An In-Sample and Out-of-Sample Empirical Investigation of the Nonlinearity in House Prices of South Africa

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Abstract

This paper first tests if housing prices in the five segments of the South African housing market, namely, large-middle, medium-middle, small-middle, luxury and affordable, exhibits non-linearity based on smooth transition autoregressive (STAR) models estimated using quarterly data covering the period of 1970:Q2 to 2009:Q3. We find overwhelming evidence of non-linearity in these five segments based on in-sample evaluation of the linear and non-linear models. We then provide further support for non-linearity by comparing one- to four-quarters-ahead out-of-sample forecasts of the non-linear time series model with those of the classical and Bayesian versions of the linear autoregressive (AR) models for each of these segments, over an out-of-sample horizon of 2001:Q1 to 2009:Q3, using an in-sample period from 1970:Q2 to 2000:Q4. Our results indicate that barring the one-, two and four-step(s)-ahead forecasts of the small-middle-segment the non-linear model always outperforms the linear models.

Keywords: Bayesian autoregressive models; Housing market; smooth transition autoregressive models; Forecast accuracy

JEL Classification: C12; C13; C22; C52; C53; R31

1. Introduction

The objectives of this paper are twofold: First, we want to address if housing prices in the five segments of the South African housing market, namely, luxury, large-middle, medium-middle, small-middle and affordable,[1] exhibits non-linearity based on smooth transition autoregressive (STAR) models estimated using quarterly data covering the period of 1970:Q2 to 2009:Q3; and second, if the five housing segments does exhibit non-linearity, which they do, we compare the one- to four-quarters-ahead out-of-sample forecasting performances of the non-linear time series models with those of the classical and Bayesian versions of the linear autoregressive (AR) models for each of these segments, over an out-of-sample horizon of 2001:Q1 to 2009:Q3, using an in-sample period from 1970:Q2 to 2000:Q4. Note that the choice of the in-sample period, especially the starting date, depends on data availability for all the five housing segments. While, the end-point of the out-of-sample horizon is data-driven, the starting point of the same precedes the rapid run-up and then collapse of housing prices experienced over the last decade in the South African economy, as indicated in Figure 1.

Related to the two stated objectives, two questions arise immediately, and define the motivations for our paper: First, why should one expect house prices to exhibit non-linearity? And, second, why should one be interested in forecasting house prices? As far as the answer to the first question is concerned, it must be realized that the behaviour of the housing market is not the same across phases of expansion and contraction of the swings that characterize the real estate

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[1] See Section 3 for further details on the data used.

sector (Kim and Bhattacharya, 2009). Seslen (2004) argued that households exhibit forward looking behaviour and have higher probability of trading up, during the upswing with equity constraints being less binding. However, the same is not true during the downswing of the housing market cycle, since when house prices are on the decline, households are less likely to trade implying downward rigidity of house prices. The aversion to loss during the downswing is more than likely to reduce the mobility of households as far as trading is concerned. Further, as pointed out by Muellbauer and Murphy (1997), the presence of lumpy transaction costs in the housing market can also cause non-linearity. Given these issues, it is important and makes sense to test if housing prices are non-linear.

As far as forecasting house prices are concerned, a large number of papers (e.g., Green 1997, Iacoviello 2005, Case *et al.* 2005, Rapach and Strauss 2006, Leamer 2007, Pariès and Notarpietro 2008, Vargas-Silva 2008a, Bao *et al.* 2009, Christensen *et al.* 2009, Ghent 2009, Ghent and Owyang 2009, Pavlidis *et al.* 2009, and Iacoviello and Neri forthcoming) show a strong link between the housing market and economic activity. This is understandable since housing contributes towards a large percentage of private sector wealth (Cook and Speight, 2007). House price impacts on the distribution of economic stability and is vital in explaining household consumption and saving patterns (Englund and Ioannides, 1997). Campbell and Cocco (2005) contend that housing can be considered as a consumption good and, hence, house prices and consumption are strongly correlated, as also vindicated by Pavlidis *et al.* 2009. In addition, Forni et al. (2003), Stock and Watson (2003) and Gupta and Das (2008) argue that house-price movements lead real activity, inflation, or both, and, hence, can indicate where the economy will head. Moreover, the recent emergence of boom-bust cycles in house prices cause much concern and interest amongst policy makers (Borio *et al.* 1994; Bernanke and Gertler, 1995, 1999), since the bust of house price bubbles always lead to significant contractions in the real economy, vouched for by the current economic downturn. Given this, models that forecast house price can give policy makers an idea about the direction the economy might be heading to, and hence, can provide a better control for designing appropriate policies. Hence, it is of paramount importance that one first deduces the underlying nature of the data-generating process for house price, i.e., whether it is linear or non-linear, since the presumption that house prices are linear could lead to incorrect forecasts for not only house prices, but the economy in general, given that one considers house prices to be a leading indicator.

To the best of our knowledge, this is the first attempt to simultaneously test formally for non-linearity in the housing market and compare forecasts generated from STAR and classical and Bayesian AR models. The only other study that we are aware of which tests for non-linearity in the housing market is by Kim and Bhattacharya (2009). The author(s) examined STAR models based on non-linear properties of house prices for the aggregate US economy and its four census regions (North East, Midwest, South and West) using monthly data over the period of 1969:01-2004:12. The authors concluded that housing prices for the entire US and all four census regions barring the Midwest was non-linear. However, this paper did not look at the ability of the non-linear framework in forecasting house prices relative to their linear counterpart.[2] One must realize that the forecasting exercise is crucial in reaching a firm and overwhelming conclusion about modelling house prices using non-linear models, since as indicated by Rapach and Wohar (2006a) while forecasting real exchange rates using (S)TAR models, gains from using a non-linear framework in forecasting relative to the linear model can be quite small, even when there is strong evidence on non-linearity in the in-sample. Beck *et al.* (2000, 2004) note that forecasting

