

## Long- and Short-Run Relationships between House and Stock Prices in South Africa: A Nonparametric Approach

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### Abstract

This paper provides empirical evidence on the long- and short-run relationships between real house and stock prices of South Africa. Standard linear tests may not detect the existence of these relationships between time series especially in the presence of structural shifts or regime changes, which, in turn, may cause nonlinearities in the observed series. Thus, in this study, both linear and nonparametric cointegration and Granger causality tests were conducted. Results from the linear cointegration test showed no long-run relationship between house and stock prices. The linear Granger causality test produced no evidence of causality either. In contrast, the nonparametric cointegration test revealed a long-run one-to-one relationship between the two series, with the nonparametric Granger causality test indicating a bi-directional causality. Therefore, stability in the housing market drives stability in the equity market and vice versa.

The recent global financial crisis makes financial stability an important issue for policymakers, financial institutions and financial markets. This has become critical at all levels: regional, national, and global. Financial stability or instability may have implications for interrelated markets. This study focuses on the interdependencies between financial and real estate markets. The understanding of the relationship between these two asset markets provides an important intuition on household welfare, asset substitution, and portfolio investment. In addition, recent evidence has suggested that both stock price and house price acts as leading indicators for output and inflation in the economy (Stock and Watson, 2003). Given this, movements in these two prices are also likely to lead to movements in monetary policy, as observed during the recent financial crisis (Castro, 2011).

Although houses are regarded as consumption goods, they are also considered as alternative investment opportunities to stocks. The causality between house prices and stock prices may be due to either the wealth or credit-price effect or both (Liow, 2006; Oikarinen, 2006; Ibrahim, 2010). The wealth effect implies causation from stock prices to house prices. The credit-price effect implies a reverse causation from the house to stock prices and implies the possibility of persistent spiraling upturns in both prices. The unanticipated gains in stock prices reflect the increasing share of the stocks in the investment portfolio and wealth. This encourages households to rebalance their portfolios by investing in or consuming more housing services. Under the credit-price effect, real



estate acts as collateral, especially to credit-constrained firms. The increase in house prices, thus, would be favorable to their balance sheet position in that they may get access to better credit terms. With the expanded investments, firms' value and, thus, firms' stock prices rise, which may lead to an increase in the demand for real estate, resulting in their persistent feedback effects (Oikarinen, 2006; Sim and Chang, 2006).

A number of studies have analyzed the relationship between house and stock prices.<sup>1</sup> The results from these studies are mixed in terms of the direction, magnitude, and significance of the causal relationship. The results vary depending on the method of analysis. Thus, the integration or segmentation between the two asset markets may be due to methodological flaws. Further, the results vary from one country to another, thus requiring country-specific analysis. In general, even though at times a bi-directional causal relationship exists, the results seem to indicate the dominance of the *wealth effect* in more developed economies, while the *credit-price effect* is found to be more prevalent in emerging markets. The results seem to make sense, since one would expect the stock and housing markets to be equally developed in advanced economies like the United States and the United Kingdom, causing the housing market to act as a near perfect substitute for investment following increases in share prices, which in turn, leads to reallocation in household portfolios towards housing. On the other hand, with housing likely to act mainly as a consumption good, and stock markets being more relevant for investment in emerging economies, movements in house prices are more prone to lead stock prices via the credit-price effect. However, given the evidence of nearly equal weights of housing and non-housing wealth in the portfolio allocation of U.S. households, it is likely that both wealth and the credit price-effects will be equally important, causing the two markets to affect each other simultaneously. Based on Iacoviello (2011), non-housing wealth (housing wealth) was calculated to be 41.04% (37.78%) of a U.S. household's total assets and 52.07% (47.93%) of a U.S. household's net worth, using figures from 2008. This line of reasoning seems to be vindicated in the wake of the recent financial crisis, which originated from the U.S. housing market. Further, as depicted by Iacoviello (2010, 2011), in the U.S., the non-housing wealth and the financial wealth nearly came together over the period of the mid-1990s until the wake of the crisis, highlighting the time-varying nature between the two-types of wealth. This is likely to be the case for most economies, and hence, researchers should examine the causal relationship in a time-varying setting, since this could provide answers to contradictory evidence found on a specific country under two different samples. Note that in South Africa, non-housing wealth (housing wealth) was calculated to be 49.95% (31.13%) of a household's total assets and 61.59% (38.41%) of a household's net worth (South African Reserve Bank, 2012). The figures are in line with our reasoning on causality discussed above. Despite the numerous important implications that the interrelations between the stock and housing markets may have on the economy, there is no research in South Africa examining these linkages. Therefore, we extend the literature by studying the long- and short-run dynamic interdependences between stock and housing markets in South Africa using Bierens' (1997a) nonparametric cointegration and Bell, Kay, and Malley's (1996) nonparametric Granger causality tests, over and above the standard linear version of the cointegration test proposed by Johansen (1988, 1991) and the linear causality test of Granger (1969). For the nonparametric framework, the sign of the predictability between the two series is also determined using the nonparametric average derivative estimates based on the additive model of Hastie and Tibshirani (1987, 1990).



Most economic time series exhibit structural breaks or regime changes at one time or another. This is more likely to be the case in emerging economies, such as South Africa, which not only are subject to foreign shocks in an integrated world, but also undergo constant changes in domestic policies, resulting in nonlinear dependence amongst variables. Continuing large shocks and policy changes result in frequent outliers. In addition, dynamic links in financial markets are asymmetric, where adjustment to the equilibrium depends on the sign of the shocks and level of the variable. Therefore, the relationship between a response variable and the explanatory variable(s) may not be constant throughout the domain of the latter. Such dynamic features of financial time series cannot be accounted by linear relationships, since these models can only capture linear dependence (Terasvirta, Tjostheim, and Granger, 2010). Hence, there is need for more methodologies to account for such nonlinearities. The nonparametric cointegration tests allow for a relatively flexible data-generating process (DGP) than the parametric linear test. Moreover, nonparametric regressions do not assume any functional form and allow general dependence between variables (Härdle, 1990; Bell, Kay, and Malley, 1996, 1998). Further, nonparametric regressions also offer an advantage over the other nonlinear approaches by allowing one to ascertain the sign of the predictability between the series using average derivative estimates (Härdle and Stoker, 1989; Stoker, 1991; Balcilar, Ozdemir, and Cakan, 2011). Thus, the nonparametric approaches are more likely to pick up possible long- and short-run relationships amongst variables, especially in the presence of nonlinearities arising out of possible regime changes and/or structural breaks.

