House Price Indices. *Urban Studies*, 49(4), 757-776.

Caporin, M., and Gupta, R. (Forthcoming). Time-Varying Persistence in US Inflation. *Empirical Economics*, doi: 10.1007/s00181-016-1144-y.

Carrington, S. and Crouch, R. (1987). A Theorem on Interest Rate Differentials, Risk and Anticipated Inflation. *Applied Economics,* 19, 1675–1683.

Case, K.E. and Shiller, R.J. (1988). The Behavior of Home Buyers in Boom and Post- Boom Markets. *New England Economic Review* (Sept./Oct.): 45–56.

Case, K. E and Shiller, R. J. (1990). Forecasting prices and excess returns in the housing market. *Real Estate Economics* 18, 253–273.

Case, K.E., Shiller, R.J., and Thompson, A.K. (2012). What Have They Been Thinking? Homebuyer Behavior in Hot and Cold Markets. *Brookings Papers on Economic Activity*, 45(2), 265-315.

Chang, K. (2016). Does REIT index hedge inflation risk? New evidence from the tail quantile dependences of the Markov-switching GRG copula. *North American Journal of Economics and Finance,* 39, 56–67.

Cho, J.S., Kim, T-H., and Shin, Y. (2015). Quantile Cointegration in the Autoregressive Distributed-Lag Modelling Framework. *Journal of Econometrics*, 188, 281-300.

Crowder, W.J. and Wohar, M.E. (1999). Are Tax Effects Important in the Long-Run Fisher Relation? Evidence from the Municipal Bond Market. *Journal of Finance*, 54 (1), 307-317.

Darby, M.A. (1975). The Financial and Tax Effects of Monetary Policy on Interest Rates. *Economic Inquiry*, 13, 266–276.

Dickey, D., and Fuller, W. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica*, 49, 1057-1072.

Elliott, G., Rothenberg, T.J., and Stock, J.H. (1996). Efficient Tests for an Autoregressive Unit Root. *Econometrica*, 64(4), 813-836.

Engel, R.F. and Granger, C.W.J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica, 55(2),* 251-276.

Fama, E. and Schwert, G. (1977). Asset Returns and Inflation, *Journal of Financial Economics, 5,* 115–46.

Fisher, I. (1930). *The Theory of Interest*. Macmillan: New York, NY.

Fogler, R., Granito, M., and Smith, L. (1985). A Theoretical Analysis of Real Estate Returns. *Journal of Finance, 40*, 711–21.

Ghysels, E., Plazzi, A., Torous, W., and Valkanov, R. (2013). Forecasting Real Estate Prices, *Handbook of Economic Forecasting*, G. Elliott and A. Timmermann (Eds.), 2(A), 509-580, Elsevier, Amsterdam, The Netherlands.

Glascock, J. L., Lu, C., and So, R. W. (2002). REIT returns and inflation: Perverse or reverse causality effects? *The Journal of Real Estate Finance and Economics* 24, 301–317.

Glascock, J. L., Feng, L., Fan, L., and Bao, H. X. (2008). Inflation hedging characteristics of real estate assets in Hong Kong (27 July 2008). SSRN: http://ssrn.com/abstract=1180658.

Gultekin, N. (1983). Stock Market Returns and Inflation Forecasts. *Journal of Finance*, *38*, 663–674.

Gyourko, J., and Linneman, P. (1988). Owner-occupied homes, income-producing real estate and REITs as inflation hedges. *Journal of Real Estate Finance and Economics*, 1(4), 347–372.

Hansen, B.E. (1992). Tests for parameter instability in regressions with I(1) processes., *Journal of Business and Economic Statistics*, 10, 321-336.

Hardin, W. G., Jiang, X., and Wu, Z. (2012). REIT stock prices with inflation hedging and illusion. *Journal of Real Estate Finance and Economics*, 45, 262–287.

Hartzell, D., Heckman, J. and Miles, M. (1987). Real Estate Returns and Inflation. *AREUEA Journal*, *15(1)*, 617–37.

Hoesli, M., Lizieri, C., and MacGregor, B. (2007). The inflation hedging characteristics of US and UK investments: a multi-factor error correction approach. *Journal of Real Estate Finance and Economics,* 36(2), 183–206.

Hong, G., Khill, J., and Lee, S-B. (2013). Stock Returns, Housing Returns and Inflation: Is there an Inflation Illusion? *Asian- Pacific Journal of Financial Studies*, 42, 511-562.

Hong, G., and Lee, B-S. (2013). Does Inflation Illusion Explain the Relation between REITs and Inflation? *Journal of Real Estate Finance and Economics* 47, 123–151.

Iacoviello, M. (2012). Housing Wealth and Consumption. *International Encyclopedia of Housing and Home*, 673-678, Elsevier, Amsterdam, The Netherlands.