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[2] In addition to this, the paper highlighted that the dynamic properties implied by the nonlinear estimation was in line with the typical patterns that have been observed in the aggregate US and regional housing markets, and also, based on non-linear Granger causality tests, the authors found housing price to cause employment and mortgage rates to cause housing price.

provides the root of inference and prediction in time-series analysis. Further, Clements and Hendry (1998) argue that in time-series models, estimation and inference essentially means minimizing of the one-step (or multi-step) forecast errors, therefore, establishing a model's superiority boils down to showing that it produces smaller forecast errors than its competitors. Thus, it is typically believed that out-of-sample comparisons over and above in-sample results provide a better measure of the appropriate data generating process, as statistical models are tested using out-of-sample observations that are not used in the estimation of the statistical model itself (Rapach and Wohar, 2006b). If the forecasts generated by the STAR model are superior to those generated by classical and Bayesian AR models, this can be considered as strong evidence in favour of the STAR model. The remainder of the paper is organized as follows: Section 2 discusses the specification of the STAR models. Section 3 outlines the details regarding the data used, while Section 4 presents the formal test of non-linearity in the five segments of the South African housing market. Section 5 compares the forecasting performance of the appropriate version of the non-linear STAR model in relation to the classical and Bayesian AR models. Finally, Section 6 concludes.
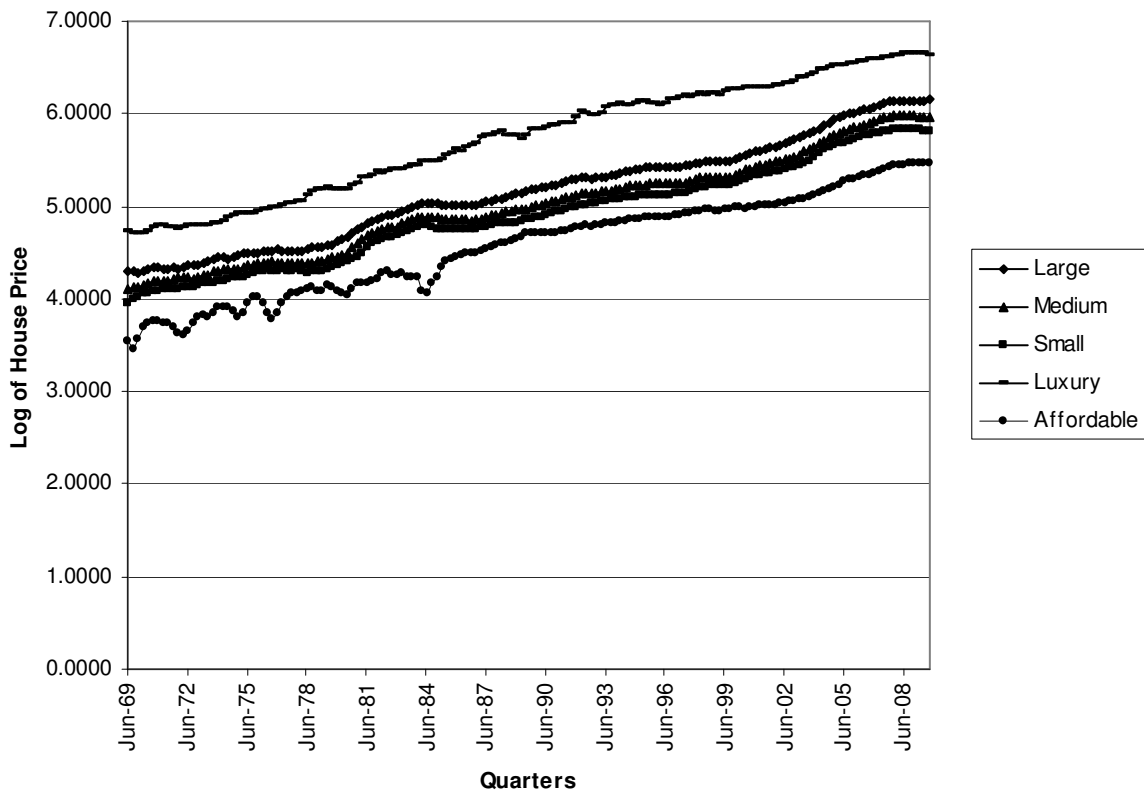

Figure 1. Home Prices in the Five Different Segments of the South African Housing Market

2. Specification and Estimation of STAR Models

We use the STAR framework, developed by Luukonnen *et al.* (1988), to model house price growth rates[3] as a non-linear and state-dependent variable. The STAR framework allows for

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[3] Note non-linear estimation, just like linear estimation, requires one to ensure that the variables used are stationary to avoid spurious estimates. Hence, house prices of all the five segments were converted to their yearly growth rates,

smooth transition across regimes to describe the dynamics of long-horizon housing price growth rates, and, hence, is preferred over the threshold autoregressive (TAR) (Tsay, 1986) and the Markov switching (Hamilton, 1989) models, since the latter two frameworks specify discrete jumps across regimes implying sudden jumps. In addition, our decision to employ the STAR model is governed by our belief that house price growth rates are better described by the STAR model rather than the TAR or Markov switching models. The low speeds of transition obtained in the estimation of the non-linear model, vindicates our decision as well.

The STAR model of order p, for variable r_t, is specified as follows[4]:

$$r_t = [\phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i}] + [\rho_0 + \sum_{i=1}^{p} \rho_i r_{t-i}].F(r_{t-d}) + u_t$$
$$= [\phi_0 + \phi(L)r_t] + [\rho_0 + \rho(L)r_t].F(r_{t-d}) + u_t \qquad (1)$$

where r_t is the housing price growth rate, and; $F(r_{t-d})$ is the transition function controlling the regime shift mechanism and is a smooth and continuous function of past realized housing price growth rates. Thus, house price growth rates evolve with a smooth transition between regimes that depends on the sign and magnitude of past realization of the housing price growth rates. The non-linearities are obtained by conditioning the autoregressive coefficients, $\varrho(L)$, to change smoothly with past housing price growth rates in such a way that the past realized home price growth rate r_{t-d} is the transition variable with d being the delay parameter, which, in turn, indicates the number of periods r_{t-d} leads the switch in dynamics.

