# HOUSING AND THE BUSINESS CYCLE IN SOUTH AFRICA

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**ABSTRACT**

This paper examines the housing-output growth nexus in South Africa by accounting for the time variation in the causal link with a bootstrapped rolling Granger non-causality test. We use quarterly data on real gross domestic product, real house prices, real gross fixed capital formation and number of building plans passed. Our data span 1971Q2-2012Q2. Using full sample bootstrap Granger causality tests, we find a uni-directional causality from output to number of building plans passed; a uni-directional causality from real house price to output and a bi-directional causal link between residential investment and output. However, using parameter stability tests, we show that estimated VARs are unstable, thus full-sample Granger causality inference may be invalid. Hence, we use a bootstrap rolling window estimation to evaluate Granger causality between the housing variables and the growth rate. In general, we find that the causality from housing to output and, vice versa, differ across different sample periods due to structural changes. Specifically speaking, house price is found to have the strongest causal relationship with output compared to residential investment and number of building plans passed, with real house price showing predictive ability in all but one downward phase of the business cycle during this period.

**Keyword:** House price, residential investment, number of building plans, GDP, bootstrap, time varying causality

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## 1. INTRODUCTION

The objective of this paper is to analyze how housing market variables, namely, the growth rates of real house price, real residential investment and number of building plans passed, affect economic growth over the phases of the business cycle in South Africa. More specifically, we analyze time-varying (rolling) bootstrapped Granger causality between the housing variables and economic growth over the period 1971Q2–2012Q2, to determine if housing variables have a leading role to play in explaining business cycles in South Africa.

The relationship between the housing market and the business cycle has received a large amount of attention in the wake of the recent sub-prime crises, with an ever growing international literature[1] on this issue. As far as South Africa is concerned, analysis of housing variables and business cycle is sparse, to say the least[2]. Though, not surprisingly, quite a sizeable literature exists regarding general business cycle analysis.[3] The only related study that we could come across is by Burger (2010), who studied the role of residential investment, besides other components of the Gross Domestic Product (GDP), on real GDP using lead and lag correlations, Granger causality, and variance decomposition analyses for three sub-samples (1960:3 to 1976:2, 1976:3 to 1994:1 and 1994:2 to 2006:2). The paper indicated high correlation between the real GDP and the investment in residential buildings during the second and third sub-samples. However, Granger causality tests and variance decomposition failed to detect any evidence of residential investment to lead real GDP. In general, the author concluded that, since 1994 volatility in the South African economy decreased significantly, while durable consumption appears to lead the business cycle. Besides this, there exists a couple of other studies that have looked into the effect of real house prices on per capita economic growth at the provincial-level in South Africa using

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[1] See for instance, Leamer (2007), Fisher (2007), (Silos, 2007), Goodhart and Hofmann (2008), Álvarez and Cabrero (2010), Álvarez et al., (2010), Bulligan (2010), Bandt et al., (2010), Ferrara and Koopman (2010), , Ferrara and Vigna (2010), Ghent and Owyang (2010), Iacoviello (2010), Iacoviello and Neri (2010), Iacoviello and Pavan (forthcoming), Kiyotaki et al., (2011), Cinquegrana (2012), Kydland *et al.*, (2012),. Note, however, there also exists a few studies, such as: Benhabib et al. (1991), Greenwood and Hercowitz (1991), McGrattan, et al., (1997), Gomme et al. (2001), Davis and Heathcote (2005), Iacoviello (2002, 2005) which had also emphasized the role of housing on business cycle way before the recent financial crisis. Interestingly, Balcilar et al., (2013) even provide evidence of the role of house prices in causing the "Great Depression".

[2] Though, there exist quite a number of studies that have looked at the spillover of real house prices on consumption in both constant and time-varying parameter models. See for instance: Aron et al., (2006), Das et al., (2011), Ncube and Ndou (2011), Peretti et al., (2012), Simo-Kengne et al., (forthcoming), and Aye et al., (forthcoming a) .

[3] See for example Du Plessis (2006), Du Plessis et al., (2007, 2008), Aye et al., (forthcoming b), who based their business cycle analyses on structural vector autoregressions (SVARs) and sign restrictions-based VARs, while, Liu and Gupta (2007), Steinbach et al., (2009), Alpanda et al., (2010) and Jooste et al., (forthcoming) used dynamic stochastic general equilibrium (DSGE) models to analyze business cycles following real and monetary shocks..

panel data regressions (Simo-Kengne et al., 2012), and panel-Granger causality between real house prices and per capita economic growth at the provincial level (Chang et al., 2013) based on annual data.[4] However, to the best of our knowledge, we are not aware of any analyses that have simultaneously looked at all three of the above-mentioned housing variables and the business cycle in South Africa using a time-varying approach. Note that it is important to carry out the causality analysis using a rolling approach, especially for an emerging economy subjected to many structural changes, to account for the existence of structural breaks (which did occur as we show below) in the relationship between the growth rate of a specific housing variable and the growth rate of real GDP, besides providing us with relevant information of how the relationship between the GDP and housing variables might have changed over time. The remainder of the paper is organized as follows: Section 2 discusses the methodology and data used. Section 3 presents the results, while section 4 concludes.

## 2. METHODOLOGY

### 2.1 Econometric Model

The paper investigates whether real house prices, residential fixed investment and building plans passed Granger cause economic growth. The null hypothesis is Granger non-causality. Granger non-causality is defined as a situation when the information set on the first variable (e.g., house prices) does not improve the prediction of the second variable (e.g., GDP) over and above its own information. The Granger non-causality test is performed to determine whether the lagged values corresponding to the first variable are jointly significant or not. Generally in the VAR framework, standard causality test statistics for joint restriction and non-asymptotic properties include the *Wald*, Likelihood ratio (*LR*) and Lagrange multiplier (*LM*) statistics. For these test statistics, it is assumed that the underlying data is stationary and when this assumption does not hold, they may not have standard asymptotic distributions. The difficulties that arise when estimating these VAR models with non-stationary data have been shown by Park and Phillips (1989) and Toda and Phillips (1993, 1994), among others.

Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), proposed a modification to

[4] In addition to this, Gupta and Hartley (forthcoming) provide evidence of the ability of real house prices, amongst other asset prices, in forecasting growth and inflation in South Africa.

the standard Granger causality test and obtained standard asymptotic distribution when the time series forming the VAR($p$), where $p$ is the lag order, are I(1). The modified Granger causality test is based on estimating a VAR($p$+1) in levels of the variables and the results obtained are valid irrespective of the integration-cointegration properties of the variables. In essence, the modification estimates a VAR($p$+1) and performs the Granger non-causality test on the first $p$ lags. Thus, one coefficient matrix, which relates to the $(p+1)^{\text{th}}$ lag, remains unrestricted under the null, giving the test a standard asymptotic distribution.

The outstanding performance (in terms of power and size) of the residual based bootstrap (*RB*) method over standard asymptotic tests, regardless of cointegration or not, has been demonstrated in a number of Monte Carlo simulations studies (Horowitz ,1994; Shukur and Mantalos, 1997a, 1997b; Mantalos and Shukur, 1998; Shukur and Mantalos, 2000; Mantalos, 2000; Hacker and Hatemi-J, 2006). Therefore, following Balcilar and Ozdemir (2013) and Balcilar et al. (2013), this current study resorts to the *RB* based modified-*LR* statistics to examine the causality between housing variables and GDP in South Africa. To illustrate the bootstrap modified-*LR* Granger causality, consider the following bivariate VAR($p$) process:

$$z_t = \Phi_0 + \Phi_1 z_{t-1} + \ \dots\ + \Phi_p z_{t-p} + \varepsilon_t, \quad t = 1,\ 2,\ \dots, T, \tag{1}$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is a white noise process with zero mean and covariance matrix Σ and $p$ is the lag order of the process. In the empirical section, the Akaike Information Criterion (*AIC*) is used to select the optimal lag order $p$. To simplify the representation, $z_t$ is partitioned into two sub-vectors, a housing variable (real house prices or residential fixed investment or building plans passed) ($z_{ht}$) and GDP ($z_{yt}$). Hence, rewrite equation (1) as follows:

$$\begin{bmatrix} z_{ht} \\ z_{yt} \end{bmatrix} = \begin{bmatrix} \phi_{h0} \\ \phi_{y0} \end{bmatrix} + \begin{bmatrix} \phi_{hh}(L) & \phi_{hy}(L) \\ \phi_{yh}(L) & \phi_{yy}(L) \end{bmatrix} \begin{bmatrix} z_{ht} \\ z_{yt} \end{bmatrix} + \begin{bmatrix} \varepsilon_{ht} \\ \varepsilon_{yt} \end{bmatrix}, \tag{2}$$

where $\phi_{ij}(L) = \sum_{k=1}^{p+1} \phi_{ij,k} L^k$ , $i, j = h,\ y$ and $L$ is the lag operator such that $L^k z_{it} = z_{it-k}$ , $i = h,\ y$ .

In this setting, the null hypothesis that GDP does not Granger cause a housing variable can be tested by imposing zero restrictions $\phi_{hy,i} = 0$ for $i = 1,\ 2,\ \dots, p$. In other words, GDP does not contain predictive content, or is not causal, for a particular housing variable if the joint zero restrictions under the null hypothesis:

$$H_0^{HF}: \quad \phi_{hy,1} = \phi_{hy,2} = \cdots = \phi_{hy,p} = 0. \tag{3}$$

are not rejected. Analogously, the null hypothesis that a particular housing variable does not

Granger cause GDP implies that we can impose zero restrictions $\phi_{yh,i} = 0$ for $i = 1, 2, \ldots, p$. In this case, the real house price does not contain predictive content, or is not causal, for GDP if the joint zero restrictions under the null hypothesis:

$$H_0^{LI}: \quad \phi_{yh,1} = \phi_{yh,2} = \cdots = \phi_{yh,p} = 0\,. \tag{4}$$

are not rejected.

