DEVELOPMENT OF A SESMA MODEL FOR SHORT-TERM INVESTMENT DECISION-MAKING

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ARIMA models have been extensively used for property market modelling. Property researchers have used this type of univariate forecasting technique to predict property rents, returns and yields. However, it has been indicated that ARIMA models could be improved. Accordingly, this current research examines an alternative specification of the ARIMA technique. The proposed model replaces the Autoregressive (AR) element with Simple Exponential Smoothing (SES) element within the ARIMA framework. This creates a SESMA model. The empirical results indicate that this mathematical manipulation improves model out-of-sample forecasting accuracy. This therefore suggests that the SESMA model could successfully be employed for short-term investment decision-making.

Keywords: Commercial Property, Exponential Smoothing, Modelling, UK.

INTRODUCTION

The issue of property market modelling and forecasting has been the subject of extensive research and empirical analysis over the last two decades (Chaplin, 1998; 1999; Stevenson and Mcgarth, 2003; Tobaccos, 2006). As Mitchell and McNamara (1997), Tsolacos (2006), and Barras (2009) noted, the area which was primarily developed within academia has been quickly adopted by practitioners. Tsolacos (2006) further suggested that property practitioners started to employ both quantitative and qualitative research methods to arrive at the final decision. Following Ball *et.al.* (1998), McDonald (2002), Barras (2009) and Lizieri (2009), these advancements resulted in the development of forecasting models, ranging from simple single-equation methods to more advanced multi-equation with stationary data techniques.

The ARIMA modelling technique has been extensively used by property researchers. Various authors used various ARIMA model specifications to model property rents, returns and yields (McGough and Tsolacos, 1995; 2001; Karakozova, 2004; Stevenson, 2007). The ARIMA modelling technique has been indicated as an applicable forecasting approach (McGough and Tsolacos, 1995; 2001; Wilson *et.al.*, 2000; Crawford and Fratantoni, 2003) and a source of useful information for short-term investment decision-making (McGough and Tsolacos, 1995; Tsy, 1997; Stevenson, 2007).

The study by McGough and Tsolacos (1995) employed the ARIMA approach to examine UK commercial rental values. Tsy (1997) assessed ARIMA’s ability to predict real estate prices in Hong Kong, while Stevenson (2007) used alternative ARIMA specifications to assess their ability to predict the UK commercial property rental series. The approach was also employed in studies that have compared alternative forecasting techniques. Wilson *et.al.* (2000) examined forecasting accuracy of Spectral Analysis, ARIMA and Exponential Smoothing

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modelling techniques. McGough and Tsolacos (2001) assessed the forecasting accuracy of Vector Error Correction Model, ARIMA, and the Regression Model. Crawford and Fratantoni (2003) compared in- and out-of-sample forecasting performance of ARIMA, Generalized Autoregressive Conditional Heteroskedastic and Regime-Switching time-series models in the US housing context. Stevenson and McGarth (2003) presented a comparison of four alternative rental forecasting models, including ARIMA, Bayesian Vector Autoregression, OLS based Single Equation and Simultaneous Equation models.

The results of these empirical studies suggested significant explanatory power of ARIMA approach. It was also indicated that ARIMA models are particularly applicable for short-term forecasting (Wilson *et.al.*, 2000; McGough and Tsolacos, 1995; 2001; Crawford and Fratantoni, 2003). Subsequently, ARIMA models became popular within the property forecasting community (McGough and Tsolacos, 1995, 2001; Brooks and Tsolacos, 2000, 2010; Wilson *et.al.*, 2000; Stevenson and McGarth, 2003).

Nevertheless, the effectiveness of this approach for the forecasting purposes was not without criticism. Stevenson and McGarth (2003), Stevenson (2007) and Miles (2008) indicated limitations of the ARIMA approach and therefore noted that a certain element of care should be paid while using it especially for longer-term forecasting.