Teräsvirta and Anderson (1992) define the transition function $F(.)$ by using two alternative forms, namely the logistic smooth transition autoregressive (LSTAR) model and the exponential smooth transition autoregressive (ESTAR) model. In the LSTAR model, $F(.)$ is defined by a logistic function, so that:

$$F(r_{t-d}) = [1 + \exp\{-\gamma(r_{t-d} - c)\}]^{-1}, \quad \gamma \succ 0 \qquad (2)$$

while, $F(.)$ in the ESTAR framework is captured as follows by an exponential function:

$$F(r_{t-d}) = 1 - \exp\{-\gamma(r_{t-d} - c)^2\}, \quad \gamma \succ 0 \qquad (3)$$

In the above equations γ is the speed of transition between regimes and c measures the halfway point or threshold between the two regimes. Equation (1) combined with equation (2) produces the *LSTAR(p)* model and equation (1) combined with equation (3) yields the *ESTAR(p)* model. In STAR models, expansion and contraction are a representation of two different economic phases, but transition between the two regimes is smooth, controlled by r_{t-d} (Sarantis, 2001). The LSTAR and ESTAR models describe different dynamic behaviour. The LSTAR model allows the expansion and contraction regimes to have different dynamics whereas the ESTAR model suggests that the two regimes have similar dynamics (Sarantis, 2001). We also take note that when $\gamma \rightarrow \infty$, then the model degenerates into the conventional *TAR(p)*, while, when $\gamma \rightarrow 0$, then the model degenerates to the linear *AR (p)* model (Teräsvirta et al, 1992).

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the stationarity of which, in turn, were confirmed by the Augmented–Dickey–Fuller (ADF) test, the Dickey-Fuller test with GLS Detrending (DF-GLS), the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test and the Phillips-Perron (PP) test. The results are available upon request from the authors.
[4] This part of the paper relies heavily on the discussion available in Kim and Bhattacharya (2009), and, hence we retain their symbolic representation of the equations.

The procedure for constructing an appropriate STAR model for a specific variable, comprises of three stages:

a) Firstly a linear AR model needs to be specified, with the value of p being chosen based on the unanimity of at least two of the popular lag-length tests, namely, LR test statistic, Akaike information criterion (AIC) and the final prediction error (FPE) criterion and the Hannan-Quinn (HQ) information criterion;

b) Then we test for linearity against a nonlinear STAR model, for different values of the delay parameter d using the linear model in (a) as the null, based on a Lagrange multiplier smooth transition (LM-STR) test for linearity. This boils down to estimating the following auxiliary regression, as proposed by Teräsvirta and Anderson (1992):

$$r_t = \phi_0 + \sum_{i=1}^{p} \varphi_{1,i} \cdot r_{t-i} + \sum_{i=1}^{p} \varphi_{2,i} \cdot r_{t-i} r_{t-d} + \sum_{i=1}^{p} \varphi_{3,i} \cdot r_{t-i} r_{t-d}^2 + \sum_{i=1}^{p} \varphi_{4,i} \cdot r_{t-i} r_{t-d}^3 + u_t \tag{4}$$

with the null hypothesis of linearity being H_{01}: $\phi_{2i} = \phi_{3i} = \phi_{4i} = 0$ for all i. To get the appropriate values of the delay parameter d, the estimation of (4) is carried out for a range of values, $1 \leq d \leq D$. In the scenario where linearity is rejected for more than one value of d, then d is chosen such that $d = arg\ min\ p(d)$ for $1 \leq d \leq D$.[5]

c) The choice between the LSTAR and ESTAR model, when linearity is rejected, is then conducted by applying the sequence of nested tests,

1. $H_{04} : \phi_{4i} = 0,$ $i = 1, \dots, p$
2. $H_{03} : \phi_{3i} = 0 | \phi_{4i} = 0,$ $i = 1, \dots, p$
3. $H_{02} : \phi_{2i} = 0 | \phi_{3i} = \phi_{4i} = 0,$ $i = 1, \dots, p$

A standard procedure, as discussed in Teräsvirta *et al.* (1992), is then followed in the selection of the appropriate STAR model. There are three possible sequential outcomes, given d:

i.   The rejection of $H_{04} : \phi_{4i} = 0,$ implies the selection of the LSTAR model.

ii.   If H_{04} is not rejected, then we move to the second part of the test, which tests if $H_{03} : \phi_{3i} = 0 | \phi_{4i} = 0,$. Rejection of H_{03} implies the selection of the ESTAR model.

iii.   If H_{03} is not rejected, then we move to the last component of the test which tests $H_{02} : \phi_{2i} = 0 | \phi_{3i} = \phi_{4i} = 0,$. Rejection of H_{02} implies selection of the LSTAR model.

Various authors (Granger and Teräsvirta, 1993; Teräsvirta, 1994; Eitrheim and Teräsvirta, 1996, and; Sarantis, 2001) argue that if this sequence of tests is strictly applied then it may lead to wrong conclusions since the higher order terms of the Taylor expansion used in the derivation of these tests are ignored. Thus it is recommended that one computes p-values for all the F-tests of (1) – (3) above. Then one can make the choice of the appropriate STAR model based on the lowest p-value or highest F-statistic.

3. Data

We use quarterly house price data obtained from the ABSA[6] Housing Price Survey, for the period 1970:Q2 to 2009:Q3. The survey distinguishes between three price categories as: affordable (R430,000 and area below 40m^2 -79m^2), middle (R430,000 to R3,1million) and luxury

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[5] $p(d)$ is the p-value of the test.
[6] ABSA is one of the leading private banks in South Africa.