The Granger causality tests in equations (3) and (4) can be linked to the *HF* (housing fundamentals) and *LI* (leading indicator) hypotheses as follows. First, under a narrow definition, rejection of $H_0^{LI}$ in equation (4) but not $H_0^{HF}$ in equation (3), establishes evidence in favor of the *LI* hypothesis. On the other hand, rejection of the null hypothesis specified under $H_0^{HF}$ in equation (3), but not the null hypothesis specified under $H_0^{LI}$ in equation (4), supports the *HF* hypothesis. Second, under the broader definition, evidence in favour of the *LI* hypothesis is established, if $H_0^{LI}$ in Eq. (4) is rejected or both $H_0^{LI}$ in Eq. (4) and $H_0^{HF}$ in Eq. (3) are rejected. Analogously, the rejection of $H_0^{HF}$ in Eq. (3) or rejection of both $H_0^{LI}$ in Eq. (4) and $H_0^{HF}$ in Eq. (3) establishes evidence in support of the *HF* hypothesis. The narrow definition requires uni-directional causality running from one variable to another, while the broader definition allows bidirectional causality. Both narrow and broader definitions are employed in this study to make causality inference.

The causality hypothesis in equations (3) and (4) can be tested using a number of testing techniques. However, this study uses the bootstrap approach pioneered by Efron (1979) which uses critical or *p* values generated from the empirical distribution derived for the particular test using the sample data. In our case, the bootstrap approach is employed to test for Granger non-causality. As previously mentioned the robustness of the bootstrap approach for testing Granger non-causality has been illustrated. In this paper, we employ the bootstrap approach with the Toda and Yamamoto (1995) modified causality tests, because of several advantages. In particular, this test applies to both cointegrated and non-cointegrated *I(1)* variables (Hacker and Hatemi-J, 2006).[5]

Granger non-causality tests assume that parameters of the VAR model used in testing are constant over time. This assumption is often violated because of structural changes and as Granger (1996) pointed out, parameter non-constancy is one of the most challenging issues

[5] See the Appendix of Balcilar and Ozdemir (2013) for technical details of the bootstrap procedure.

confronting empirical studies today. Although the presence of structural changes can be detected beforehand and the estimations can be modified to address this issue using several approaches, such as including dummy variables and sample splitting, such an approach introduces pre-test bias. Therefore, this study adopts rolling bootstrap estimation in order to overcome the parameter non-constancy and avoid pre-test bias.[6] To examine the effect of structural changes, the rolling window Granger causality tests, which are also based on the modified bootstrap test, are used. Structural changes shift the parameters and the pattern of the causal relationship may change over time. To deal with structural changes and parameter non-constancy, this paper in addition to full sample estimation, applies the bootstrap causality test to rolling window subsamples for $t = \tau\text{-}l+1, \tau\text{-}l, ..., \tau$, $\tau = l, l+1, ..., T$, where $l$ is the size of the rolling window.

Prior to investigating Granger causality, we test for the stationarity of the data using the $Z_\alpha$ Phillip (1987) and Philips and Perron (1988) (PP) unit root test. We also test for cointegration using the Johansen's (1991) maximum likelihood cointegration method. Further, the parameter values and the pattern of the (no) cointegration and (no) causal relationship may change over time due to structural changes. The results of the cointegration and Granger causality tests will be sensitive to sample period used and order of the VAR model, if the parameters are temporally instable (Balcilar and Ozdemir, 2013). Hence, conflicting results for the causal links between housing variables and GDP can be found by studies using different sample periods and different VAR specifications. The results of cointegration and Granger causality tests based on the full sample also become invalid with structural breaks because they assume parameter stability. Therefore, this study tests for parameter stability in the estimated VAR models following (Balcilar and Ozdemir, 2013) and Balcilar, et al. (2013).

In practice, a number of tests exist for examining the temporal stability of VAR models (e.g. Hansen, 1992; Andrews, 1993; Andrews and Ploberger, 1994). These tests can be applied in a straightforward manner to stationary models. However, there is a possibility that the variables in the VAR models may be nonstationary and or cointegrated. This integration (cointegration) property needs to be accounted for. This is because the variables form a VECM in a cointegrated VAR. Therefore, both long-run cointegration and short-run dynamic adjustment parameters needs to be investigated for stability. The model exhibits long-run

[6] Details of the rolling window technique are also explained in Appendix of Balcilar and Ozdemir (2013).

stability if the long-run or cointegration parameters are stable. Additionally, the model can be said to exhibit full structural stability if the short-run parameters are also stable. Given the super consistency of the estimators of cointegration parameters, the parameter stability testing can be split into two steps. First, the stability of the cointegration parameters are tested. Second, if long-run parameters are stable, the stability of the short-run parameters can be tested. To examine the stability of the cointegration parameters, we use the $L_c$ tests of Nyblom (1989) and Hansen (1992). The Nyblom-Hansen $L_c$ test is an *LM* test for parameter constancy against the alternative hypothesis that the parameters follow a random walk process and, therefore, time-varying, since the first two moments of a random walk are time dependent (Balcilar et al., 2013). The $L_c$ test is calculated using the fully modified OLS (FM-OLS) estimator of Phillips and Hansen (1990). Next, the *Sup-F*, *Ave-F* and *Exp-F* tests developed by Andrews (1993) and Andrews and Ploberger (1994) are used to investigate the stability of the short-run parameters. These tests are computed from the sequence of *LR* statistics that tests constant parameters against the alternative of a one-time structural change at each possible point of time in the full sample. These tests exhibit non-standard asymptotic distributions and the critical values are reported in Andrews (1993) and Andrews and Ploberger (1994). To avoid the use of asymptotic distributions, the critical values and *p*-values are obtained using the parametric bootstrap procedure. Specifically, the *p*-values are obtained from a bootstrap approximation to the null distribution of the test statistics, constructed by means of Monte Carlo simulation using 2000 samples generated from a VAR model with constant parameters. The *Sup-F*, *Ave-F* and *Exp-F* tests needs to be trimmed at the ends of the sample. Following Andrews (1993) we trim 15 percent from both ends and calculate these tests for the fraction of the sample in [0.15, 0.85].

### 2.2 Data

The data used for the analysis is quarterly data and spans from 1971:Q1 to 2012:Q2. As a measure for house prices, we use the entire middle-segment nominal house price index obtained from Amalgamated Bank of South Africa (ABSA) – one of the major private banks in South Africa. This index is available at a monthly frequency, and is converted to quarterly values based on a three-month average. Note that, ABSA categorises South African housing market into three major price segments, namely, luxury (ZAR 3.5 million – ZAR 12.8 million), middle (ZAR 480,000 – ZAR 3.5 million) and affordable (below ZAR 480,000 and area between 40 square metres - 79 square metres). The middle-segment is further categorized into three more segments based on sizes, namely large-middle (221 square metres

– 400 square metres), medium-middle (141 square metres – 220 square metres) and small-middle (80 square meters – 140 square meters). We use the entire middle-segment house price data as it is believed to be the most representative of the general house price level prevailing in the economy. The Consumer Price Index (CPI), also available monthly but converted to quarterly frequencies through temporal aggregation, sourced from the International Monetary Fund (IMF) database is then used to deflate the nominal house price index to obtain the real house price (*HP*). We also use real gross domestic product (GDP), real gross fixed capital formation in residential buildings (residential investment) (*GFCF*), both at 2005 South African Rand (ZAR) values, as well as, the number of building plans passed of flats, townhouses and houses bigger than 80 square metres (*NUM*)[7] obtained from South Africa Reserve Bank (SARB). All the series were obtained in their seasonally adjusted forms. The plots of the quarter-on-quarter growth rates of each series are presented in Appendix 3. Since, we work with growth rates our effective sample starts from 1971:Q2. Note that the starting point of the sample is driven by the common date of data availability for all these variables, while the end-point (2012:Q2) is also based on availability of data at the time of writing this paper.

The preliminary inspection of the growth rates of both GDP and housing variables show that these series exhibit some volatility. In general, the growth rates of housing variables slowed down before each of the downward phases of the business cycle. This might be an indication that housing might have contributed to the downward phases in the economy.

## 3. RESULTS

Using the Phillip (1987) and Philips and Perron (1988) (PP) unit root test, we examine the stationarity of the series. We report results for intercept, as well as intercept and trend. The results for unit root tests are reported in Table 1. The critical value refers to the Mackinnon (1996) criteria. The null hypothesis of non-stationarity for *GDP*, *HP*, *GCFC* and *NUM* cannot be rejected at the 5 per cent significance level. This is robust to intercept as well as intercept and trend assumptions. However, the results show that when the series are tested in their first differences, they are all stationary, meaning they are integrated of order one i.e. I(1). We also test for a common stochastic trend, which implies a cointegration relationship between output and housing variables. We use Johansen's (1991) maximum likelihood cointegration method. We use optimal lag order of two for the VAR comprising of the growth rates of the GDP and

[7]This definition is applied to exclude low-cost housing provided by Government as part of the Reconstruction and Development (RDP) programme.

both house price and residential investment, and five for the VAR with the growth rates of GDP and the number of building plans passed as determined by the Akaike Information Criterion (AIC).[8] The null hypothesis of no cointegration could not be rejected in any of the pairs. We therefore conclude that there is no long run relationship between GDP and any of the housing variables studied. We use the *Lc* of Nyblom (1989) and Hansen (1992) test to determine the parameter stability of the estimated VAR for each equation and found significant evidence of parameter instability. This again points to the non-existence of stable long-run parameters between output and housing.[9]

**Table 1**: **Unit root test results**

| | Level | | First differences | |
|---|---|---|---|---|
| Series | (constant) | (constant and trend) | (constant) | (constant and trend) |
| *GDP* | 0.41 | -1.22 | -8.9*** | -8.9*** |
| *GFCF* | -1.94 | -2.02 | -12.08*** | -12.06*** |
| *HP* | -1.01 | -1.29 | -4.40*** | -4.49*** |
| *NUM* | -1.96 | -2.24 | -12.39*** | -12.36*** |

*** indicates 1% level of significance

Given that no cointegration is found, the next step is to determine the full sample Granger causality using bivariate VARs (comprising of the growth rates of the real GDP and the specific housing variable) rather than VECM. The results are presented in the first panel of Table 2. We use *Wald*-statistics to test for Granger causality in the estimated VAR. We reject the null hypothesis that house price does not Granger cause output at 1 percent level of significance. However, we cannot reject the null hypothesis that output does not Granger cause house price. Therefore, the *Wald* test indicates that house price has predictive content for output, but output does not have predictive content for house price. For robustness check, we also perform the bootstrap *LR* causality test. The bootstrap *LR*-test uses the *p*-values obtained with 2000 replicates. Similar results are obtained as in the *Wald* test case. Given the complementarity between the *Wald* and bootstrap *LR* tests, it can be concluded at the moment that based on the full sample of quarterly data spanning 1970 to 2011, there is a no long-run relationship between house price and GDP. However, there is a uni-directional short-run

[8]The cointegration results based on the Trace and maximum Eigen-value statistics are reported in Appendix 1.
[9]See Appendix 2 for the Nyblom-Hansen *Lc* test results for individual equations for the VAR model in levels. The results indicate that in each of the equations, parameter constancy is rejected at 1 percent and hence, there are no stable long-run parameters. This, along with the lack of cointegration, justifies our non-inclusion of error correction term in the models. So, our VARs in growth rates-form are not misspecified.

relationship between house price and GDP with the direction flowing from house price to output.