The results of this study reveal the existence of a long-run one-to-one relationship between house and stock prices. Also, results show a bi-directional causality between the two series. These imply that stability in the housing market drives stability in the equity market and vice versa. These results are, however, only subject to non-linear and nonparametric specifications of the relationship between stock and house prices. The remainder of the paper is organized as follows: Section 2 presents the empirical methodologies, while the data and results are discussed in Section 3. Finally, Section 4 concludes.

## **Empirical Methodologies**

### **Linear Parametric and Nonparametric Cointegration Tests**

Having verified the stochastic property of our two variables, the Johansen (1988, 1991) linear parametric and Bierens (1997a) nonparametric cointegration tests were applied. The lack of cointegration implies that dynamics between the series are only short-run in nature. The existence of a cointegrating vector between the variables indicates that long-run interdependence also exists. In other words, cointegration implies that there is at least one stationary long-run relationship between the variables. Given that the Johansen test is now standard in time series literature, the specifications and procedures are not explained here. Hence, we turn to a brief description and explanation of Bierens (1997) nonparametric approach. The nonparametric tests are conducted analogous to Johansen's (1988, 1991) tests, in which Bierens (1997a) consistently estimated a basis for the space of cointegrating vectors (cointegration rank), using the eigenvectors of the generalized eigenvalue problem. However, the two matrices were constructed independently of the DGP, unlike in Johansen's (1988, 1991) methods. The general framework within which



the Bierens (1997a) nonparametric tests and estimators are considered assumes a  $q$ -variate unit root process  $z_t$ , observable for  $t = 1, 2, \dots, T$ , and generated as:

$$z_t = \pi_0 + \pi_1 t + y_t, \quad (1)$$

where  $\pi_0(q \times 1)$  and  $\pi_1(q \times 1)$  are optional mean and trend terms, and  $y_t$  is a nonstationary process such that  $\Delta y_t$  is stationary and ergodic. Apart from these regularity conditions, the method does not require further specification of the DGP for  $z_t$ ; hence, it is completely nonparametric. Taking advantage of the contrasting behavior of  $z_t$  and  $\Delta z_t$ , Bierens (1997a), defined two matrices as:

$$A_m = \frac{8\pi^2}{T} \sum_{k=1}^m k^2 \left( \frac{1}{T} \sum_{t=1}^T \cos(2k\pi(t - 0.5)/T) z_t \right) \times \left( \frac{1}{T} \sum_{t=1}^T \cos(2k\pi(t - 0.5)/T) z_t \right)',$$

$$B_m = 2T \sum_{k=1}^m \left( \frac{1}{T} \sum_{t=1}^T \cos(2k\pi(t - 0.5)/T) \Delta z_t \right) \times \left( \frac{1}{T} \sum_{t=1}^T \cos(2k\pi(t - 0.5)/T) \Delta z_t \right)' \quad (2)$$

which are based on weighted means of  $z_t$  and  $\Delta z_t$ . Although there are many possible choices for the weight functions,  $\cos(2k\pi(t - 0.5)/T)$  is recommended since it ensures invariance of the test statistic to drift terms (Coakley and Fuertes, 2001).

By defining the pair of random matrices,  $P_T = A_m$  and  $Q_T = (B_m + T^{-2}A_m^{-1})$ , the ordered generalized eigenvalues  $\hat{\lambda}_{1,m} \geq \dots \geq \hat{\lambda}_{n,m}$  obtained as solutions to the problem  $\det[P_T - \lambda Q_T] = 0$  have similar properties to those in the Johansen (1988, 1991) approach and therefore can be used for testing the hypothesis about the cointegration rank  $r$ .

First, Bierens (1997a) proposes the lambda-min test statistic  $\hat{\lambda}_{q-r_0,m}$  to test for the null hypothesis  $r = r_0$  against the alternative  $r = r_0 + 1$ . The corresponding asymptotic null distribution is nonstandard and he tabulates the critical values. The null is rejected if the test statistic is too small. The parameter  $m$  is a natural number such that  $m \geq q$ , where  $q$  is the dimension of the underlying system. The choice of  $m$  is made an integral part of these testing and estimation procedures by providing optimal values, tabulated in Bierens (1997a), for different significance levels and values of  $r_0$  and  $q$ , such that the lower bound of the power of the test is maximized. The lambda-min test statistic is analogous to Johansen's (1988, 1991) maximum eigenvalue statistic.

Second, Bierens' (1997a) approach provides the  $g_m(r_0)$  statistics for estimating  $r$  consistently, which again is calculated from his generalized eigenvalues:

$$\begin{aligned} \hat{g}_m(r_0) &= \left( \prod_{k=1}^q \hat{\lambda}_{k,m} \right)^{-1} && \text{if } r_0 = 0; \\ &= \left( \prod_{k=1}^{q-r_0} \hat{\lambda}_{k,m} \right)^{-1} \left( T^{5^{2r_0}} \prod_{k=q-r_0+1}^q \hat{\lambda}_{k,m} \right) && \text{if } r_0 = 1, \dots, q-1; \\ &= T^{2q} \prod_{k=1}^q \hat{\lambda}_{k,m} && \text{if } r_0 = q \end{aligned} \quad (3)$$

This statistic employs the tabulated optimal values for  $m$  when  $r_0 < q$ , while  $m = q$  is chosen for  $r_0 = q$ . It verifies  $g_m(r_0) = O_p(1)$  for  $r = r_0$  and converges in probability to



infinity if  $r \neq r_0$ . A consistent estimate of  $r$  is thus given by  $\hat{r} = \arg \min_{r_0 \leq q} g_m(r_0)$ .