(R3,1 million to R11.5 million). The data is further subdivided for the middle segment of the housing market, based on sizes (square meters), into small ($80m^2$ – $140m^2$), medium ($141m^2$ – $220m^2$) and large ($221m^2$ – $400m^2$). Given that Genesove and Mayer (2001) and Engelhardt (2001) point out that sellers are averse to realizing losses in nominal and not real terms, we follow Kim and Bhattacharya (2009) and use nominal house prices, since it is nominal changes in house prices that causes asymmetric effects on mobility and the housing market in general. We use annual growth rate of housing prices, which are measured with respect to the same quarter in the previous year.

4. Empirical Results[7]

In this section, we first start of with the LM-STR test for linearity of housing price growth rates, and then we conduct hypothesis tests to select between the LSTAR and ESTAR models. Once we select the appropriate STAR model, we then estimate the specific STAR model and the linear AR model and compare the in-sample performance over the period of 1970:Q2 till 2009:Q3. When conducting the (LM-STR) test for linearity, as discussed above, the optimal lag, p, was selected based on the unanimity of at least two of the popularly-used lag-length tests, We allowed the delay lag, d, to vary over the range $1 \le d \le 8$. The optimal delay lag d is estimated on the basis of lowest p-value or highest F-statistic associated with the null hypothesis: $H_{01}: \phi_{2i} = \phi_{3i} = \phi_{4i} = 0$ for all i.

Table 1.   LM-STR Test for Linearity

	Large p*=8	Medium p* =7	Small p*=8	Luxury p*=8	Affordable p*=6
Optimal delay d	3 (0.0213)	3 (0.0303)	3 (0.0000)	4 (0.0347)	4 (0.0000)

Notes: The numbers in parenthesis are the lowest p-values associated with the $H_{01}: \phi_{2i} = \phi_{3i} = \phi_{4i} = 0$ in equation (4) with the corresponding d.

From Table 1, we can conclude that the null hypothesis of linearity can be rejected for all the five segments, with the null being rejected at the one percent level for the small-middle and affordable sections and at the five percent level for the large-middle, medium-middle and luxury segments of the South African housing market. Since all five categories of housing price growth rates are nonlinear, we now need to specify the appropriate STAR model to capture accurately the non-linear dynamics. As proposed by Teräsvirta *et al.* (1992), and outlined in Section 2, we need to test for the sequence of nested hypothesis tests H_{04}, H_{03}, and H_{02} for the choice between LSTAR and ESTAR alternatives.

Table 2. Test of the Appropriate STAR Model

	Optimal delay d	$H_{04} : \varphi_{4i} = 0$, $i = 1,...,p$	$H_{03} : \varphi_{3i} = 0$, given $\varphi_{4i} = 0$	$H_{02} : \varphi_{3i} = 0$, given $\varphi_{3i} = \varphi_{4i} = 0$	Selection of model	Optimal lag p
Large	3	0.0090*	0.0862	0.7736	LSTAR	8
Medium	3	0.0039*	0.3477	0.6431	LSTAR	7
Small	3	0.0014*	0.0310	0.0103	LSTAR	8

| Luxury | 4 | 0.0037* | 0.6221 | 0.4193 | LSTAR | 7 |
| Affordable | 4 | 0.0038* | 0.0000 | 0.0000 | LSTAR | 6 |

Notes: The values in the table are the *p*-values for the nested tests H_{04}, H_{03}, and H_{02}. A '*' indicates the lowest *p*-value for the three tests.

As observed from Table 3, we can deduce that the LSTAR model is best-suited in describing the non-linear dynamics of all the five segments of the South African housing market. The choice of the LSTAR model suggests that the dynamics of the house price growth rates is characterized by asymmetric dynamics during the phases of contraction and expansion.

Next, we provide further evidence of nonlinearity by providing in-sample comparison based on the estimation of the linear AR model, given in equation (5), and the nonlinear LSTAR model described in equation. (6):

$$r_t = [\phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i}] + u_t \tag{5}$$

and

$$r_t = [\phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i}] + [\rho_0 + \sum_{i=1}^{p} \rho_i r_{t-i}].[1 + \exp\{-\frac{\gamma}{\sigma(r_t)}(r_{t-d} - c)\}]^{-1} \tag{6}$$

Teräsvirta (1994) contends that for LSTAR models it is not easy to carry out the joint estimation of $(\gamma, c, \phi_0, \varrho_0, \phi_i, \rho_i)$ since one faces difficulties with the estimation of c and γ. When γ is large then c is steep and a large number of observations in the neighbourhood of c would be required to estimate γ, i.e., relatively large changes in γ would have only a minor effect on shape of *F(.)*. Thus the sequence of estimates for γ may converge slowly. Note if γ is statistically insignificant then equation (6) becomes the linear AR model. In accordance with Teräsvirta (1994) we standardize the exponent of the function *F(.)* of the LSTAR model by multiplying it by the term $1/\sigma(r_t)$, where $\sigma(r_t)$ is the standard deviation of the corresponding yearly housing price growth rate r_t.

The results of the estimation of the LSTAR model and the AR model have been tabulated in Tables 3 and 4, where we use the nonlinear least-squares (NLS) to estimate the LSTAR model.[8] Note, it is the logistic function which conditions the autoregressive parameters to change smoothly with lagged realized changes in the growth rates of home prices in the LSTAR model that generates the endogenous nonlinearity. When we compare the estimation results over the period of 1970:Q2 to 2009:Q3 of the AR and the LSTAR models, the following features pointing to the superiority of the non-linear estimation emerges: (a) The measures of the standard error and the log likelihood value of the nonlinear regression show a significant improvement over the corresponding values obtained from the linear regression; (b) The adjusted R^2 value in the nonlinear regression is always higher than the corresponding value under the linear regression, implying that a large portion of variance in the housing price growth rates in the long-run is associated with nonlinear dynamics; (c) As reported, most of the estimates of the coefficients of the nonlinear portion of equation (6), i.e., ϱ_is, are statistically significant, and; (d) The value of γ, which governs the speed of transition between regimes, is always positive as