We also perform the *Wald* and bootstrap *LR*-test for causality between residential investment (*GCFC*) and output based on the full sample. The results are presented in the second panel of Table 2. We reject the null hypothesis that residential investment does not Granger cause output at the 5 percent level of significance. We also reject the null hypothesis that output does not Granger cause residential investment at 1 percent level of significance. This finding is robust to both the *Wald* and bootstrap *LR* tests. This implies that there is a bi-directional causal link between residential investment and output for South Africa, at least based on the full sample. Therefore, residential investment has predictive content for output and output also has predictive content for residential investment. We now turn to the causality between number of building plans passed (*NUM*) and output. The results are reported in the third panel of Table 2. Results from both the *Wald* and bootstrap *LR* tests are similar. The null hypothesis of non-Granger causality between number of building plans passed and output could not be rejected at any of the conventional significance level. This implies that *NUM* has no predictive content for output. However, we found that output has predictive content for *NUM* as the non-Granger causality hypothesis is rejected at 10 percent level of significance based on the full sample.

**Table 2: Full Sample Granger Causality Tests**

| | **$H_0$: *HP* does not Granger cause *GDP*** | | **$H_0$: *GDP* does not Granger cause *HP*** | |
|---|---|---|---|---|
| | Statistics | *p*-value[a] | Statistics | *p*-value[a] |
| *WALD* test | 22.02 | 0.000 | 4.21 | 0.485 |
| *LR* | 20.37 | 0.000 | 4.14 | 0.485 |
| | **$H_0$: *GFCF* does not Granger cause *GDP*** | | **$H_0$: *GDP* does not Granger cause *GFCF*** | |
| *WALD* test | 5.91 | 0.047 | 10.85 | 0.003 |
| *LR* | 5.80 | 0.047 | 10.48 | 0.003 |
| | **$H_0$: *NUM* does not Granger cause *GDP*** | | **$H_0$: *GDP* does not Granger cause *NUM*** | |
| *WALD* test | 2.36 | 0.300 | 4.65 | 0.088 |
| *LR* | 2.35 | 0.305 | 4.58 | 0.088 |

Note: [a]*p*-values are calculated using 2000 bootstrap repetitions.

The parameter constancy tests as previously described are used to investigate the temporal stability of the coefficients of the VAR model formed by GDP and a specific housing series. The results for both housing and output equations along with the associated *p*-values are presented in Tables 2-4. The $L_c$ test statistics is reported for the unrestricted bivariate VAR model as a whole.[10] For the relationship between output and residential investment (Table 3), the VAR model as a whole proves unstable at 1 percent level as indicated by the system $L_c$ statistics. Similarly, parameter stability is rejected for the case of GDP and house price (Table 4) and GDP and number of building plans passed (Table 5) at both the 1 and 5 percent levels, respectively. These findings support the notion that parameters of the VAR system in each of the bivariate VARs are unstable.

**Table 3 Parameter Stability Tests for *GCFC* and *GDP* VAR(2) Model in Growth Rates**

| | Residential investment Equation | | Output Equation | | VAR (2) system | |
|---|---|---|---|---|---|---|
| | Statistics | Bootstrap *p*-value[a] | Statistics | Bootstrap *p*-value[a] | Statistics | Bootstrap *p*-value[a] |
| *Sup-F* | 20.15** | 0.02 | 36.56*** | <0.01 | 42.40*** | <0.01 |
| *Ave-F* | 12.71*** | <0.01 | 14.90*** | <0.01 | 27.19*** | <0.01 |
| *Exp-F* | 7.28** | 0.02 | 14.21*** | <0.01 | 18.24*** | <0.01 |
| *Lc*for system[b] | | | | | 4.93*** | 0.01 |

Notes: *, **, and *** denote significance at 10, 5 and 1 percent, respectively.

[a]*p*-values are calculated using 2000 bootstrap repetitions.

[b]Hansen-Nyblom parameter stability test for all parameters in the VAR(2) jointly.

[10]See Appendix 2 for the *Lc* statistics for individual equations for VAR model in levels. The results indicate that in each of the equations, parameter constancy is rejected at 1 percent and hence there are no stable long-run parameters. This justifies our non-inclusion of error correction term in the models.

**Table 4: Parameter Stability Tests for *HP* and *GDP* VAR Model (2) in Growth Rates**

| | House Price Equation | | Output Equation | | VAR (2) system | |
|---|---|---|---|---|---|---|
| | Statistics | Bootstrap *p*-value[a] | Statistics | Bootstrap *p*-value[a] | Statistics | Bootstrap *p*-value[a] |
| *Sup-F* | 73.87*** | <0.01 | 104.47*** | <0.01 | 64.56*** | <0.01 |
| *Ave-F* | 31.96*** | <0.01 | 24.99*** | <0.01 | 35.03*** | <0.01 |
| *Exp-F* | 32.39*** | <0.01 | 48.20*** | <0.01 | 27.73*** | <0.01 |
| $L_c$ for system[b] | | | | | 5.57*** | 0.01 |

Notes: *, **, and *** denote significance at 10, 5 and 1 percent, respectively.

[a]*p*-values are calculated using 2000 bootstrap repetitions.

[b]Hansen-Nyblom parameter stability test for all parameters in the VAR(2) jointly.

**Table 5: Parameter Stability Tests for *NUM* and *GDP* VAR Model (5) in Growth Rates**

| | *DNUM* Equation | | *DGDP* Equation | | VAR (5) system | |
|---|---|---|---|---|---|---|
| | Statistics | Bootstrap *p*-value[a] | Statistics | Bootstrap *p*-value[a] | Statistics | Bootstrap *p*-value[a] |
| *Sup-F* | 17.90** | 0.05 | 30.80*** | <0.01 | 39.32*** | <0.01 |
| *Ave-F* | 13.11*** | <0.01 | 18.40*** | <0.01 | 23.85*** | <0.01 |
| *Exp-F* | 7.26** | 0.02 | 12.54*** | <0.01 | 16.08*** | <0.01 |
| $L_c$ for system[b] | | | | | 2.68** | 0.03 |

Notes: *, **, and *** denote significance at 10, 5 and 1 percent, respectively.

[a]*p*-values are calculated using 2000 bootstrap repetitions.

[b]Hansen-Nyblom parameter stability test for all parameters in the VAR(5) jointly.

Among parameter constancy statistics used for testing short-run parameter stability in this study, *Sup-F* statistics tests parameter constancy against a one-time sharp shift in parameters. However, if the regime shift is gradual, then the *Ave-F* and *Exp-F*, which assumes that parameters follow a martingale process, are appropriate. Both the *Ave-F* and the *Exp-F* statistics test the overall constancy of the parameters, i.e., they are appropriate to investigate whether the underlying relationship among the variables stays stable over time. The *Ave-F* and *Exp-F* are both optimal tests as shown by Andrews and Ploberger (1994). The results for the sequential *Sup-F*, *Ave-F*, and *Exp-F* tests, reported in Table 4, suggests that significant evidence of parameter non-constancy exists in all the six equations, as well as the entire VAR system. These results corroborate the results from the $L_c$ test. These findings indicate instability in the short-run parameters of the VAR model as evidence of both a one-time shift and gradual shifting of the parameters are supported.  Overall, Granger causality tests based on the full sample VAR model estimated for the GDP and housing variables for South Africa are not reliable, since the parameters of the VAR model are not constant over the sample period.

The parameter constancy tests point to structural change. This indicates that in the presence of structural changes, the dynamic relationship between output and housing will show instability across different subsamples. This study attempts to investigate this by estimating the VAR model described above using rolling window regression techniques. The rolling window estimators, also known as fixed-window estimators, are based on a changing subsample of fixed length that moves sequentially from the beginning to the end of sample by adding one observation from the forward direction and dropping one from the end. Assume that each rolling subsample includes $l$ observations, i.e., the window size is equal to $l$. In each step, we perform the causality test using residual based bootstrap method on this subsample. This provides us with a $T-l$ sequence of causality tests, instead of just one. The rolling estimation adopted here is justified for a number of reasons. First, rolling estimation allows the relationship between the variables to evolve through time. Second, the presence of structural changes introduces instability across different subsamples and rolling estimation conveniently captures this, in our case, by considering a sequence of 125 different subsamples (starting with 1971Q2 and ending with 2012Q2) for a 40 quarter fixed window.

An important choice parameter in rolling estimations is the window size *l*. The window size is the parameter that controls the number of observations covered in each subsample. The window size also determines the number of rolling estimates, since a larger window size will reduce the number of observations available for estimation. More importantly, the precision and representativeness of the subsample estimates are controlled by the window size. A large window size increases the precision of estimates, but may reduce the representativeness, particularly, in the presence of heterogeneity. On the contrary, a small window size will reduce heterogeneity and increase representativeness of the parameters, but it may increase the standard error of estimates, which reduces accuracy (Balcilar and Ozdemir, 2013).

Therefore, the window size should be set in such a way that not a too large or too small proportion of observations are included in each subsample regression. By so doing, the trade-off between accuracy and representativeness is balanced. Following Koutris et al., (2008) and Balcilar and Ozdemir (2013) we use a rolling window of small size to guard against heterogeneity. Our choice of small window size may lead to imprecise estimates. Therefore, we apply bootstrap technique to each subsample estimation so as to obtain parameter estimates and tests with better precision.