Once the dimension of the cointegration space is determined, one can deploy tests for linear restrictions on the cointegrating vectors. Bierens (1997a) proposes nonparametric trace tests on the basis of the ordered solutions of the following eigenvalue problem:

$$[H^T A_m H - \lambda H^T (A_m + T^{-2} A_m^{-1})^{-1} H] = 0, \quad (4)$$

which involves the random matrix  $A_m$  and the matrix of hypothesized restrictions,  $H$ . For the test of linear restriction, Bierens (1997a) proposes the trace and lambda-max statistics and recommends  $m = 2q$  as a rule of thumb for both. He also derives their asymptotic distributions and corresponding critical values.

### Linear Granger Causality Test

Granger's (1969) causality definition is the source of causality tests between two stationary series. Formally, a time series  $y_t$  Granger-causes another time series  $x_t$ , if series  $x_t$  can be predicted better by using past values of  $y_t$  than by using only the historical values of  $x_t$ . Suppose  $x_t$  and  $y_t$  of length  $n$  are real house price ( $rbp$ ) and real stock price ( $rsp$ ), respectively. Testing for causal relations between the two stationary series can be based on the following bivariate autoregression model:

$$\Delta rbp_t = \alpha_0 + \sum_{p=1}^n \alpha_p \Delta rbp_{t-p} + \sum_{p=1}^n \beta_p \Delta rsp_{t-p} + \varepsilon_{rbp,t}. \quad (5)$$

$$\Delta rsp_t = \phi_0 + \sum_{p=1}^n \phi_p \Delta rbp_{t-p} + \sum_{p=1}^n \theta_p \Delta rsp_{t-p} + \varepsilon_{rsp,t}, \quad (6)$$

where  $\Delta$  is the first difference operator,  $\alpha_0$  and  $\phi_0$  are constants,  $\alpha_p$ ,  $\beta_p$ ,  $\phi_p$ , and  $\theta_p$  are parameters;  $\varepsilon_{rbp,t}$  and  $\varepsilon_{rsp,t}$  are uncorrelated disturbance terms with zero means and finite variances. The test presented in this paper for whether  $rsp_t$  Granger causes  $rbp_t$  involves a standard joint  $F$ -test on whether lagged coefficients of  $rsp_t$  have significant linear predictive power on  $rbp_t$ . The null hypothesis is that of no linear causality, implying that in equation (5), the coefficients of  $\beta_p$  are not jointly significantly different from zero. Similarly, in the case of testing whether  $rbp_t$  causes  $rsp_t$ , the test will be conducted on the coefficients contained in the lag polynomial  $\phi_p$  to see whether they are jointly significantly different from zero. If both  $\beta_p$  and  $\phi_p$  joint tests for significance show they are different from zero, then there exists bi-directional causality (or feedback) between real house price and real stock prices, which implies that both credit-price and wealth (feedback) effects exist.

### Nonparametric Granger Causality Test and Sign of Predictability

The basic idea of nonparametric regression, in general, is to assume the following model:

$$y_t = g(x_t) + \varepsilon_t, \quad (7)$$



where  $y_t$  is the response variable,  $x_t$  is a vector of  $k$  explanatory variables,  $x_t = (x_{1t}, x_{2t}, \dots, x_{kt})'$ ,  $g$  is an unknown smooth function, and  $\varepsilon_t$  is an error term with zero mean and constant variance. In our case, the covariates  $x_t$  includes  $p$  lags of the first-difference of real house price ( $\Delta rhp_{t-i}$ ) and real stock prices ( $\Delta rsp_{t-i}$ ) with  $i = 1, \dots, p$ , and  $y_t$  could be either  $\Delta rhp_t$  or  $\Delta rsp_t$ . The  $k$ -dimensional regressor vector  $x_t$  is characterized by the density function  $f(x)$  and a nonsingular covariance matrix  $\Sigma$ . There are several regression smoothing methods for estimating the underlying function  $g(\cdot)$  from the given data set. These include, among others, kernel smoothing, splines, local regression, etc. (Bell, Kay, and Malley, 1996; Balcilar, Ozdemir, and Cakan, 2011). A variety of methods are also available for estimating the density function  $f(x)$ , with kernel density estimation being the most popular.

Our major goal for estimating equation (7) is to ascertain the sign of the impact of real stock prices on real house prices and vice versa. In this study, a response coefficient that measures the global curvature of the function  $g(\cdot)$  with respect to  $x$  is preferred to that which measures the response with respect to varying levels of  $x$  (partial derivative). In this respect, the additive derivative (AD) is selected. The AD is defined as  $\bar{\delta} = E[\bar{\beta}_j(x)] = \int_x \beta_j(x) dx$  for  $j = 1, 2, \dots, k$ . Then, the vector of average derivatives is given by  $\bar{\delta} = E[g'(x)]$ . Using integration by parts, Hardle (1990) showed that:

$$\bar{\delta} = E[g'(x)] = -E \left[ y \frac{f'(x)}{f(x)} \right]. \quad (8)$$

In practice, there are three commonly-used alternative sample estimators of AD (Balcilar, Ozdemir, and Cakan, 2011). All three are used in this study. The first is Powell, Stock, and Stocker's (1989) indirect estimator, given as:

$$\bar{\delta}_p = -\frac{1}{T} \sum_{t=1}^T y_t \frac{\hat{f}'(\mathbf{x})}{\hat{f}(\mathbf{x})}, \quad (9)$$