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[8] Following the suggestions of van Dijk et al. (2002), a battery of misspecifications tests, namely, no residual autocorrelation parameter constancy, no remaining non-linearity, no autoregressive conditional heteroskedasticity (ARCH), besides the test of normality, were carried out for the LSTAR model. The estimated LSTAR models for all the five segments were found to be free from any type of misspecification. These results are available upon request from the authors.

expected and is statistically significant at the 10 percent level or less. The statistical significance of γ confirms the presence of nonlinearity outlined by the LSTAR model. These results together provide strong evidence that the LSTAR model appropriately captures the inherent non-linearity in the long horizon housing price growth rates in the five segments of the South African housing market. Thus a linear model would clearly be misspecified since it does not allow the dynamics of home price growth rates to evolve smoothly between regimes depending on the sign and magnitude of past realization of home price growth rates.[9]

It is important to note that the γ is relatively small for all the categories of housing price growth rates except for the small-middle segment. Relatively small estimates of γ suggests a slower transition from one regime to another, which is, in turn, in contrast with the TAR or Markov switching models where one witnesses sudden switch between regimes, given that the estimate of γ tends to infinity. The fact that the parameter γ takes a value of 126.8074 for the small-middle segment is an indication of the households in this category to trade up very quickly especially during the upswing phase of the housing market. The parameter c representing the half-way point between regimes is positive for all the five segments of the housing market, and, hence, indicates that similar value of housing price growth rate shock triggers a shift in regimes. However note, the value of c is not significant for the large-middle and the luxury housing categories.

Table 3. Estimation of the LSTAR Model

Large: Adjusted R^2 = 0.942435, SER = 2.1282, LLV = -326.1296

$$
\begin{aligned}
r_t &= 0.9527(0.0172) + 1.9295 r_{t-1}(0.0000) - 1.7276 r_{t-2}(0.0000) + 1.3858 r_{t-3}(0.0000) \\
&- 1.4175 r_{t-4}(0.0000) + 1.2626 r_{t-5}(0.0000) - 0.6366 r_{t-6}(0.0000) + 0.1037 r_{t-8}(0.0021) \\
&+ (5.9853(0.0013) - 0.5839 r_{t-1}(0.0001) + 1.3606 r_{t-2}(0.0000) - 1.5065 r_{t-3}(0.0000) \\
&+ 1.1312 r_{t-4}(0.0046) - 1.0456 r_{t-5}(0.0009) + 0.7290 r_{t-6}(0.0019) \\
&- 0.3042 r_{t-8}(0.0111)) \times [1 + \exp\{-8.8080(r_{t-3}(0.0032) - 19.8674(0.9981))\}]^{-1}
\end{aligned}
$$

Medium: Adjusted R^2 = 0.965983, SER = 1.7804, LLV = -301.3587

$$
\begin{aligned}
r_t &= 0.39504(0.1399) + 2.0503 r_{t-1}(0.0000) - 1.71736 r_{t-2}(0.0000) + 1.2947 r_{t-3}(0.0000) \\
&- 1.5777 r_{t-4}(0.0000) + 1.5711 r_{t-5}(0.0000) - 0.8225 r_{t-6}(0.0000) \\
&+ 0.1725 r_{t-7}(0.0462) + (9.7308(0.0090) - 0.9474 r_{t-1}(0.0000) + 1.2618 r_{t-2}(0.0000) \\
&- 1.2712 r_{t-3}(0.0002) + 1.4053 r_{t-4}(0.0047) - 0.9035 r_{t-5}(0.0077)) \\
&\times [1 + \exp\{-5.5690(r_{t-3}(0.0156) - 30.7287(0.0000))\}]^{-1}
\end{aligned}
$$

Small: Adjusted R^2 = 0.956223, SER = 2.0193, LLV = -318.2516

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[9] The Ramsey model specification test provides further evidence of nonlinearity in the housing price growth rates of the five segments. The null hypothesis that the correct specification is a linear AR model, against a nonlinear LSTAR model, is rejected at the one percent level of significance for all the five cases. Note the appropriate F-statistic for the test is: $\frac{(R^2_{nonlinear} - R^2_{linear})/m}{(1 - R^2_{nonlinear})/(n-k)}$, where $R^2_{nonlinear}$ (R^2_{linear}) is the R^2 of the LSTAR (AR) model, m denotes the number of restrictions in the linear AR model and k measures the number of parameters in the LSTAR model. The values of the F-statistic for the large, medium, small, luxury and affordable sections were respectively: 21.3594, 11.7915, 34.8803, 11.6411 and 124.4432.

$$r_t = 1.3205(0.0010) + 1.4527r_{t-1}(0.0000) - 0.7125r_{t-2}(0.0000) + 0.8697r_{t-3}(0.0000)$$
$$-1.4370r_{t-4}(0.0000) + 0.9296r_{t-5}(0.0000) - 0.3852r_{t-6}(0.0504) + 0.5676r_{t-7}(0.0000)$$
$$-0.3978r_{t-8}(0.0000) + (-2.1363(0.2096) + 0.3755r_{t-1}(0.0096) - 0.4890r_{t-2}(0.0093)$$
$$+0.8497r_{t-5}(0.0005) - 0.4908r_{t-6}(0.0712)$$
$$-0.3101r_{t-8}(0.0017)) \times [1 + \exp\{-126.8074(r_{t-3}(0.0188) - 21.5245(0.0000))\}]^{-1}$$

Luxury: Adjusted R^2 = 0.721693, SER = 5.2717, LLV = -465.2763

$$r_t = 3.4527(0.0006) + 1.1511r_{t-1}(0.0000) - 0.5182r_{t-2}(0.0000) + 0.3160r_{t-3}(0.0008)$$
$$-0.7613r_{t-4}(0.0000) + 0.3923r_{t-5}(0.0000) + (3.9178(0.0347)$$
$$-0.2680r_{t-7}(0.0007)) \times [1 + \exp\{-29.4707(r_{t-4}(0.0000) - 11.7210(0.9995))\}]^{-1}$$