Inglesi-Lotz, R., and Gupta, R. (2013). The long-run relationship between house prices and inflation in South Africa: an ARDL approach. *International Journal of Strategic Property Management*, 17(2), 188-198.

Jochmann, M., and Koop, G. (2015). Regime-switching cointegration. *Studies in Nonlinear Dynamics & Econometrics*, 19(1), 35-48.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control*, 12(2–3), 231–254.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59, 1551-1580.

Kapetanios, G., Shin, Y., and Snell, A. (2003). Testing for a unit root in the nonlinear STAR framework. *Journal of Econometrics*, 112, 359–379.

Koenker, R., and Bassett, G. (1978). Regression Quantiles. *Econometrica* 46 (1), 33‑49.

Kuriyama, N. (2016). Testing cointegration in quantile regressions with an application to the term structure of interest rates. *Studies in Non-linear Dynamics and Econometrics*, 20(2), 107-121.

Leamer, E.E. (2007). Housing is the business cycle. Proceedings - Economic Policy Symposium - Jackson Hole, Federal Reserve Bank of Kansas City, 149-233.

Lee, J. and Strazicich, M.C. (2003). Minimum LM Unit Root Test with Two Structural Breaks. *Review of Economics and Statistics*, 63, 1082-1089.

Lumsdaine, R. L and. Papell, D. H. (1997). Multiple Trend Breaks and the Unit Root Hypothesis. *Review of Economics and Statistics*, 79 (2), 212-218.

Mandelker, G. and Tandon, K. (1985). Common Stock Returns, Real Activity, Money and Inflation: Some International Evidence. *Journal of International Money and Finance*, 4, 267–86.

Martins, L.F. and Gabriel, V.J (2014). Modelling long run comovements in equity markets: A flexible approach. *Journal of Banking and Finance*, 47, 288–295.

Martins, L.F. (Forthcoming). Bootstrap Tests for Time Varying Cointegration, *Econometric Reviews*, http://dx.doi.org/10.1080/07474938.2015.1092830.

Meng, M., Lee, J., and Payne, J.E. (Forthcoming). RALS-LM unit root test with trend breaks and non-normal errors: application to the Prebisch-Singer hypothesis. *Studies in Nonlinear Dynamics & Econometrics*, doi: https://doi.org/10.1515/snde-2016-0050.

Nelson, C. (1976). Inflation and Rates of Return on Common Stock. *Journal of Finance, 31*, 471–83.

Ng, S., and Perron, P., (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica* 69, 1519-1554.

Nyakabawo, W., Miller, S.M., Balcilar, M., Das, S., and Gupta, R. (2015). Temporal causality between house prices and output in the US: A bootstrap rolling-window approach. *The North American Journal of Economics and Finance*, 33, 55–73.

Park J.Y., and Hahn, S.B. (1999). Cointegrating regression with time varying coefficients. *Econometric Theory*, 15, 664–703

Park, J. Y., Mullineaux, D. J., & Chew, I. K. (1990). Are REITs inflation hedges? *Journal of Real Estate Finance and Economics*, 3(1), 91–103.

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica,* 57, 1361-1401.

Phillips, P. C. B., and Hansen, B. E. (1990). Statistical Inference in Instrumental Variables Regression with I(1) Processes. *Review of Economic Studies*, 57 (1), 99‑125.

Phillips, P. and Perron, P. (1988), Testing for a Unit Root in Time Series Regression *Biometrica*, 75(2), 335-346.

Phillips, P. C. B., and Ouliaris, S. (1990). Asymptotic Properties of Residual-Based Tests for Cointegration. *Econometrica* 58 (1):165‑193.

Pierdzioch, C., Risse, M., Gupta, R., and Nyakabawo, W. (2016). On REIT Returns and (Un-) Expected Inflation: Empirical Evidence Based on Bayesian Additive Regression Trees. *Department of Economics, University of Pretoria, Working Paper No. 201677.*

Rubens, J., Bond M., and Webb, J. (1989). The Inflation-Hedging Effectiveness of Real Estate. *Journal of Real Estate Research*, 4(2), 45–56.

Saikkonen, P. (1991). Asymptotically efficient estimation of cointegration regressions. *Econometric Theory*, 7, 1–21.

Simpson, M.W., Ramchander, S. and Webb, J.R. (2007). The Asymmetric Response of Equity REIT Returns to Inflation. *The Journal of Real Estate Finance and Economics,* 34, 513–529.

Stulz, R. (1986). Asset Pricing and Expected Inflation. *Journal of Finance*, 41, 209–24.

Tracy, J., Schneider, H. and Chan, S. (1999). Are Stocks Overtaking Real Estate in Household Productivity? *Current Issues in Economics and Finance*. Federal Reserve Bank of New York (April): 1–6.