The selection of window size in rolling window estimation has no strict criterion. Pesaran and Timmerman (2005) examined the window size under structural change in terms of root mean square error. They show that optimal window size depends on persistence and size of the break. Their Monte Carlo simulations showed that the bias in autoregressive (AR) parameters are minimized with a window size as low as 20 when there are frequent breaks. In determining the window size, we need to balance between two conflicting demands. First, the accuracy of parameter estimates which depends on the degree of freedom and requires a larger window size for higher accuracy. Second, the presence of multiple regime shifts increases the probability of including some of these multiple shifts in the windowed sample. To reduce the risk of including multiple shifts in the subsamples, the window size needs to be small. Based on the simulation results in Pesaran and Timmerman (2005) we use a window size of 40 (this excludes the observations required for lags and hence is the actual number of observations in the VAR). We estimate the bootstrap $p$-value of observed $LR$-statistic rolling over the whole sample period 1971:Q2-2012:Q2 in order to further examine the likely temporal changes in the causality relationship. To do this, the VAR model in Eq. (1) is estimated for a time span of 40 quarters (10 years) rolling through $t = \tau - 39, \tau - 38, \ldots, \tau, \tau = 40, \ldots, T$ and calculate the bootstrap $p$-values of the null hypothesis that housing does not Granger cause output and that output do not Granger cause housing using the residual based method. More precisely, we compute the residual based $p$-values of the modified $LR$-statistics that tests the absence of Granger causality from housing to output or *vice-versa.* These are computed from the VAR($p$+1) defined in Eq. (2) fitted to a rolling windows of 40 observations.

The magnitude of the effect of each housing variable on output and the effect of output on each housing variable is also calculated. The effect of housing on output is calculated as the mean of the all the bootstrap estimates, that is, $N_b^{-1}\sum_{k=1}^{p}\hat{\phi}^{*}_{hy,k}$ , where $N_b$ equals the number of bootstrap repetitions. Analogously, the effect of output on housing is calculated as the mean of the all bootstrap estimates, that is $N_b^{-1}\sum_{k=1}^{p}\hat{\phi}^{*}_{yh,k}$ . We calculate these results rolling through the whole sample with a fixed window size of 40 quarters. The estimates $\hat{\phi}^{*}_{hy,k}$ and $\hat{\phi}^{*}_{yh,k}$ are the bootstrap least squares estimates from the VAR in equation (2) estimated with the lag order of *p* determined by the AIC. The 90-percent confidence intervals are also calculated, where the lower and upper limits equal the 5$^{th}$ and 95$^{th}$quantiles of each of $\hat{\phi}^{*}_{hy,k}$ and $\hat{\phi}^{*}_{yh,k}$ , respectively.

The plots of the bootstrap *p*-values of the rolling test statistics and the magnitude of the impact of each series on the other are given in Figures 1 to 6, with the horizontal axes showing the final observation in each of the 40-quarter rolling windows.[11] Figure 1a shows the bootstrap *p*-values of the rolling test statistics, testing the null hypothesis that residential investment does not Granger-cause output. The non-causality tests are evaluated at 10 percent significance level. Figure 1b shows the bootstrap estimates of sum of the rolling coefficients for the impact of residential investment on output. Figure 1a shows that the *p*-values change substantially over the sample and the null hypothesis that residential investment does not have predictive power for outputs during a downward phase is rejected at the 10 percent significance level in 1988Q2, that is, before the third downward phase. This therefore implies that residential investment contributed to at least one downward phase of the business cycle. Figure 1b shows that for most of the sub-periods, the sign of the impact of residential investment on output is positive with the effect being significant during 1986Q3-1988Q4 just before the third downward phase and between 1990Q1-1993Q1 during the third downward phase. The bootstrap rolling-sample results from Figures 1a and 1b indicate that residential investment has rather a weak causal link with output. The *HF* hypothesis that output is driven by residential investment is supported, although weakly.

Figure 2a shows the bootstrap *p*-values of the rolling test statistics, testing the null hypothesis that output does not Granger-cause residential investment. Figure 2b shows the bootstrap estimates of sum of the rolling coefficients for the impact of output on residential investment. Similar to Figure 1a, Figure 2a shows that the reported *p*-values change substantially over the

[11]Shaded areas correspond to a downward phase in the business cycle.

sample period suggesting there have been important changes in the causal link over the sample period. We find that output has predictive ability for residential investment before the first downward phase (1981Q2-1981Q3), during the first downward phase (1981Q4-1983Q2), before the second downward phase (1986Q2-1986Q3), before the fourth downward phase (1995Q2-1996Q1), before (2001Q1-2008Q1) and during the most recent downward phase (2008Q2-2009Q2). Figure 2b shows that output has positive and significant effect on residential investment at 10 percent level before the first downward phase (1981Q2-1981Q3), during the first downward phase (1981Q4-1983Q1) and before the most recent downward phase (2000Q1-2007Q1). Although output had a negative effect on residential investment during the third and most recent downward phases, these effects are not significant at 10 percent level. In brief, the results in Figure 2 indicate this. Hence, the *LI* hypothesis that residential investment is growth driven is supported in at least three out of five downward phases. Bi-directional causality between output and residential investment can be concluded.

Figure 3a shows the bootstrap *p*-values of the rolling test statistics, testing the null hypothesis that number of building plans passed (*NUM*) does not Granger-cause output. Figure 3b shows the bootstrap estimates of sum of the rolling coefficients for the impact of *NUM* on output. Again the *p*-values reported in Figure 3a have markedly changed over the sample period. However, the figure indicates that *NUM* has no predictive content for output at 10 percent, neither before nor during any of the downward phases. Hence, the null hypothesis that *NUM* does not Granger cause output cannot be rejected at 10 percent level. Figure 3b shows that the impact of *NUM* on output is positive during the first three downward phases and negative during the last two. However, there is no clear significant effect of *NUM* on output at any of the sub-periods. In general the *HF* hypothesis is not supported, meaning that the number of building plans passed holds no predictive content during any of the downward phases.

Figure 4a shows the bootstrap *p*-values for the null hypothesis that output does not Granger-cause number of building plans passed (*NUM*). Figure 4b shows the bootstrap estimates of sum of the rolling coefficients for the impact of output on *NUM*. Again the *p*-values as reported in Figure 4a have changed substantially over time. From the bootstrapped rolling window *p*-values, it is observed that output has predictive content for *NUM* before (2002Q2-2003Q3 and 2006Q3) and after (2009Q2-2009Q4) the most recent downward phase. Figure 4b shows that the output has a positive and significant impact on *NUM* before the most recent downward phase (2002Q3 and 2006Q3-2007Q1). Hence the leading indicator hypothesis is supported in this case.

Figure 5a shows the bootstrap *p*-values for the null hypothesis that house price does not Granger-cause output. Figure 5b shows the bootstrap estimates of sum of the rolling coefficients for the impact of house price on output. Figure 5a suggests there have been important changes in the causal link over the sample period. The null hypothesis that house price does not Granger cause output is rejected at 10 percent level for four out of five downward phases. There are rejections before (1981Q2-1981Q3) and during (1981Q4-1983Q1) the first downward phase, before (1983Q2-1984Q2) and during (1984Q3-1986Q2) the second downward phase, before (1994Q2-1996Q1) and during (1997Q2) the third downward phase, and during (2009Q3) the most recent downward phase. Figure 5b shows that house price has a positive and significant impact on output before (1981Q2) the first downward phase, before (2006Q2-2006Q4) and during (2008Q3-2009Q3) the most recent downward phase. Even after the most recent downward phase (2009Q4-2012Q2), house price continued to have a significant positive effect on output. Although, house price has a negative impact on output during the fourth and later part of the first downward phase, these impacts are not significant at 10 percent. Therefore, it can be concluded that house price leads output during downward phases, thus supporting the *HF* hypothesis.

Figure 6a shows the bootstrap *p*-values for the null hypothesis that output does not Granger-cause house price. Figure 6b shows the bootstrap estimates of sum of the rolling coefficients for the impact of output on house price. In line with Figure 5a, Figure 6a suggests there have been important changes in the causal link over the sample period. Output has predictive content for house price before (1986Q4-1987Q2) and during (1989Q4-1992Q1) the third downward phase of the business cycle. The predictive ability is also observed even after (2012Q1-2012Q2) the most recent downward phase. Figure 6b shows that the impact of output on house price during the most recent downward phase (2009Q1 and 2009Q3) is negative and significant at 10 percent level. Overall, house price appear to have more predictive content for output compared to residential investment and building plans passed as is evident in the number of times it led output before downward phases.

From the above discussion, it is evident that housing plays an important role in affecting growth in South Africa over the phases of the business cycle. However, the different structural changes that have occurred in South Africa have impacted on the dynamic causal relationship between housing and growth and, therefore, needs to be accounted for by appropriate policy recommendations.