The current research, therefore, proposes an alternative ARIMA model specification. Certainly, there were previous studies on the subject offering alternatives to the conventional ARIMA approach. One of these studies is Karakozova's (2004) comparative empirical research where the author incorporated a vector of explanatory variable (X) into ARIMA framework creating a special case known as Integrated Autoregressive-Moving Average model with Exogenous Explanatory Variable, or so called ARIMAX model. The researcher hypothesised that by incorporating relevant explanatory variable(s), in that case it was GDP of the Finnish economy, a greater forecasting accuracy can be achieved. As results of the study indicated, the ARIMAX model was more accurate than Regression and Error Correction models. It therefore suggested that incorporation of an additional exogenous explanatory variable(s) improves ARIMA model accuracy.

In the current paper, however, the use of the ARIMA approach is re-examined strictly in a univariate time-series modelling context. Following Stevenson and McGarth (2003) and Brooks and Tsolacos (2010), it implies that the model generates forecasts using only current and past estimates of the time-series itself. This approach is known as being atheoretical, whereas it is not based upon any underlying economic or financial theory explaining the behaviour of the dependent variable. Forecasts are produced only by capturing empirically relevant properties of selected series. According to Brooks and Tsolacos (2010), this type of modelling is of benefit when structural models are inappropriate, e.g. when data on explanatory variable is not available and it is of different frequency.

Certainly, Karakozova's (2004) research evidenced that ARIMA model accuracy can be improved by incorporating exogenous explanatory variable(s). Nonetheless, based on Makridakis' *et.al.* (1998) observations, there can be an issue in identifying all possible explanatory variables and then incorporating them into the modelling framework. Koop (2006) also noted statistical issues it may encounter, i.e. presence of autocorrelated disturbances and heteroscedasticiry.

ARIMA METHOD

The Autoregressive Integrated Moving Average (ARIMA) specification is a class of time series models (Makridakis *et.al.*, 1998; Brooks and Tsolacos, 2010). There the AR component of the specification implies that future values of the times series can be approximated and predicted from the current and past values of time series itself. The MA component, instead, captures current and past effects of random shocks or error terms in the series (Barras and Ferguson, 1987; Stevenson and McGarth, 2003; Karakozova, 2004).

The basic representation of Autogression (AR) is as follows (Makridakis *et.al.*, 1998; Brooks and Tsolacos, 2010):

$$Y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + u_t \tag{1}$$

As it is seen, in the AR part of the model the current value of variable Y_t depends on past values of the variable itself plus an error term. There μ is a constant term, ϕ_j is *j*th autoregressive parameter, and u_t is the error term at a time *t*.

The principal representation of Moving Average (MA) process is follows:

$$Y_t = \mu + b_1 u_{t-1} + b_2 u_{t-2} + \cdots + b_q u_{t-q} + u_t \tag{2}$$

It is important to note that Moving Average (MA) within ARIMA structure differs from the conventional moving average concept. There it is defined not as an average of observations y_t, but as a moving average of the errors (Johnson, 1992; Makridakis *et.al.*, 1998).

Subsequently, both AR and MA processes can be paired together, creating class of time series models ARIMA (*p*,*d*,*q*), which is presented as follows (Box *et.al.*, 1994; Makridakis *et.al.*, 1998; Brooks and Tsolacos, 2010):

$$Y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + b_1 u_{t-1} + b_2 u_{t-2} + \cdots + b_q u_{t-q} + u_t \tag{3}$$

SESMA METHOD

The results of the review indicated that ARIMA models have been widely used to model the property market. The technique proved to be effective especially for short term forecasting. However, the arguments suggested that there is still room for improvement. Certainly, one way of improving ARIMA is by incorporating a vector of explanatory variable(s) (X). However, the current research proposes model improvement strictly in a univariate time-series modelling context.