Xiao, Z., (2009). Quantile cointegrating regression. *Journal of Econometrics*, 150, 248–260.

Xiao, Z., and Phillips, P. C. B. (2002). A CUSUM Test for Cointegration Using Regression Residuals. *Journal of Econometrics*, 108 (1), 43‑61.

Zivot, E. and Andrews, K. (1992), "Further Evidence On The Great Crash, The Oil Price Shock, and The Unit Root Hypothesis", *Journal of Business and Economic Statistics*, 10 (10), 251–70.

Figure 1: Data Plots

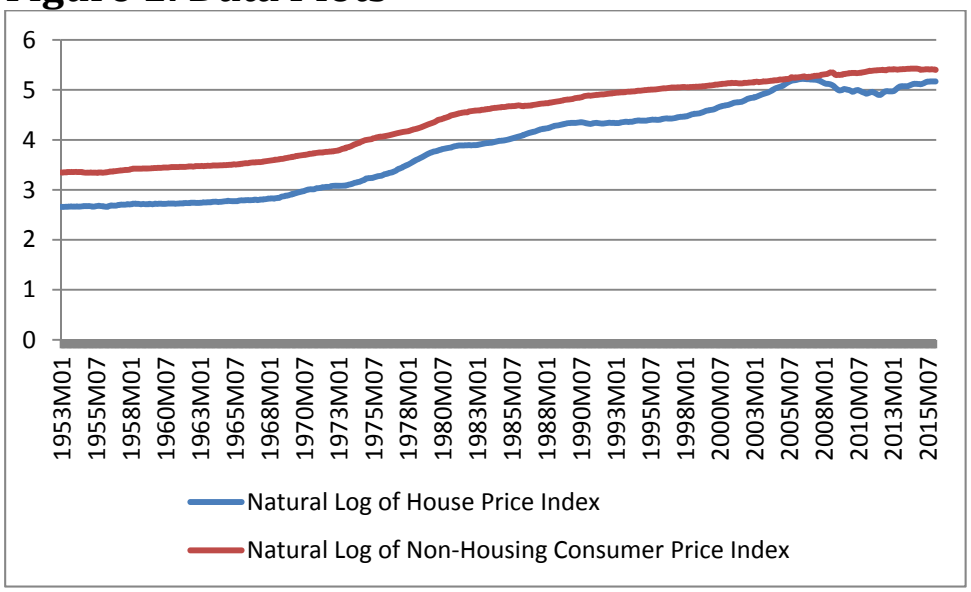

Table 1: Unit root Tests

Levels								
	ADF		DF-GLS		PP		Ng-Perron	
	C	C+T	C	C+T	C	C+T	C (MZa)	C+T (MZa)
House prices	-0.526	-3.938	-1.053	-2.984	-0.003	-1.712	1.377	-2.238
Inflation	-1.140	0.522	1.268	-0.956	-0.810	-0.189	1.237	-0.761
First difference								
	ADF		DF-GLS		PP		Ng-Perron	
	C	C+T	C	C+T	C	C+T	C (MZa)	C+T (MZa)
House prices	-3.515***	-3.506**	-2.451**	-3.246**	-9.679***	-9.643***	-128.295***	-156.670***
Inflation	-4.028***	-4.120***	-1.514	-2.265	-18.441***	-18.471***	-138.036***	-270.351***

Notes: *** indicates significance at a 1% level;
ADF and PP: a constant is included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% significance critical value equals -3.439, -2.865,-2.569, respectively.

ADF and PP: a constant and a linear trend are included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% critical values equals -3.970, -3.416, -3.130, respectively.

Ng-Perron: a constant is included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% significance critical value equals -13.800, -8.100, -5.700, respectively.

Ng-Perron: constant and a linear trend are included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% critical values equals -23.800, -17.300, -14.200, respectively.

DF-GLS: a constant is included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% significance critical value equals -2.568, -1.941, -1.616, respectively.

DF-GLS: constant and a linear trend are included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% critical values equals -3.480, -2.890, -2.57, respectively.

Table 2A: Zivot and Andrews (1992) one break unit root test

Series	Test statistic	Breakpoint
LNHPI	**-5.57**	**2002:01**
LNHCPI	**-3.71**	**1973:08**

Notes: Allowing for Break in both Intercept and Trend Breaks Tested for 1962:10 to 2006:10. Including 5 Lags of Difference selected by user. The critical values for the Zivot and Andrews (1992) test are -5.57 per cent, -5.08 per cent and -4.82 per cent at the 1 per cent, 5 per cent and 10 per cent levels of significance respectively (Zivot and Andrews, 1992).