Figure 1a: Bootstrap *p*-values of *LR* test statistic testing the null hypothesis that *GFCF* does not Granger cause *GDP*

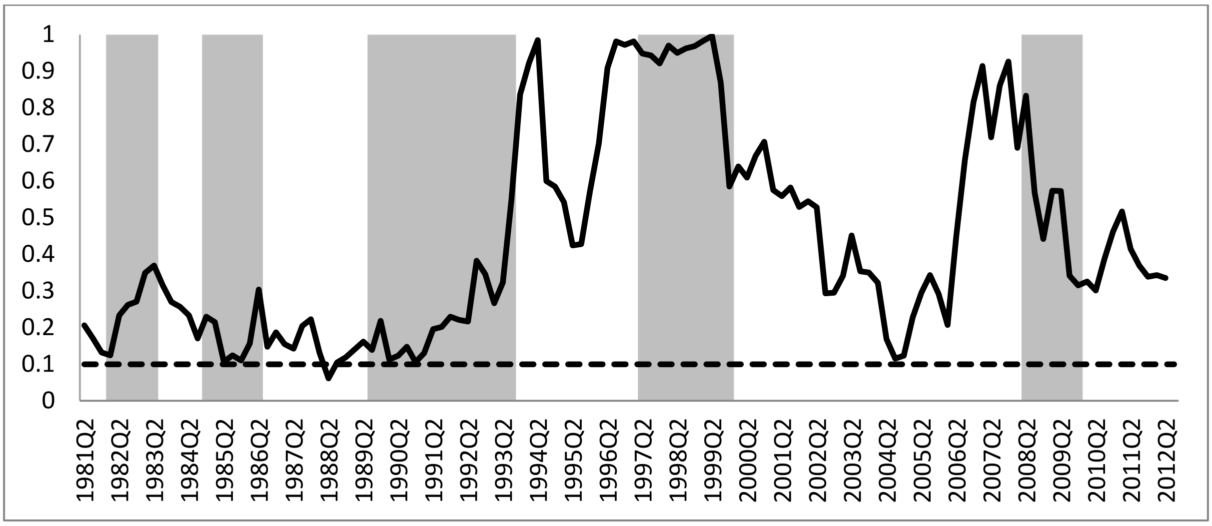



Figure 1b: Bootstrap estimates of the sum of the rolling window coefficients for the impact of *GFCF* on *GDP*

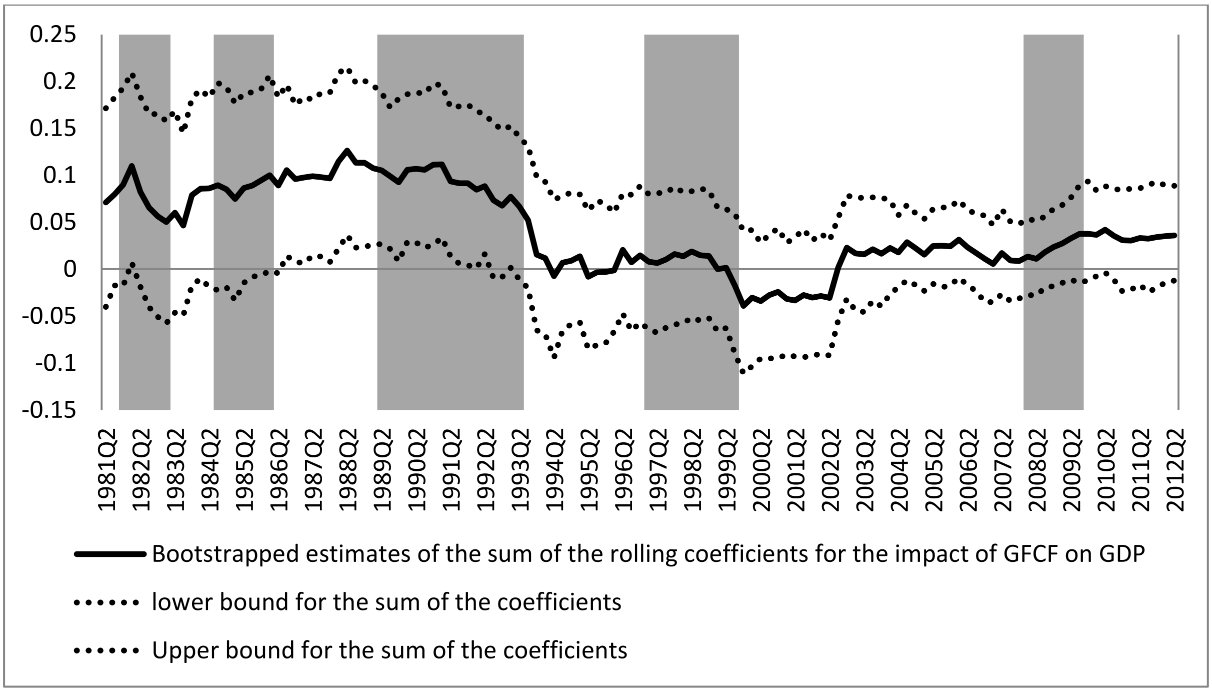


Figure 2a: Bootstrap *p*-values of *LR* test statistic testing the null hypothesis that *GDP* does not Granger cause *GFCF*

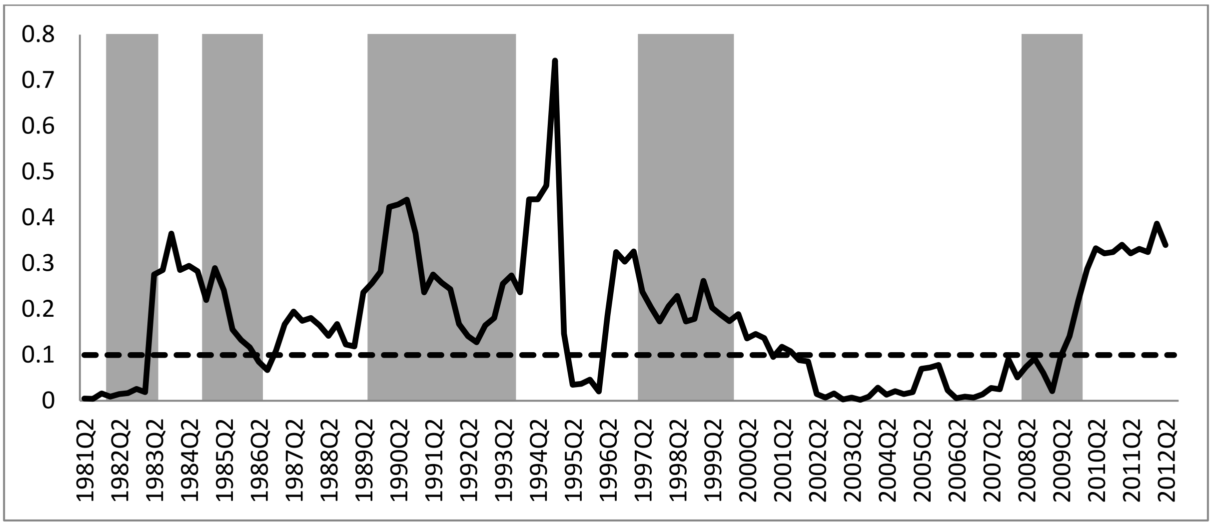


Figure 2b: Bootstrap estimates of the sum of the rolling window coefficients for the impact of *GDP* on *GFCF*

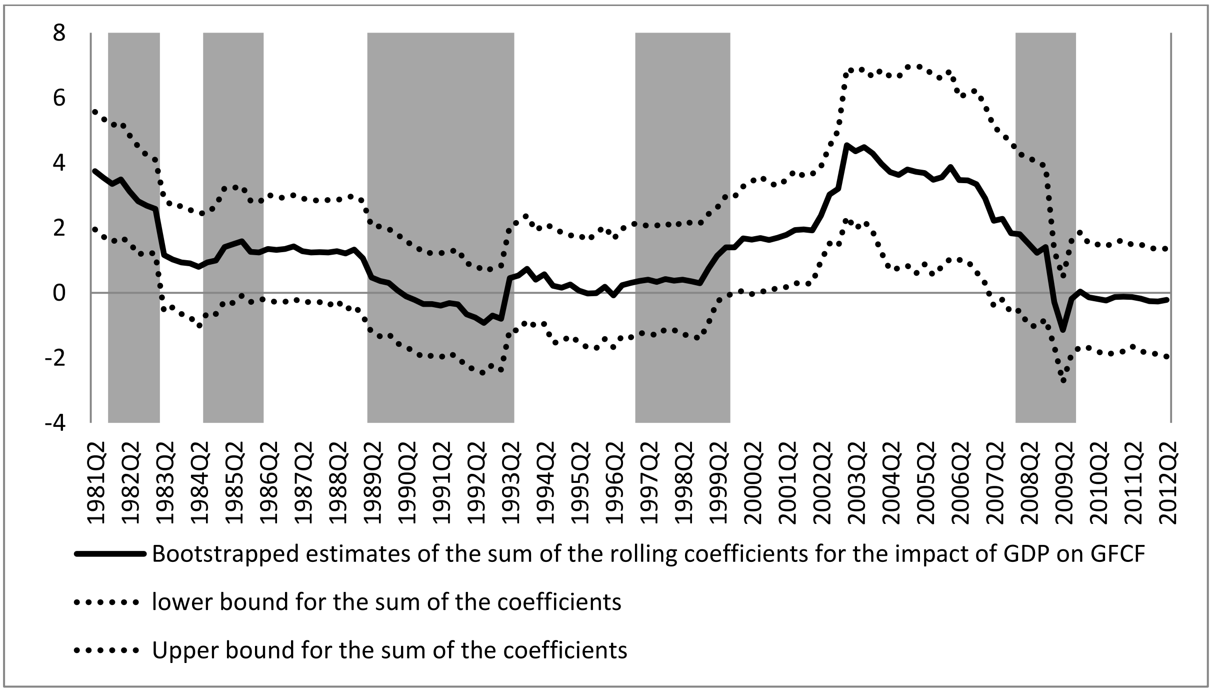


Figure 3a: Bootstrap *p*-values of *LR* test statistic testing the null hypothesis that *NUM* does not Granger cause *GDP*

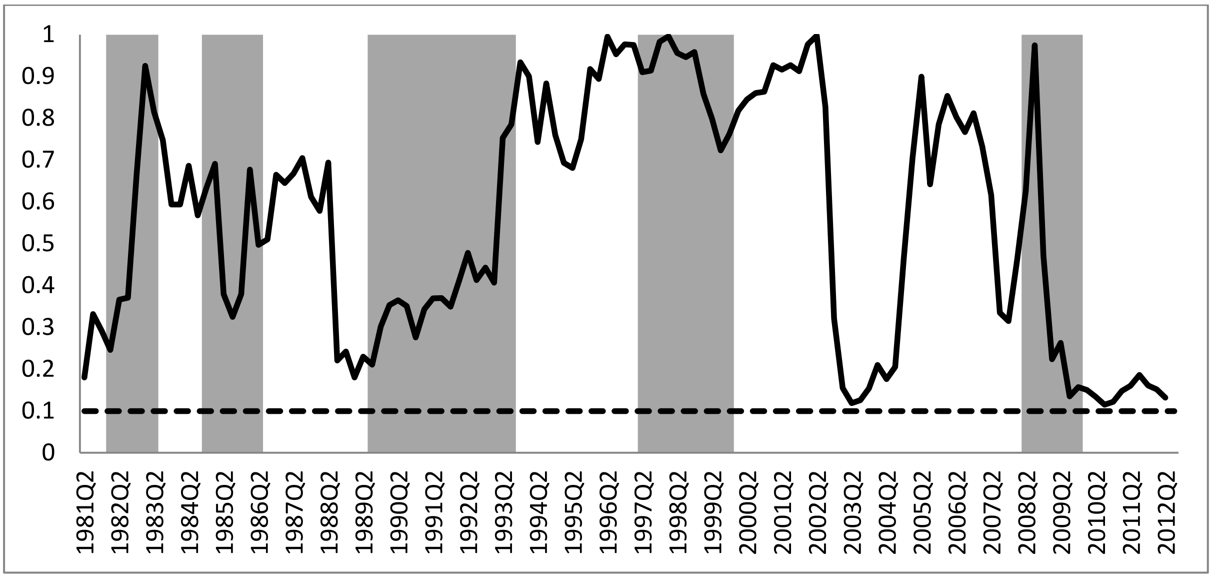



Figure 3b: Bootstrap estimates of the sum of the rolling window coefficients for the impact of *NUM* on *GDP*