Affordable: Adjusted R^2 = 0.9008, SER = 6.5703, LLV = -501.8283

$$r_t = -13.4349(0.0002) + 1.2648r_{t-1}(0.0000) - 1.1212r_{t-2}(0.0000) - 2.0792r_{t-4}(0.0000)$$
$$+1.1639r_{t-5}(0.0000) - 0.7423r_{t-6}(0.0000) - 0.3852r_{t-6}(0.0000)$$
$$+(16.6382(0.0000) + 0.2220r_{t-1}(0.0706) + 0.7424r_{t-3}(0.0000) + 1.4184r_{t-4}(0.0000)$$
$$-0.6588r_{t-5}(0.0066) + 0.5022r_{t-6}(0.0000))$$
$$\times [1 + \exp\{-7.7768(r_{t-4}(0.0537) - 11.5396(0.0000))\}]^{-1}$$

Notes: The values in the parenthesis corresponds to the p value; SER, standard error of regression; LLV, log likelihood value. We include only significant lags following Teräsvirta (1994) and Sarantis (2001).

Table 4. Estimation of the AR Model

Large: Adjusted R^2 = 0.937389, SER = 2.365968, LLV = -337.3782

$$r_t = 0.849136\ (0.0275) + 1.780462r_{t-1}(0.0000) - 1.359759r_{t-2}(0.0000) + 0.987180r_{t-3}(0.0000) - 0.994519r_{t-4}(0.0000) + 0.846320r_{t-5}(0.0000) + 0.172149r_{t-8}(0.0234)$$

Medium: Adjusted R^2 = 0.965060, SER = 1.908279, LLV = -307.7264

$$r_t = 0.627505(0.0306 + 2.041448r_{t-1}\ (0.0000) - 1.749766r_{t-2}(0.0000) + 1.319690r_{t-3}(0.0000) - 1.570302r_{t-4}\ (0.0000) + 1.575341r_{t-5}(0.0000) - 0.882169r_{t-6}\ (0.0000) + 0.208929r_{t-7}(0.0104)$$

Small: Adjusted R^2 = 0.947878, SER = 2.339952, LLV = -335.7197

$$r_t = 1.460725(0.0001) + 1.580604r_{t-1}(0.0000) - 0.907154r_{t-2}(0.0000) + 0.864273r_{t-3}(0.0000) - 1.420194r_{t-4}\ (0.0000) + 1.072038r_{t-5}(0.0000) - 0.413761r_{t-6}\ (0.0096) + 0.499351r_{t-7}(0.0007) - 0.398282r_{t-8}(0.0000)$$

Luxury: Adjusted R^2 =0.698159, SER =5.663563, LLV =-468.3081

r_t = 4.980659(0.0000) + 1.121342 r_{t-1} (0.0000) - 0.511161 r_{t-2} (0.0001)+ 0.378676 r_{t-3} (0.0052) - 0.726343 r_{t-4} (0.0000) + 0.498261 r_{t-5} (0.0002)

Affordable: Adjusted R^2 = 0.819200, SER = 9.309189, LLV = -551.2078

r_t = 5.418556(0.0000) + 1.538784 r_{t-1} (0.0000) - 1.325532 r_{t-2} (0.0000) + 0.945101 r_{t-3} (0.0000) - 1.000029 r_{t-4} (0.0000) + 0.782214 r_{t-5} (0.0000) − 0.351645 r_{t-6} (0.0000)

Notes: The values in the parenthesis corresponds to the *p* value; SER, standard error of regression; LLV, log likelihood value. We include only significant lags following Teräsvirta (1994) and Sarantis (2001).

It is important to note that the γ is relatively small for all the housing price growth rates except for the housing category small. In the small category the γ estimate is very large as compared to the other categories indicating that the speed of transition between small to other housing categories is very fast. This could be possibly due to the income effect, i.e. as an individual's income increases they move from small houses to other categories. For the other categories of houses the speed of transition from one regime to another is relatively slow. The parameter *c* representing the half-way point between regimes, is not significant for the large and luxury housing categories. This could be attributable to the fact that our data on growth rates have both negative and positive values.

5. Forecast Accuracy

Having established that house price growth rates in the South African housing market should be modelled via a LSTAR framework, in this section, we compare the forecast performances of the non-linear model with those of the classical and Bayesian versions of the linear AR models. The decision to use a Bayesian variant of the classical linear AR framework emanates from the general finding in the forecasting literature that Bayesian models which impose prior restrictions on the mean and variance of the classical AR models tend to perform better.[10] For the forecasting exercise, we choose an out-of-sample horizon of 2001:Q1 to 2009:Q3 and, thus, use an in-sample of 1970:Q2 to 2000:Q4. This leaves 35 observations for out-of-sample forecast performance evaluation. While, the end-point of the out-of-sample horizon is data-driven, the starting point of the same precedes the rapid run-up and then collapse of housing prices experienced over the last decade in the South African economy, as indicated in Figure 1.

Before we present the forecast performances of the alternative models, it is important to outline the prior restrictions imposed by the Bayesian AR (BAR) model on the classical AR framework. The Bayesian method imposes restrictions on the coefficients across different lag lengths, assuming that the coefficients of longer lags may more closely approach zero than the coefficients on shorter lags. If, however, stronger effects come from longer lags, the data can override this initial restriction. Researchers impose the constraints by specifying normal prior distributions with zero means and small standard deviations for most coefficients, where the standard deviation decreases as the lag length increases and implies that the zero-mean prior holds with more certainty. The first own-lag coefficient in each equation proves the exception

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[10] Refer to Das *et al.* (forthcoming a, 2009) and Gupta and Das (2008) for further details.

with a unitary mean. Finally, a diffuse prior is imposed on the constant. We employ this "Minnesota prior" in our analysis, where we implement Bayesian variants of the classical AR models.