where  $\hat{f}(\mathbf{x})$  is the kernel density estimator of the density function  $f(\mathbf{x})$  and  $\hat{f}'(\mathbf{x})$  is the estimator of the first derivative of  $f(x)$ . Hardle and Stoker (1989) point out that the ratio  $\hat{f}'(\mathbf{x})/\hat{f}(\mathbf{x})$  will be ill-behaving when  $\hat{f}(\mathbf{x})$  is small and propose a trimmed estimator defined as:

$$\bar{\delta}_{bs} = -\frac{1}{T} \sum_{t=1}^T y_t \frac{\hat{f}'(\mathbf{x})}{\hat{f}(\mathbf{x})} I[\hat{f}(\mathbf{x}) > b], \quad (10)$$

where  $b$  is a trimming parameter that converges toward zero as  $T$  gets large and  $I[\cdot]$  is the indicator function taking a value of one when  $\hat{f}(\mathbf{x}) > b$  and zero otherwise. The third is Stoker's (1991) direct estimator of AD, given as:

$$\bar{\delta}_s = \frac{1}{T} \sum_{t=1}^T [\hat{g}'(\mathbf{x}) I[\hat{f}(\mathbf{x}) > b]], \quad (11)$$

where  $\hat{g}'(\mathbf{x})$  is the estimate of the first derivative of the regression function  $g(\cdot)$  and  $I[\cdot]$  is as above.



Bell, Kay, and Malley's (1996) nonparametric additive model for estimating the unknown function was employed in this study. This approach works well for detecting nonlinear causal links. The additive model is also robust and loss of power is minimal when the true causal links are linear (Bell, Kay, and Malley, 1996; Balcilar, Ozdemir, and Cakan, 2011). An additive model representing the bivariate causal links between real house price and real stock price is specified as:

$$\Delta rhp_t = \mu_{rhp} + \sum_{j=1}^p g_{rbprhp}^{(j)}(\Delta rhp_{t-j}) + \sum_{j=1}^p g_{rbprsp}^{(j)}(\Delta rsp_{rbp,t-j}) + \varepsilon_{rhp,t}. \quad (12)$$

$$\Delta rsp_t = \mu_{rsp} + \sum_{j=1}^p g_{rsprhp}^{(j)}(\Delta rhp_{t-j}) + \sum_{j=1}^p g_{rsprsp}^{(j)}(\Delta rsp_{rsp,t-j}) + \varepsilon_{rsp,t}, \quad (13)$$

where the functions  $\{g_{il}^{(j)}\}$ ,  $i, l = rsp, rhp$ , are unknown and will be estimated from the data using the nonparametric regression estimation. Unknown functions  $\{g_{il}^{(j)}\}$  are univariate and can be estimated as one-dimensional nonparametric regressions, avoiding the curse of the dimensionality problem (Härdle, 1990). Bell, Kay, and Malley (1996) proposed causality tests by imposing appropriate restrictions on equations (12) and (13). The hypothesis that real stock prices do not Granger-cause real house prices can be tested by imposing the restriction:

$$H_0 : g_{rbprsp}^{(1)} = g_{rbprsp}^{(2)} = \dots = g_{rbprsp}^{(p)} = 0, \quad (14)$$

on equation (12) and estimating the restricted model:

$$\Delta rhp_t = \mu_{rhp}^* + \sum_{j=1}^p g_{rbprhp}^{*(j)}(\Delta rhp_{t-j}) + \varepsilon_{rhp,t}^*. \quad (15)$$

Similarly, the null hypothesis that real house prices do not Granger-cause real stock prices can be tested by imposing the restrictions:

$$H_0 : g_{rsprhp}^{(1)} = g_{rsprhp}^{(2)} = \dots = g_{rsprhp}^{(p)} = 0 \quad (16)$$

on equation (13) and estimating the restricted additive model:

$$\Delta rsp_{rbp,t} = \mu_{rsp}^* + \sum_{j=1}^p g_{rsprsp}^{*(j)}(\Delta rsp_{t-j}) + \varepsilon_{rbp,t}^*. \quad (17)$$

Let  $RSS_R$  be the restricted residual sum of squares from equation (15) or (17) and  $RSS_U$  be the unrestricted sum of squares from equation (12) or (13). Then, the  $F$ -statistic to test the null hypotheses in equations (14) and (16) is given by:

$$F = \frac{(RSS_R - RSS_U)/(d_U - d_R)}{RSS_U/(T - d_U)}, \quad (18)$$

where  $d_U$  and  $d_R$  are the degrees of freedom of the unrestricted and restricted models, respectively. Hastie and Tibshirani (1990) argue that the test statistic in equation (18) is approximately distributed as  $F(d_U - d_R, T - d_U)$  and the null of no Granger causality is



rejected, if the value obtained from equation (17) is greater than the  $(1 - \alpha)$ th quintile of the standard  $F$  distribution.

The additive models in equations (12) and (13) fit separate nonparametric regressions to each regressor. A variety of estimation methods are available, each requiring several choices and control parameters. A commonly-used algorithm for fitting the additive models is the local scoring algorithm of Hastie and Tibshirani (1987, 1990). The back-fitting algorithm (Härdle, 1990) is the core of the local scoring algorithm. In this paper, the back-fitting algorithm was used to estimate the two additive models in equations (12) and (13). There are also several choices for estimating the nonlinear functions,  $\{g_{il}^{(j)}\}$ ,  $i, l = rhp, rsp$ , commonly known as “smoothing” methods. Here, the Nadaraya-Watson kernel regression estimator, also called “kernel smoothing,” was used. In order to determine the appropriate kernel to use for smoothing, all commonly-used kernels were examined and the best kernel selected based on the highest R-squared values and smallest mean square error (MSE). The choice of the kernel type is not crucial in terms of the MSE criterion (Härdle, 1990; Bell, Kay, and Malley, 1997). Härdle (1990) points out that the choice of bandwidth ( $h$ ) is the most important parameter having significant impact on the estimates. The bandwidth controls the span of the data used in smoothing. A too-small bandwidth may result in interpolation of the data by joining points and yield ultra-rough estimates. On the other hand, a too-large bandwidth may fit a function close to a linear one, resulting in ultra-smooth estimates. At least as a starting point, using one of the automatic bandwidth selection procedures may be quite useful. For each component of the additive model, the cross-validation (CV), or leave-one-out, method was used to select the bandwidth parameter, which is optimal in terms of the prediction ability across different subsamples (Stone, 1977). The robustness of nonlinear causality tests and AD estimates was checked by repeating the estimates with alternative bandwidth choices following Balcilar, Ozdemir, and Cakan (2011).