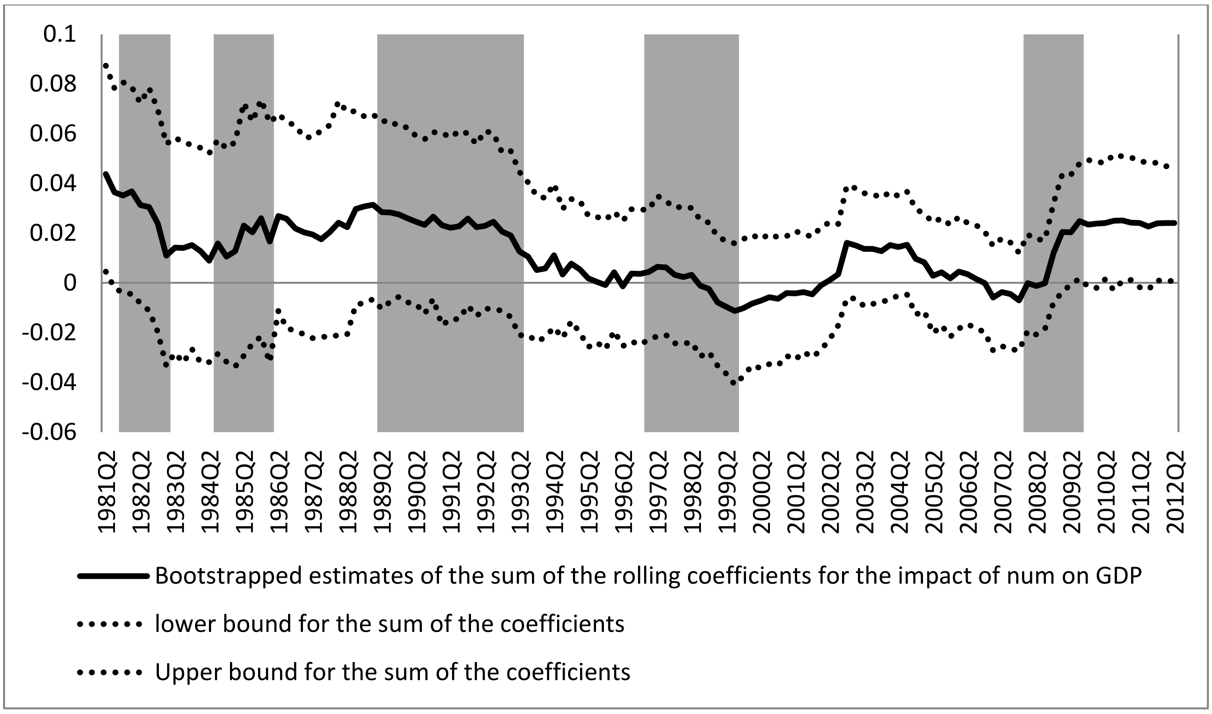


Figure 4b: Bootstrap *p*-values of *LR* test statistic testing the null hypothesis that *GDP* does not Granger cause *NUM*

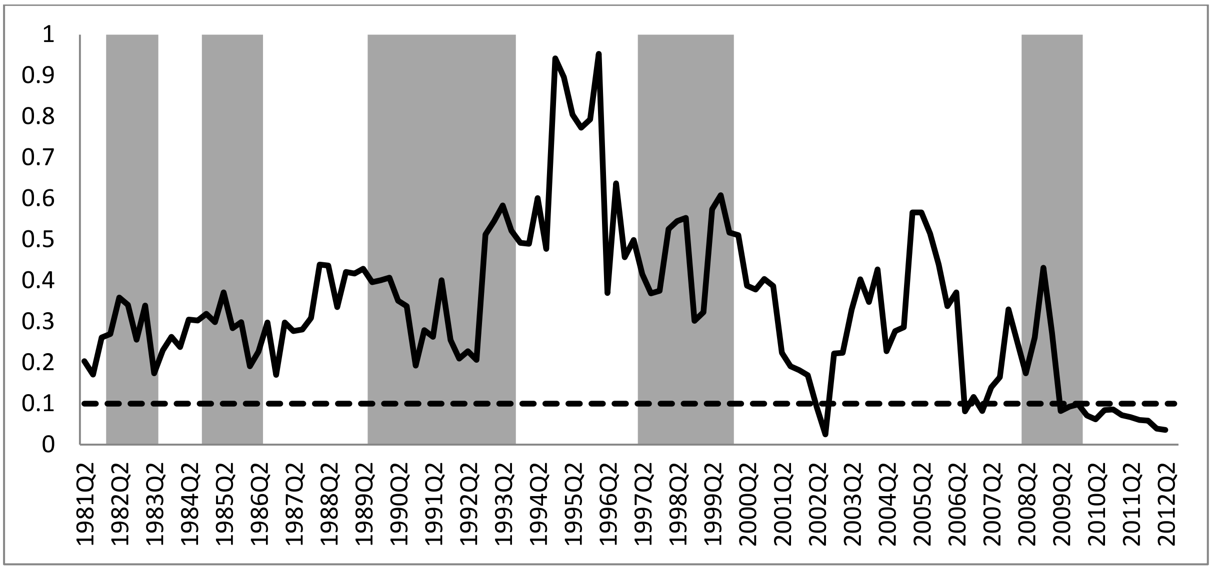



Figure 4b: Bootstrap estimates of the sum of the rolling window coefficients for the impact of *GDP* on *NUM*

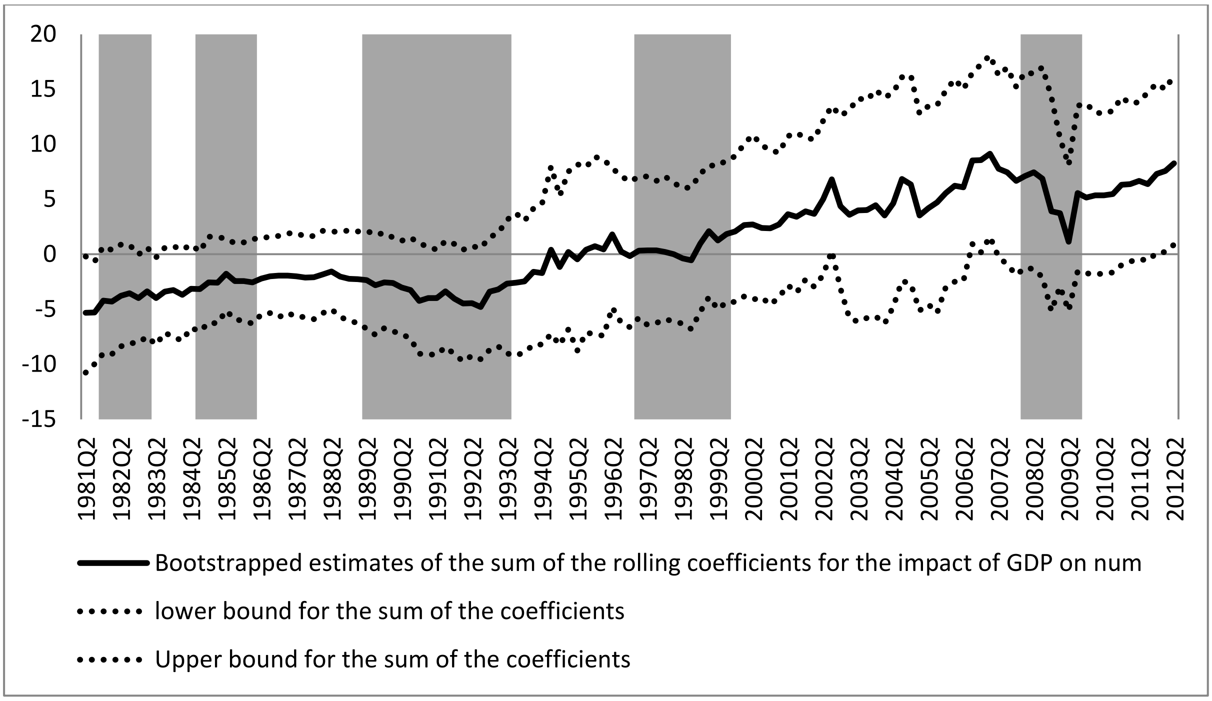


Figure 5a: Bootstrap *p*-values of *LR* test statistic testing the null hypothesis that *HP* does not Granger cause *GDP*