Formally, the means of the Minnesota prior take the following form:

$$\phi_i \sim N(1, \sigma^2_{\phi_i}) \text{ and } \phi_j \sim N(0, \sigma^2_{\phi_j}) \tag{7}$$

where ϕ_i equals the coefficients associated with the lagged dependent variable in each equation of the AR model (i.e., the first own-lag coefficient), while ϕ_j equals any other coefficient. In sum, the prior specification reduces to a random-walk with drift model for each variable, if we set all variances to zero. The prior variances, $\sigma^2_{\phi_i}$ and $\sigma^2_{\phi_j}$, specify uncertainty about the prior means, $\bar{\phi}_i = 1$, and $\bar{\phi}_j = 0$. However, given that in our case, all the five yearly house price growth rates are stationary, we adopt the specification in Banbura *et al.* (forthcoming) and Bloor and Matheson (2008), and set a white-noise prior (i.e., $\bar{\phi}_i = 0$).

Doan *et al.,* (1984) propose a formula to generate standard deviations that depend on a small numbers of hyper-parameters: *w, d*, and a weighting matrix *f(i, j)*. The specification of the standard deviation of the distribution of the prior imposed on variable *j* in equation *i* at lag *m*, for all *i, j* and *m*, equals *S(i, j, m)*, defined as follows:

$$S(i, j, m) = [w \times g(m) \times f(i, j)] \frac{\hat{\sigma}_i}{\hat{\sigma}_j}, \tag{8}$$

where *f(i, j) = 1*, if $i = j$ and k_{ij} otherwise, with $(0 \leq k_{ij} \leq 1)$, and $g(m) = m^{-d}$, with *d > 0*. The estimated standard error of the univariate autoregression for variable *i* equals $\hat{\sigma}_i$. The ratio $\hat{\sigma}_i / \hat{\sigma}_j$ scales the variables to account for differences in the units of measurement and, hence, causes the specification of the prior without consideration of the magnitudes of the variables. The term *w* indicates the overall tightness, with the prior getting tighter as the value falls. The parameter *g(m)* measures the tightness on lag *m* with respect to lag 1, and equals a harmonic shape with decay factor *d*, which tightens the prior at longer lags. The parameter *f(i, j)* equals the tightness of variable *j* in equation *i* relative to variable *i*, and by increasing the interaction (i.e., the value of k_{ij}), we loosen the prior. We estimate the alternative BARs using Theil's (1971) mixed estimation technique. Essentially, the method involves supplementing the data with prior information on the distribution of the coefficients. The number of observations and degrees of freedom increase artificially by one for each restriction imposed on the parameter estimates. For the BAR models, we start with a value of *w* = 0.1 and *d* = 1.0, and then increase the value to *w* = 0.2 to account for more influences from variables other than the first own lags of the dependant variables of the model. In addition, as in Dua and Ray (1995), Gupta and Sichei (2006), Gupta (2006), and Gupta and Miller (2009a, forthcoming), we also estimate the BAR with *w* = 0.3 and *d* = 0.5. We also introduce *d = 2* to increase the tightness on lag *m*. Finally, k_{ij} is set equal to 0.001 (Gupta and Sichei, 2006).

In Table 5, we compare the forecast performances of the LSTAR, classical AR and BAR models, with the latter being estimated under different parameterization of *w* and *d* to account for various degrees of tightness (from most loose to most tight) of the prior-structure. We estimate the univariate models over the period 1970:Q2 to 2000:Q4, and then forecast from 2001:Q1 through 2009:Q3. Since we use eight, seven, eight, eight and six lags for the large, medium, small, luxury and affordable segments respectively, the initial eight, seven, eight, eight and six quarters from 1970:Q2 for the respective categories feed the lags. We re-estimate the models each quarter over the out-of-sample forecast horizon in order to update the estimate of

the coefficients, before producing the four-quarters-ahead forecasts. We implemented this iterative estimation and the four-quarters-ahead forecast procedure for 35 quarters, with the first forecast beginning in 2001:Q1. This produced a total of 35 one-quarter-ahead forecasts, …, up to 35 four-quarters-ahead forecasts.[11] We calculate the root mean squared errors (RMSE)[12] for the 35 one-, two-, three-, and four-quarters-ahead forecasts for the real house price index of the models. We then examine the average of the RMSE statistic for one-, two-, three-, and four-quarters ahead forecasts over 2001:Q1 to 2009:Q3.

As can be seen from Table 5, barring the one-, two and four-quarters-ahead forecast obtained from the classical AR model for the small-middle segment, the LSTAR model always outperforms the AR models whether estimated under classical or Bayesian models. Interestingly, unlike in the literature, the classical AR model outperforms all the BAR models. The result is in line with the fact that many of the coefficients on the longer lags in the linear AR model is significant and different from zero, as seen from Table 4, and, hence, tends to invalidate the Bayesian prior assumption on the mean of the coefficients. The evidence on the best performing BAR models is mixed. Following the literature (see for example, Das *et al.* forthcoming a, b, 2009, and references cited there in for further details) on forecasting with Bayesian (V)AR models, we use the average RMSEs over one- to four-quarters-ahead to find that BAR1 ($w = 0.3$ and $d = 0.5$) performs the best for the medium- and small-middle segments, the BAR4 ($w = 0.2$ and $d = 2.0$) outperforms other BAR models for the large-middle and luxury segments, while, for the affordable section of the housing market, the best suited BAR model is the BAR 5 model, with ($w = 0.1$ and $d = 2.0$).