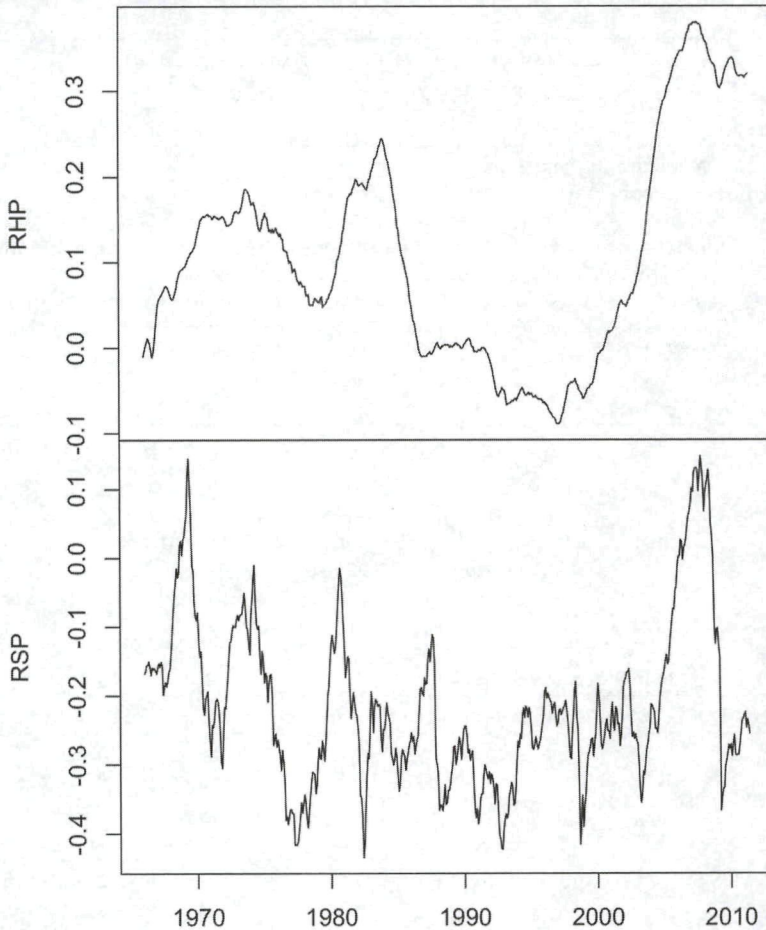
## Results and Discussions

### The Data and Preliminary Analysis (Unit Root Tests)

The framework in this study consists of two variables, namely, house prices and stock prices deflated by South Africa's consumer price index (CPI), with a base year of 2000. House prices are sourced from the Allied Bank of South Africa (ABSA). Stock prices, specifically, the All Share Index (ALSI) and the CPI are obtained from the International Financial Statistics (IFS). The sample covers the monthly period of 1966:01 to 2011:06, with the start- and end-points determined by the availability of data. Note that although the ALSI and the CPI are available for dates earlier than 1966:01, data on the house price index is only available from 1966 onwards. Prior to the core analysis, following Balcilar, Ozdemir and Cakan (2011), both series in their log levels were subjected to the nonparametric Phillips and Perron (1988) [PP]  $p$ -test for unit roots. Note that the PP test has a null of non-stationarity. The PP statistic is computed with a truncation parameter  $p = [CT]^k$  in the Newey-West variance estimator, where  $c = 5$  and  $k = 0.2$  are adopted following Bierens (1997b). Since the PP tests may be subject to size distortion in finite samples, its  $p$ -values are simulated on the basis of 1,000 replications of a Gaussian AR(1) process for the underlying variables in first differences. As Exhibits 1 and 2 show, the



**Exhibit 1. Time Series Plots of Real House Price (*rhp*) and Real Stock Price (*rsp*): 1966:01–2011:06**



test results validate modeling both *rhp* and *rsp* as  $I(1)$  processes. Note that the two series were found to be stationary in their first differences; hence they are integrated of order 1.<sup>2</sup>

### Linear versus Nonparametric Cointegration Tests

The Johansen cointegration tests require a prior specification of the lag length. In this paper, three lags were found optimal based on the Schwarz information criterion (SIC) and the Hannan-Quinn (HQ) information criterion applied to a vector autoregressive model of *rhp* and *rsp* in levels.<sup>3</sup> The linear cointegration test results are presented in Panel A of Exhibit 3. Johansen's (1988, 1991) cointegration test indicates no evidence of a long-run relationship between real house price and real stock price. The Bierens (1997) nonparametric test results based on the generalized eigenvalues of matrices  $A$  and  $B$  for  $m = 2$  are presented in Panel B of Exhibit 3. In contrast to the parametric linear cointegration test, the nonparametric test shows evidence of one cointegrating vector



### Exhibit 2. Unit Root Test Results for the Real House and Real Stock Prices

Series	Level		
	$Z(t)^a$	$Z(t_\mu)^b$	$Z(t_r)^c$
Real House Price	0.073(0.706)	-0.762(0.828)	-0.912(0.953)
Real Stock Price	-1.306(0.177)	-2.791**(0.0602)	-2.977(0.140)

Notes: Simulated  $p$ -values are in parentheses.

<sup>a</sup>Test allows for neither a constant nor a trend; one-sided test of the null hypothesis that the variable is nonstationary; 1%, 5%, and 10% critical values are -2.570, -1.941, and -1.616, respectively.