Table 2B: Lumsdaine and Papell (1997) two breaks unit root test

Series	Test statistic	Breakpoint 1	Breakpoint 2
LNHPI	**-3.69**	**1976:06**	**2002:02**
LNHCPI	**-5.15**	**1966:04**	**1978:12**

Notes: Regression period 1953:07 to 2016:02. The critical values for the Lumsdaine and Papell (1997) two break test are -7.19 per cent, -6.75 per cent and -6.48 per cent at the 1 per cent, 5 per cent and 10 per cent levels of significance respectively.

Table 2C: Lee and Strazicich (2003) LM two breaks unit root test

Series	Test statistic	Breakpoint 1	Breakpoint 2
LNHPI	**-0.79**	**1965:12**	**1978:11**
LNHCPI	**-1.57**	**1969:08**	**1981:05**

Notes: Regression period 1953:02 to 2016:02. The critical values for the Lee and Strazicich (2003) two break test are -6.32 per cent, -5.71 per cent and -5.33 per cent at the 1 per cent, 5 per cent and 10 per cent levels of significance respectively.

Table 2D: Kapetanios, Shin and Snell (2003) nonlinear unit root test

Series	Test statistic
LNHPI	**-1.91**
LNHCPI	**2.38**

Notes: *** indicates significance at a 1% level; ** indicate significance at a 5% level; * indicate significance at a 10% level
The critical values for the Kapetanios, Shin and Snell (2003) KSS test are: -3.93 (1-percnt level); -3.40 (5-percent level); and -3.13 (10-percent level) (Kapetanios, et al., 2003, Table 1).

Table 3A: Engle and Granger (1987) cointegration test

Statistic	Value	Prob
Engle-Granger tau-statistic	**-3.777438**	**0.0151**
Engle-Granger z-statistic	**-40.02597**	**0.0006**

Notes: Tests null hypothesis of no cointegration against the alternative of cointegration.

Table 3B: Phillips and Ouliaris (1990) cointegration test

Statistic	Value	Prob*
Phillips-Ouliaris tau-statistic	**-1.215704**	**0.8546**
Phillips-Ouliaris z-statistic	**-3.257794**	**0.8614**

Notes: Tests null hypothesis of no cointegration against the alternative of cointegration.

Table 3C: Park (1992) added variables test

	Value	df	Probability
Chi-square	**60.38389**	**2**	**0.0000**

Notes: Tests null hypothesis of cointegration against the alternative of no cointegration.

Table 3D: Johansen'Cointegration Test

Series	H_0[a]	H_1	Trace Statistic	Maximum-Eigen Value Statistic
LHCPI and LNHPI	$r = 0$	$r > 0$	7.75	5.74
	$r \leq 1$	$r > 1$	0.49	0.65

Notes: [a]One-sided test of the null hypothesis (H_0) that the variables are not cointegrated against the alternative (H_1) of at least one cointegrating relationship. The critical values are taken from MacKinnon et al., (1999) with 5-percent critical values equal to 15.49 for testing $r = 0$ and 3.84 for testing $r \leq 1$ for the Trace test. The corresponding values for the Maximum Eigenvalue tests are 14.26 and 3.84.

Table 3E: Hansen Parameter Instability Test

L_c Statistic	Stochastic Trends(m)	Deterministic Trends (k)	Excluded Trends (p2)	Prob*
3.047	**1**	**0**	**0**	**<0.01**

Notes:Hansen (1992b) Lc(m2=1, k=0) p-values, where m2=m-p2 is the number of stochastic trends in the asymptotic distribution. Test null hypothesis of parameter stability against the alternative of instability.

Table 4: Kuriyama's methodology (2016)

	τ=0.05	τ=0.10	τ=0.20	τ=0.30	τ=0.40	τ=0.50	τ=0.60	τ=0.70	τ=0.80	τ=0.90	τ=0.95
α	**-1.40*** **	**-1.37*** **	**-1.17*** **	**-1.19*** **	**-1.26*** **	**-1.30*** **	**-1.37*** **	**-1.42*** **	**-1.47*** **	**-1.61*** **	**-1.74**
β	**1.16*** **	**1.15*** **	**1.11*** **	**1.12*** **	**1.15*** **	**1.16*** **	**1.18*** **	**1.20*** **	**1.23*** **	**1.28*** **	**1.31*** **
H_0: β=1, *t*-statistic	**11.72*** **	**7.24*** **	**4.24*** **	**3.49*** **	**5.27*** **	**6.39*** **	**7.35*** **	**7.72*** **	**6.80*** **	**7.69*** **	**2.30*** **
$CS_T(\tau)$	**0.74**	**0.82**	**1.02**	**1.48** **	**1.76** **	**1.65** **	**1.84** **	**1.74** **	**1.83** **	**1.30** **	**2.82**

Notes: *** (**) indicates the rejection of the null of β=1 (cointegration) at 1 percent (5 percent) level of of significance for a specific quantile (τ).