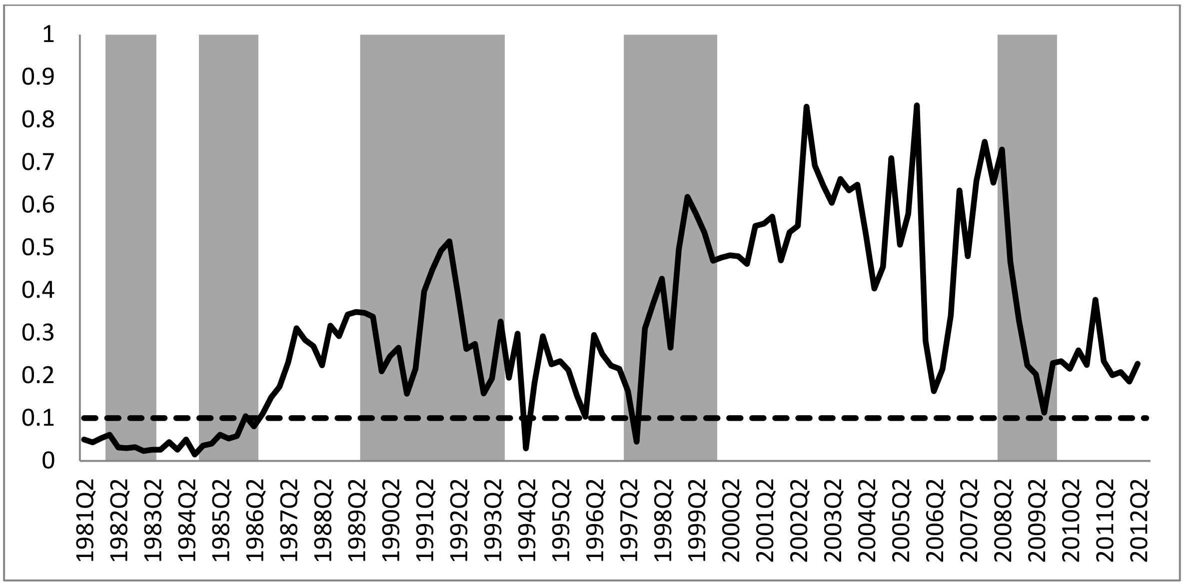



Figure 5b: Bootstrap estimates of the sum of the rolling window coefficients for the impact of *HP* on *GDP*

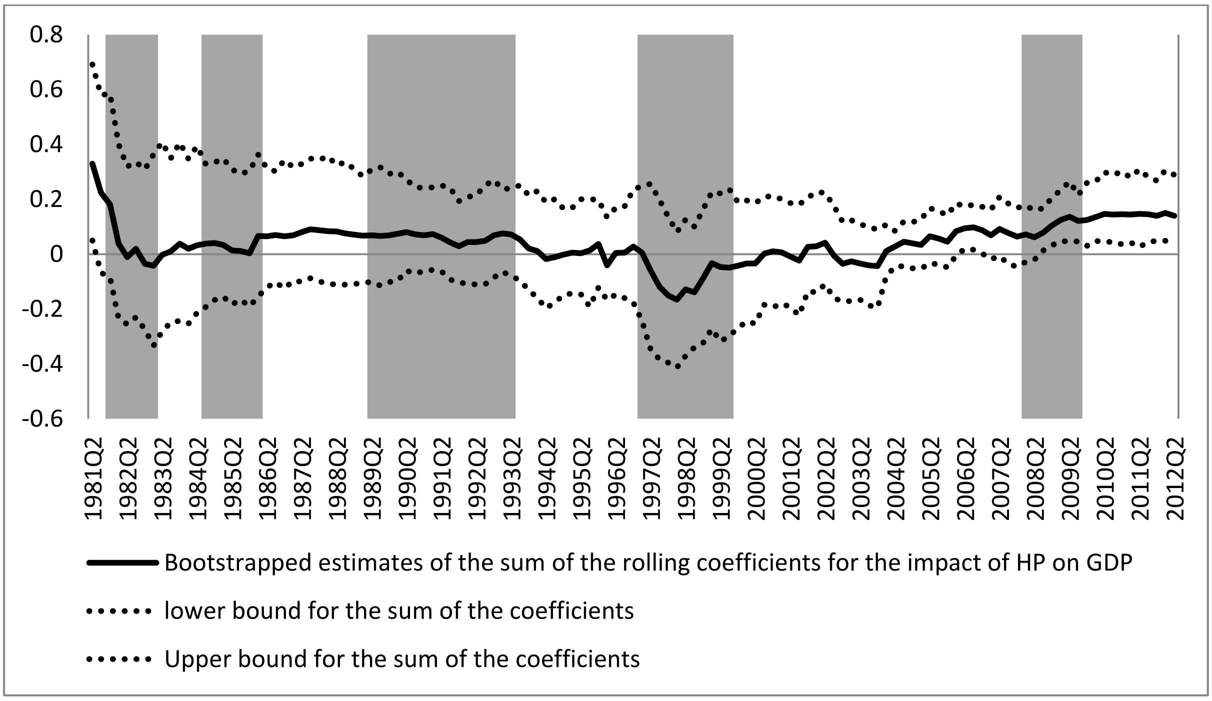


Figure 6a: Bootstrap *p*-values of *LR* test statistic testing the null hypothesis that *GDP* does not Granger cause *HP*

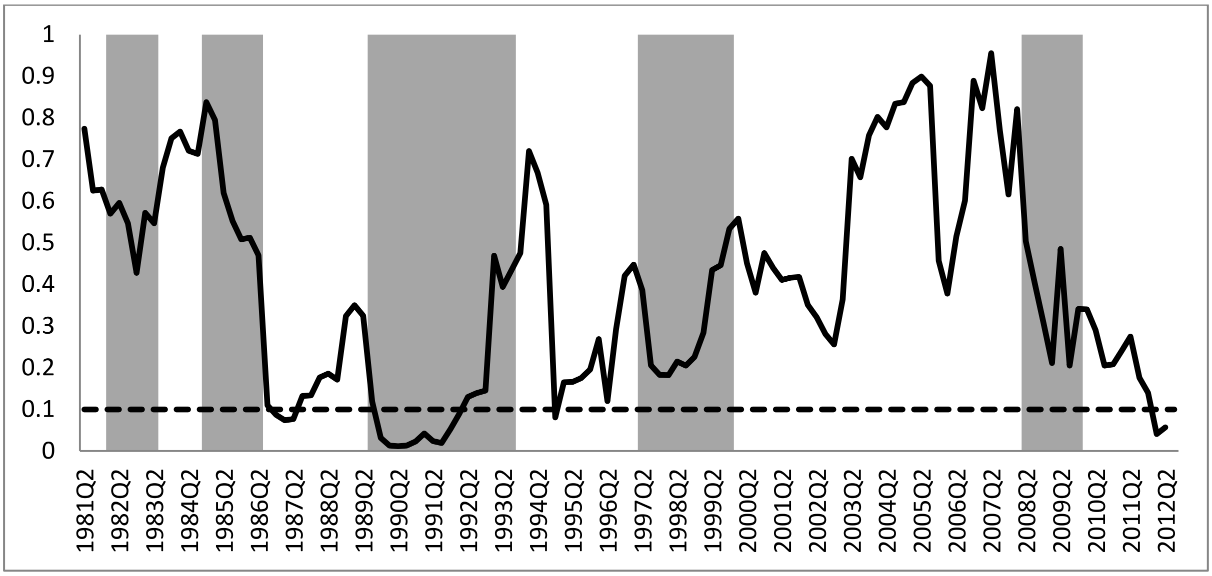
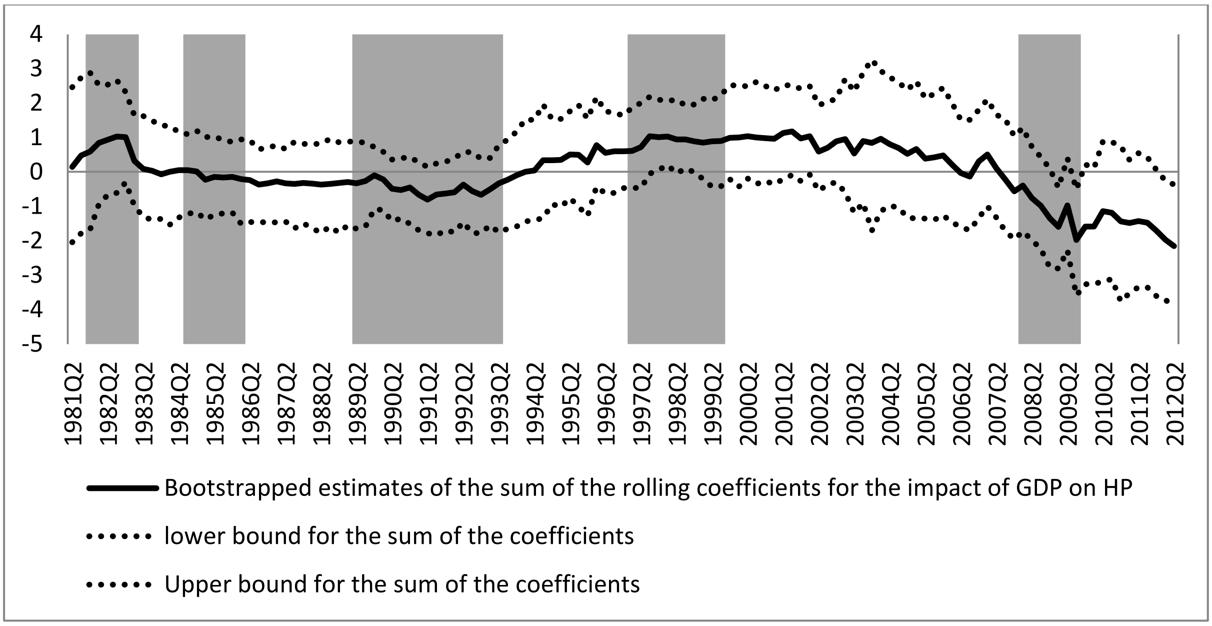



Figure 6b: Bootstrap estimates of the sum of the rolling window coefficients for the impact of *GDP* on *HP*