<sup>b</sup>Test allows for a constant; one-sided test of the null hypothesis that the variable is nonstationary; 1%, 5%, and 10% critical values are -3.442, -2.867, and -2.570, respectively.

<sup>c</sup>Test allows for a constant and a linear trend; one-sided test of the null hypothesis that the variable is nonstationary; 1%, 5%, and 10% critical values are -3.975, -3.431, and -3.132, respectively.

\*Significant at the 1% level.

\*\*Significant at the 5% level.

\*\*\*Significant at the 10% level.

### Exhibit 3. Linear and Nonparametric Cointegration Tests between Real House and Real Stock Prices

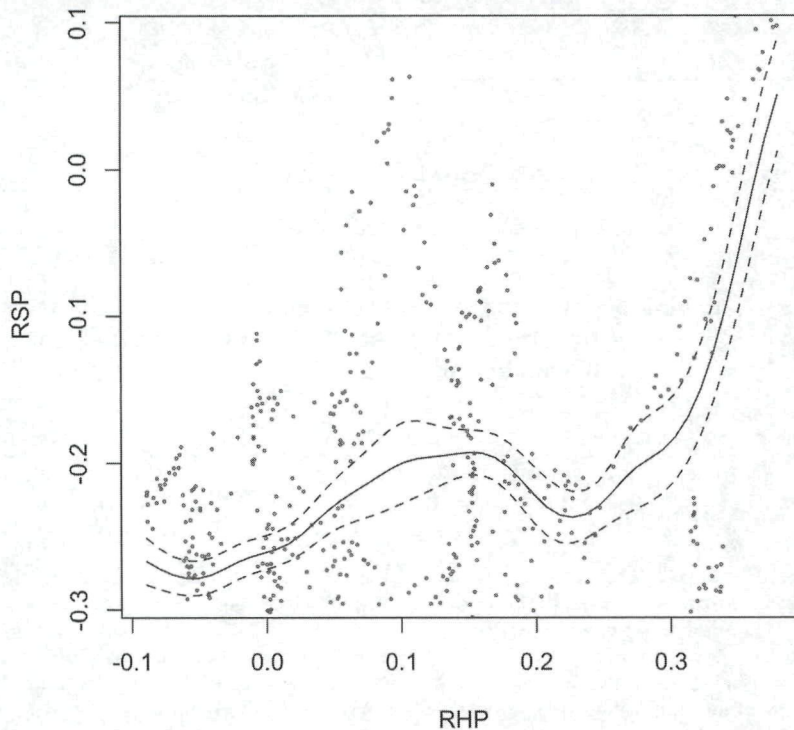
Test	$r$	Test Statistic	Critical Value		Conclusion		Final Remark
			10%	5%	10%	5%	
Panel A: Johansen (1988, 1991) Cointegration Test between Real House and Real Stock Prices							
Lambda-max	0	14.0	12.1	14.0	Reject	Accept	$r = 0$
	1	1.1	2.8	4.0	Accept	Accept	
Trace	1	1.1	2.8	4.0	Accept	Accept	
	0	15.1	13.3	15.2	Reject	Accept	
Panel B: Bierens (1997a) Nonparametric Cointegration Test between Real House and Real Stock Prices							
Lambda-min	0	0.00	0,0.005	0,0.017	Reject	Reject	$r = 1$
	1	0.52	0,0.111	0,0.054	Accept	Accept	
	0	67.51E+005	—	—	—	—	
$\hat{g}_m(r_0)$	1	16.33E-002 <sup>a</sup>	—	—	—	—	
	2	13.067+003	—	—	—	—	

Note:

<sup>a</sup>Minimum value of statistic:  $\hat{r} = \arg \min_{r_0 \leq q} \hat{g}_m(r_0)$  which determines the number of cointegration vector.

between real house and real stock prices.<sup>4</sup> This implies that there is a long-run relationship between the real house price and the real stock price. The standardized cointegrating vector is  $rsp = 0.89 \times rhp$ , which suggests that for a one percentage increase in real house price, real stock prices increase by around 0.89%. More importantly, the linear restriction  $\beta = [1, -1]$  cannot be rejected at the 5% level of significance. This implies that statistically there is a one-to-one long-run relationship between real house prices and real stock prices. Based on these results, the standard (linear) parametric cointegration framework clearly suffers from a misspecification problem.



**Exhibit 4. Real House Price versus Real Stock Price**

Notes: Figure plots the Nadaraya-Watson kernel regression function (straight line) using a second order Gaussian kernel along with 95% asymptotic variability bounds (dashed lines). Dots denote the actual data.

### Linear versus Nonparametric Granger Causality Tests

The linear Granger causality requires that all data series are stationary; otherwise, the inference from the  $F$ -statistic might be spurious because the test statistics would have non-standard distributions (Granger, 1988). In addition, we also considered whether real house price has a nonlinear predictive power for real stock price and/or vice versa, to compare our results with the linear versions of the same. Note that the Bierens (1997a) nonparametric method found a cointegrating relationship and the Johansen (1988, 1991) linear method could not, which implies that important non-linearities are associated with the short-run adjustment of real house prices and real stock prices to their implied fundamental values.

As a preliminary analysis, to detect both linear and nonlinear dynamic relationships between the two series, their scatter plot diagram is shown in Exhibit 4. The scatter plot displays an unclear relationship between the two series, especially in the lower and middle portions. The scatter plot, however, seems to imply a nonlinear dynamic link between the two series. In Exhibit 4, we also show the estimated Nadaraya-Watson kernel regression function using a second order Gaussian kernel along with asymptotic variability



**Exhibit 5. Pair-wise Linear Granger Causality Tests between Real House and Stock Prices**

Null Hypothesis	Lag	F-Statistic	P-value
$\Delta rsp \neq \Delta rhp$	2	0.041	0.960
$\Delta rhp \neq \Delta rsp$	2	0.824	0.439

Note: The symbol " $\neq$ " implies does not linearly Granger cause.