Table 5. One- to Four-Quarters-Ahead RMSEs of House Price Growth Rates (2001:Q1-2009:Q3)

Segments	Models	QA			
		1	2	3	4
Large	AR	2.3064	4.6731	6.6471	8.4807
	BAR1	2.3279	4.7211	6.7797	8.6807
	BAR2	2.6149	4.9080	6.8485	8.5741
	BAR3	2.9304	5.1872	7.0297	8.5801
	BAR4	2.6828	4.8503	6.6489	8.1957
	BAR5	2.9498	5.1455	6.8889	8.3117
	LSTAR	2.2385	4.6511	6.2433	7.4299
Medium	AR	1.7399	4.1979	6.6155	8.7820
	BAR1	1.7956	4.2276	6.6694	8.9093
	BAR2	2.0599	4.5086	6.8608	8.9309
	BAR3	2.4757	4.9960	7.2755	9.2147
	BAR4	2.2659	4.7665	7.0346	8.9682
	BAR5	2.7259	5.3257	7.5269	9.3277

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[11] For this, we used the Kalman filter algorithm in RATS (Version 7.0) for the AR and BAR models. While, the recursive forecasts from the LSTAR model is based on 2000 bootstrap replications, since analytical point forecasts are not available for non-linear AR models when the disturbance term is Gaussian even when $h \geq 2$, as $E[f(x)] \neq f[E(x)]$, where h is the number of steps-ahead for the forecasts. Details of the bootstrapping procedure are available upon request from the authors.

[12] Note that if A_{t+h} denotes the actual value of a specific variable in period $t + h$ and $_tF_{t+h}$ equals the forecast made in period t for $t + h$, the RMSE statistic equals the following: $\sqrt{\sum_1^N \left(_tF_{t+h} - A_{t+h} \right)^2 / N}$ where N equals the number of forecasts.

	LSTAR	1.3021	3.3834	5.5225	7.6528
	AR	1.9980	4.4696	6.8375	9.0661
	BAR1	2.0772	4.5347	6.9668	9.3587
	BAR2	2.3815	4.9128	7.2607	9.2880
Small	BAR3	2.8626	5.5046	7.7538	9.5257
	BAR4	2.6718	5.3166	7.5621	9.3572
	BAR5	3.0905	5.7886	7.9398	9.5765
	LSTAR	2.0152	4.5746	6.7427	9.2772
	AR	3.4589	5.6949	6.6357	7.0589
	BAR1	3.4620	5.6302	6.5750	6.9553
	BAR2	3.7279	5.7850	6.6256	6.8933
Luxury	BAR3	4.1238	5.9977	6.6285	6.7480
	BAR4	3.7173	5.5956	6.2984	6.5621
	BAR5	4.0765	5.8547	6.4217	6.5728
	LSTAR	3.2237	5.2773	5.8535	6.5774
	AR	2.9728	6.4199	8.6318	9.2449
	BAR1	3.2095	6.6379	8.7709	9.3920
	BAR2	3.3060	6.2919	8.1404	8.6139
Affordable	BAR3	3.5814	6.0777	7.4544	7.8011
	BAR4	2.9433	5.2845	6.6985	7.2397
	BAR5	3.1979	5.2267	6.3584	6.8426
	LSTAR	2.2766	5.0528	7.0189	8.0698

Notes: QA: Quarter(s) Ahead; BAR1: w = 0.3, d = 0.5; BAR2: w = 0.2, d = 1.0; BAR3: w = 0.1, d = 1.0; BAR4: w = 0.2, d = 2.0; BAR5: w = 0.1, d = 2.0.

6. Conclusion

A large number of recent papers have shown that there exists a strong link between the housing market and economic activity. In addition, these papers have also highlighted the fact that house-price movements lead real activity, inflation, or both. Given this, models that forecast house price movements can give policy makers an idea about the direction the economy might be heading to, and hence, can provide a better control for designing appropriate policies. Hence, it is of paramount importance that one first deduces the underlying nature of the data-generating process for house price, i.e., whether it is linear or non-linear, since the presumption that house prices are linear could lead to incorrect forecasts for not only house prices, but the economy in general.

Against this backdrop, this paper first tests if housing prices in the five segments of the South African housing market, namely, large-middle, medium-middle, small-middle, luxury and affordable, exhibits non-linearity based on smooth transition autoregressive (STAR) models estimated using quarterly data covering the period of 1970:Q2 to 2009:Q3. And, second, we compare the one- to four-quarters-ahead out-of-sample forecasting performances of the non-linear time series models with those of the classical and Bayesian versions of the linear

autoregressive (AR) models for each of these segments, over an out-of-sample horizon of 2001:Q1 to 2009:Q3, using an in-sample of 1970:Q2 to 2000:Q4. We find overwhelming evidence of non-linearity in these five segments based on in-sample statistical tests. Specifically, we obtain that the LSTAR framework is statistically preferable over the ESTAR framework in describing house price growth rate movements in all the five segments of the South African housing market, implying that the expansion and contraction regimes have different dynamics. More importantly, our results imply that a linear model would clearly be misspecified since it does not allow the dynamics of home price growth rates to evolve smoothly between regimes depending on the sign and magnitude of past realization of home price growth rates. We then provide further support for non-linearity by comparing one- to four-quarters-ahead out-of-sample forecasts of the LSTAR model with those of the classical and Bayesian versions of the linear autoregressive (AR) models over an out-of-sample horizon of 2001:Q1 to 2009:Q3, using an in-sample of 1970:Q2 to 2000:Q4. Our results indicate that barring the one-, two and four-step(s)-ahead forecasts of the small-middle-segment the LSTAR model always outperforms the linear models. Our paper, thus, highlights the importance of not presuming the movements of house prices as linear, since prediction of the future path of house prices and the overall economy would then be incorrect.

Rapach and Strauss (2007, 2008) and Das *et al.* (forthcoming a, b, 2009) report evidence that numerous economic variables, such as, income, interest rates, construction costs, labor market variables, stock prices, industrial production, and consumer confidence index potentially predict movements in house prices and the housing sector, and, hence, shows that large-scale models like the dynamic factor model (DFM), factor-augmented VAR (FAVAR) or large-scale Bayesian VAR forecasts much better than small-scale pure time series models of house prices (i.e., models that contain only the house price in levels or growth rates). Given this, one might want to consider comparing the forecast performance of these large-scale models, involving hundreds of variables, with an appropriate pure non-linear time series model, especially if there is evidence to suggest that the underlying data generating process for house price is non-linear. In addition, one can go beyond point forecasts and look at interval and density forecast comparisons across linear and non-linear models as in Rapach and Wohar (2006a).

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