## 3. CONCLUSION

This study investigated the dynamic relationship between house price, residential investment, number of building plans passed and gross domestic product in South Africa. We use the modified bootstrapped rolling Granger non-causality test to account for the time variation in the causal nexus that arise due to structural changes. The modified bootstrap tests enable us to make inferences without considering whether the series are integrated-cointegrated. We also estimate the rolling sums of the coefficients using bootstrap estimation in order to determine the magnitude and the direction of the dynamic relation between the housing series and output. Using data from 1971:Q2 to 2012:Q2, the full sample modified bootstrap Granger causality tests indicates a uni-directional short-run relationship between house price and output with the direction flowing from house price to output. Further, we find a bi-directional causal link between residential investment and output for based on the full sample. Number of building plans passed has no predictive content for output, however, we found that output has predictive content for number of building plans passed. To determine the stability of the parameters in our bivariate VARs, we use the Nyblom-Hansen $L_C$, *Sup-F*, *Ave-F* and *Exp-F* parameter stability tests. We found strong evidence of parameter instability both in the long and short-run. Therefore, we use bootstrap rolling window estimation to show that causality is not uniform in different sub-samples. Our results indicate that residential investment has predictive power for output and this is evident in one out of five downward phases. The impact is positive and significant. Output has predictive power for residential investment at 10 percent level evidenced in four pre-downward phases and two downward phases. Number of building plans passed has no predictive content for output at 10 percent before or during any of the downward phases. However, output has predictive content for number of building plans passed with impacts being significant at 10 percent for one downward phase. The null hypothesis that house price does not Granger cause output is rejected at 10 percent level in four out of five downward phases. Results show that house prices have a positive and significant impact on output during the 1981Q1, 2006Q4, 2008Q3-2009Q3 and 2009Q4-2012Q2 periods. Output has predictive ability for house price in one out of five downward phases. The effect of output on house price is negative and significant during the most recent downward phase (2009Q1 and 2009Q3). Overall, we found a sort of complementarity between housing and growth in South Africa at different sub-periods. This is particularly stronger for house prices, as it shows predictive ability for, and significant positive effect on, output in four out of five downward phases that occurred over our sample. This implies that policy makers need to closely monitor the housing sector, especially real house prices, since a slump in the housing market is likely to lead to a downward phase in the economy. Having said this, policy makers need to strike a balance between ensuring steady growth in the housing-sector, but prevent the sector from getting overheated and getting detached from fundamentals to avoid the emergence of any bubbles. So, in one hand, the policy makers need to ensure that credit constraints are reduced, but on the other hand, they need to closely monitor the financial authorities from carrying out reckless or irrational lending activities without proper back-up of collateral.

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**Appendix 1: Multivariate Cointegration test results**

| Series | $H_0$ [a] | $H_1$ | Trace Statistic | Maximum Eigen Statistic |
|---|---|---|---|---|
| *GFCF* and *GDP* | $r = 0$ | $r > 0$ | 6.19 | 6.09 |
| | $r \leq 1$ | $r > 1$ | 0.10 | 0.10 |
| *LHP* and *GDP* | $r = 0$ | $r > 0$ | 6.16 | 6.14 |
| | $r \leq 1$ | $r > 1$ | 0.02 | 0.02 |
| *LNUM* and *GDP* | $r = 0$ | $r > 0$ | 6.41 | 6.35 |
| | $r \leq 1$ | $r > 1$ | 0.06 | 0.06 |

Notes: ** indicates significance at the 5 percent level.

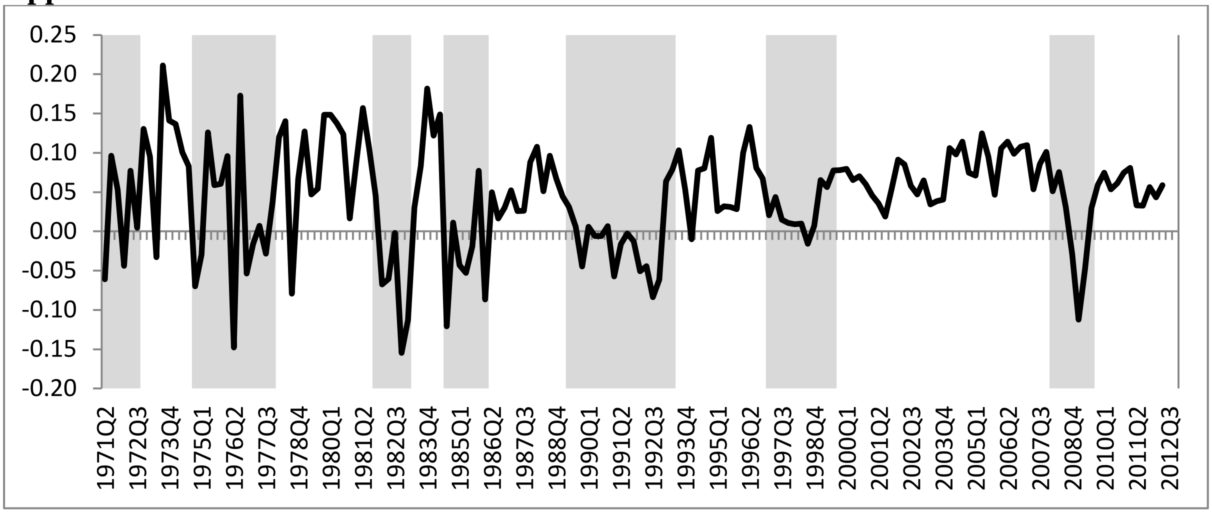
[a] One-sided test of the null hypothesis ($H_0$) that the variables are not cointegrated against the alternative ($H_1$) of at least one cointegrating relationship. The critical values are taken from MacKinnon et al., (1992)(1992) with 5 percent critical values equal to 15.49 for testing $r = 0$ and 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.

**Appendix 2: Parameter Stability Tests for VAR Models in Levels**

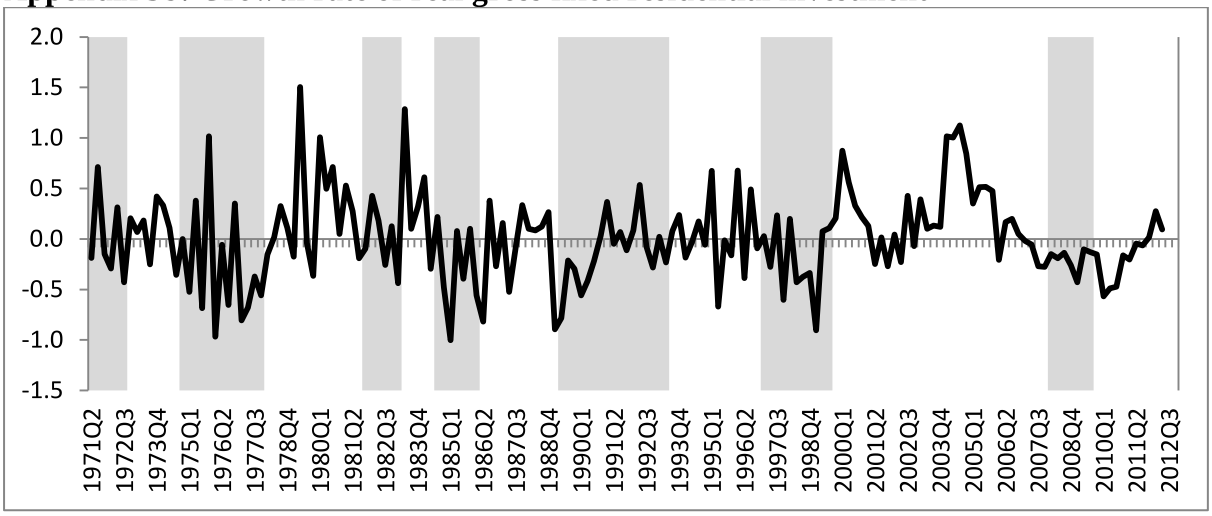
| | *LGDP*vs*LGFCF* | | | *LGDP*vs*LHP* | | | *LGDP*vs*LNUM* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *LGDP* Eq. | *LGFCF* Eq. | VAR(2) System | *LGDP* Eq. | *LHP* Eq. | VAR(2) System | *LGDP* Eq. | *LNUM* Eq. | VAR(5) System |
| $L_c$ | 2.83 | 2.10 | 4.93 | 4.69 | 4.21 | 8.90 | 2.99 | 2.55 | 5.54 |
| *P*-value | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

Note: *p*-values are calculated using 2000 bootstrap repetitions.

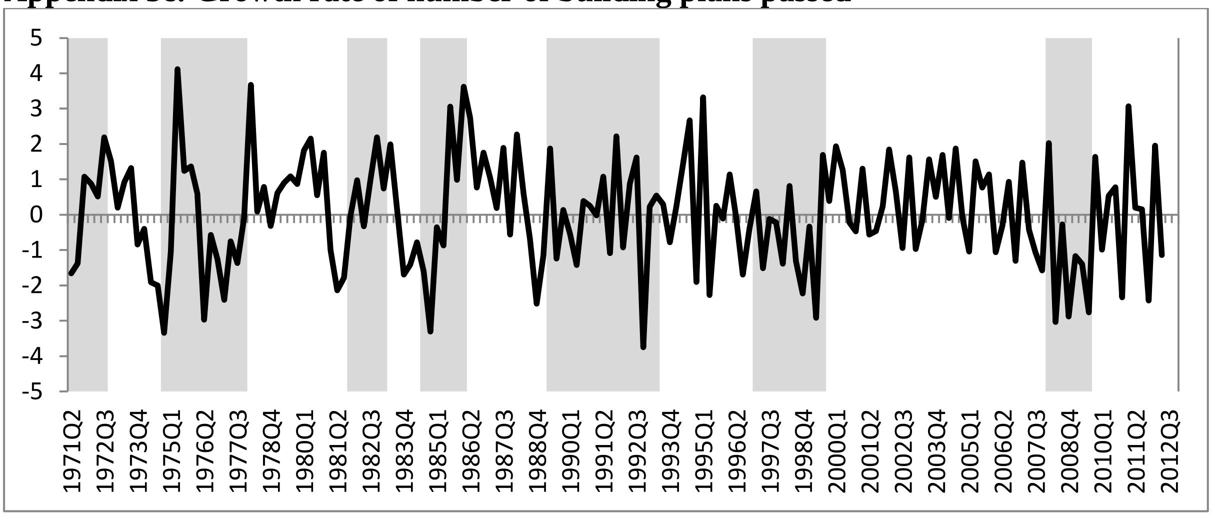
**Appendix 3a: Growth rate of real *GDP***




**Appendix 3b: Growth rate of real gross fixed residential investment**




**Appendix 3c: Growth rate of number of building plans passed**



**Appendix 3d: Growth rate of real house prices**