**Exhibit 6. Pairwise Nonlinear Granger Causality Tests between the Real House and Real Stock Prices based on the Nonparametric Additive Model**

Null Hypothesis	Lag	$h$ -CV	$h = 0.10$	$h = 0.15$	$h = 0.20$
$RSP \neq RHP$	2	F(0.784,526.180) = 2.993* (0.092)	F(0.800,516.403) = 3.203* (0.082)	F(0.846,512.067) = 3.111* (0.084)	F(0.836,507.162) = 3.084* (0.086)
$RHP \neq RSP$	2	F(5.361,516.328) = 2.633** (0.020)	F(5.470,507.402) = 2.854** (0.012)	F(5.381,502.475) = 2.861** (0.012)	F(5.444,497.413) = 2.811** (0.013)

Notes: This table provides the results of the nonlinear causality tests based on the additive models, applied for the real house and stock prices.  $F(v_1, v_2)$  is the  $F$ -statistic defined in equation (17), with  $v_1$  denoting the numerator degrees of freedom ( $d_U - d_R$ ) and  $v_2$  denoting the denominator degrees of freedom ( $T - d_U$ ).  $h$  is the bandwidth used for the kernel estimator such that observation falling in the range  $[x - k(h), x + k(h)]$  are used to obtain smoothed estimates at  $x$ .  $h$ -CV refers to the estimates where the bandwidth is automatically selected for each smooth component of the additive model using cross-validation. For other bandwidths reported, the same bandwidth is used for all smooth components.  $p$ -values of the tests are reported in the parentheses below each test. The symbol " $\neq$ " implies does not nonlinear Granger cause. The test statistic is approximately distributed as  $F$  and the critical values can be obtained from the standard  $F$ -distribution tables.

\*Rejection of the null hypothesis at the 10% significance level.

\*\* Rejection of the null hypothesis at the 5% significance level.

bounds. The nonlinear relationship between the real stock price and the real house price is evidenced by the Nadaraya-Watson kernel regression function plotted as a straight line.

The Granger causality test was conducted using two lags on the first difference of  $rhp$  and  $rsp$ , or in other words on the growth rates of these two variables, as they were expressed in log-levels. Recall that the VAR based on levels of  $rhp$  and  $rsp$  were estimated with three lags, as suggested by the SIC and the HQ criteria.<sup>5</sup> The linear pair-wise Granger causality tests are presented in Exhibit 5. As can be seen, we cannot reject either the hypothesis that real house prices do not Granger-cause real stock prices or vice versa. Therefore, there is no evidence of either the wealth effect or the credit-price effect based on the linear causality tests.

The results of the nonlinear Granger causality tests based on the nonparametric additive model estimates are presented in Exhibit 6. All tests are performed for four different bandwidths. The bandwidth  $h$  was chosen such that  $h \rightarrow 0$  as  $T \rightarrow \infty$ . The sample size for each series is moderately large and the range for each series is small. The automatic



bandwidths chosen by the CV method are all less than 0.1. Therefore, the robustness of additive model causality tests and AD estimates were checked using bandwidths,  $h = 0.1$ ,  $h = 0.15$ , and  $h = 0.2$ . The degrees of freedoms,  $d_U$  and  $d_R$ , for the model need to be obtained in order to compute the  $F$ -statistic in equation (17). Denoting additive models in equations (12) or (13) compactly as  $y = g(\mathbf{x}) + \varepsilon$ , then the Nadaraya-Watson kernel regression estimate of the function  $g$  can be written as  $\hat{g} = \mathbf{P}y$ , where  $\mathbf{P}$  is a matrix that contains the weights used for smoothing. Although there are alternative definitions of model degrees of freedom, the definitions proposed by Hastie and Tibshirani (1990) were used to obtain the degrees of freedom used to compute the  $F$ -statistic as  $d = 2\text{trace}(\mathbf{P}) - \text{trace}(\mathbf{P}'\mathbf{P})$ .

Exhibit 6 reports the  $F$ -tests performed on additive model estimates with the degrees of freedom estimates also given in the parentheses. These vary across models and bandwidths, since the weights used in smoothing vary in each case. According to the  $F$ -test results, a bi-directional nonlinear causal link exists between the real house price and the real stock price. Moreover, the results are robust to the various bandwidths. First, consider the tests with automatic bandwidth selection reported under the column named  $h$ -CV. In this case, the null hypotheses of no Granger causality from stock prices to house prices and no Granger causality from house prices to stock prices are both rejected at the 10% and 5% significance level, respectively. Therefore, there is strong evidence of bi-directional nonlinear causality based on the automatic choice of optimal bandwidth. When other bandwidths are considered, the results obtained with the  $h$ -CV are preserved.

Nonlinear causality tests based on the nonparametric additive model established strong evidence in favor of the bi-directional nonlinear causality between real house prices and real stock prices. It is also interesting to establish the sign of the predictability between the two series. Since more than one lagged value of each series enter into equations (12) and (13), Exhibit 7 reports the sum of the average derivative estimates. The results show that all total impact estimates are positive, irrespective of the bandwidth choice and the type of estimator used. This is the most noteworthy observation in Exhibit 7 relating to the sign of the predictability between the two series. The majority of the estimates are significant, suggesting that an increase in real stock prices will raise real house prices and vice versa, hence, supporting both the wealth effect and credit-price effect hypotheses. There is, however, stronger evidence of the credit-price hypothesis in the data, which vindicates our line of reasoning that, given the lower weight on housing as an investment vehicle, relative to stocks, in emerging market economies, the credit-price effect is likely to dominate the wealth effect.

Note that the untrimmed estimator gave much higher total impact estimates in some cases, mainly for the impact of real stock prices on real house prices. As pointed out above, the estimator  $\bar{\delta}_p$  is ill-behaved for values of the density function estimate  $\hat{g}(\mathbf{x})$  that are close to zero. As  $\hat{g}(\mathbf{x})$  approaches zero, it inflates the average derivative estimate  $\bar{\delta}_p$ , yielding an overestimate of the response. Hence, Hardle and Stoker (1989) proposed the trimmed estimator ( $\bar{\delta}_{hs}$ ). Our results show that the untrimmed estimator behaves well in most cases, but likely results in inflated estimates for the responses of real stock price on real house price.



**Exhibit 7. Average Derivative Estimates for the Sign of the Predictability between the Real House and Stock Prices based on the Nonparametric Additive Model**

	Lag	<i>h</i> -CV	<i>h</i> = 0.10	<i>h</i> = 0.15	<i>h</i> = 0.20
$\bar{\delta}_{hs} : RSP \Rightarrow RHP$	2	0.605 (0.342)**	0.575 (0.380)*	0.565 (0.369)*	0.527 (0.330)*
$\bar{\delta}_{hs} : RHP \Rightarrow RSP$	2	0.560 (0.350)*	0.516 (0.321)*	0.496 (0.303)*	0.496 (0.309)*
$\bar{\delta}_s : RSP \Rightarrow RHP$	2	0.441 (0.111)***	0.431 (0.091)***	0.402 (0.014)***	0.347 (0.097)***
$\bar{\delta}_s : RHP \Rightarrow RSP$	2	0.325 (0.026)***	0.295 (0.045)***	0.289 (0.059)***	0.244 (0.087)***
$\bar{\delta}_p : RSP \Rightarrow RHP$	2	0.573 (0.361)*	0.509 (0.442)	0.422 (0.403)	0.414 (0.432)
$\bar{\delta}_p : RHP \Rightarrow RSP$	2	0.519 (0.248)**	0.463 (0.240)**	0.458 (0.170)***	0.399 (0.208)**

Notes: This table provides the estimates of the average derivatives (AD). The estimates reported in rows labeled  $RSP \Rightarrow RHP$  are the sum of the average derivative estimates relating to lags of RSP series in the RHP equation (12). Analogously, the sum of the average derivative estimates relating to lags of RHP in RSP equation are labeled with  $RHP \Rightarrow RSP$ . *h* is the bandwidth used for the kernel estimator such that observation falling in the range  $[x - k(h), x + k(h)]$  are used to obtain smoothed estimate at *x*. *h*-CV refers to the estimates where the bandwidth is automatically selected for each smooth component of the AD using cross-validation. For other bandwidths reported, the same bandwidth is used for all smooth components. The standard errors of the sum of the ADs are obtained by the delta method and given in parentheses. The tests are asymptotically normally distributed and the critical values can be obtained from the standard normal distribution tables.

\*Rejection of the null hypothesis at the 10% significance level.

\*\*Rejection of the null hypothesis at the 5% significance level.

\*\*\*Rejection of the null hypothesis at the 1% significance level.

## Conclusion

We assess the long- and short-run relationships between real house and stock prices for South Africa using both linear and nonparametric approaches. Whereas the linear parametric tests indicated neither cointegration nor causality between real house price and real stock prices, when nonlinearity was taken into account, there are contrasting results. On the one hand, the nonparametric cointegration indisputably suggested the presence of cointegration (and a one-to-one statistical relationship) between real house price and real stock price. On the other hand, nonparametric Granger causality tests showed strong evidence of bi-directional causality. Taking together these two results from the nonparametric approaches implies that the two asset markets not only move together in the long-run, but also short-run interdependencies in the form of a wealth effect and a credit-price effect are prevalent in the South African economy.

It is thus clear that stability in the real estate market is critical for stability in the stock market and vice versa. Hence, South African policymakers need to be cautious in implementing policies so that instabilities are not generated in either of these two markets, since stability in the financial markets would be expected to enhance household welfare, reduce poverty, increase investment in portfolio assets, and promote economic growth. Overall, our results call for more careful attention in modeling of time series data, as linear models could lead to misspecification in the true nature of economic relationships, thus leading to wrong policy recommendations.



## Endnotes

- <sup>1</sup> While a group of studies such as Ibbotson and Siegel (1984), Hartzell (1986), Worzala and Vandell (1993), Eichholtz and Hartzell (1996), and Quan and Titman (1999) mainly concentrated on analyzing correlation between stock and house prices, the other group of studies by Liu, Hartzell, Greig and Grissom (1990), Lizieri and Satchell (1997), Okunev and Wilson (1997), Okunev, Wilson, and Zurbrugg (2000, 2002), Chen (2001), Fu and Ng (2001), Tse (2001), Sutton (2002), Kakes and Van den End (2004), Kapopoulos and Siokis (2005), Liow (2006), Oikarinen (2006), Sim and Chang (2006), and Ibrahim (2010) were concerned with the causal relationship, based on formal Granger-causality tests, between the two prices.
- <sup>2</sup> The unit root tests on first-differenced *rhp* and *rsp* results are available upon request from the authors.
- <sup>3</sup> Our results are unaffected when we choose seven lags based on the sequential modified likelihood ratio (LR) test statistic Akaike information criterion (AIC), the final prediction error (FPE) criterion. These results are available upon request from the authors. In the text, we decided to report results based on the SIC and the HQ criteria following Bierens (1997). This is because a smaller number of lags helps in preventing the problem of overparametrization encountered with the nonparametric approaches leading to inefficient estimates.
- <sup>4</sup> We also looked at the Breitung (2002) test of nonparametric cointegration. We detected one cointegration relationship between real house and stock prices when the variables were assumed to not have a drift term. However, cointegration could not be detected if the two variables were assumed to contain a drift term. These results are available upon request from the authors.
- <sup>5</sup> Similar results were obtained when we used six lags suggested by the LR, AIC, and FPE criterion for the growth rates of *rhp* and *rsp*. These results are available upon request from the authors.

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