In simple terms, AR, which is an element of ARIMA framework, can be identified as being a Moving Average (MA) of time-series. This similarity between AR and MA comes from the fact that both specifications approximate current and past values of the time series itself. As noted above, the AR element depends on past values of the variable itself plus an error term, what can be connoted to be a special case of MA, i.e. Simple Exponential Smoothing (SES). As Makridakis *et.al.* (1998) suggest, SES produces a forecast of a time series simply by adding a forecast from the previous period with an adjustment for the error that occurred in the last forecast. Subsequently, it allows it to be hypothesised that the AR component could be replaced with the SES element within the ARIMA framework. Following Makridakis *et.al.* (1998), SES eliminates some of the randomness in the series by producing a smooth trend-cycle component. Subsequently, the hypothesis of the current research is that a SES specification can generate better model predictive outcomes than the AR element. The principle SES formula is as follows (Makridakis *et.al.*, *ibid.*):

$$F_{t+1} = \alpha Y_t + (1 - \alpha)F_t \quad (4)$$

Where F_t is the forecast, F_{t+1} is the forecast for the next period, Y_t is the most recent observation and α is a constant between 0 and 1.

The advantage of the SES forecasting technique is that it requires little storage of historical data and fewer computations. However, the caveat of this technique is its reliance on α. As Makridakis *et.al.* (*ibid.*) argue, when a small value of α is chosen, the initial forecast becomes of greater importance and vice-versa. Therefore, finding an optimal value for α is the biggest difficulty with SES. To deal with this difficulty, the current model uses the principle of negative feedback, i.e. the error of past forecast is used to correct the subsequent forecast in a direction opposite to that of the error, which continues until the error is corrected. Accordingly, the principle SESMA structure can be expressed as follows:

$$Y_t = \alpha Y_t + (1 - \alpha)F_t + b_1 u_{t-1} + b_2 u_{t-2} + \cdots + b_q u_{t-q} + u_t \quad (5)$$

As it is seen, the SESMA specification has a less complicated structure than original ARIMA model.

DATA

The property market can be measured using various indicators, including returns (RICS, 1999; Brooks and Tsolacos, 2001; MacGregor and Schwann, 2001; Karakozova, 2004; Tsolacos, 2006; Feng and Wongwachara, 2009), rents (Wheaton and Torto, 1994; Tsolacos, 1995; Wheaton *et.al.*, 1997; Chaplin, 1998; D'Arcy *et.al.*, 1999; White *et.al.*, 2000; Stevenson and McGarth, 2003; Mouzakis and Richards, 2004; Stevenson, 2007), and capital values (Barras, 1984; Kummerow, 1999; Barras, 2005), with rents being the most popular. The time-series data employed for this study comprises chain-linked IPD UK All Property Rental Value Growth Index (IPD, 2011). The use of this particular data-set was primarily governed by data availability and suggestions from the previous studies on the subject. Researchers including Baum (2001), Ball (2003), McAllister *et.al.* (2005a; 2005b) considered that IPD indices are the most reliable property market benchmarks in the UK, which are also well regarded within the UK property investment community.

The modelling of property rents, as Barras (1984), Scott (1996), Ball *et.al.* (1998), and Baum and Crosby (2008) suggest, is of particular importance for investors and analysts. Following Barras (1984), rent level determines the profitability for developers and investors and this affects the level of supply of new developments. Ball *et.al.* (1998) documents that in the user market, rent is payment an organisation makes in order to use commercial property. In the capital market, rent is used to estimate the value of the property. What is more, rent plays a very important role in bringing four inter-related property markets (user, financial, development and land market) into simultaneous equilibrium. Accordingly, Hendershott *et.al.* (2002, p.165) suggest that rent, the price of space, is *"the most important variable in property economics"*. Consequently, rent determination has been a subject of extensive study over the last few decades, and is also the subject of the current research.

The original IPD series is available from 1976, which up to year 2010 gives 35 data-points only (IPD, 2011). There has been a debate as to the minimum number of observations required to produce an adequate ARIMA model. Researchers including Holden *et.al.* (1991), McGough and Tsolacos (1995), Tse (1997) and Stevenson (2007) argued the need of at least 50 sample observations. However, studies by Stevenson and McGarth (2003) and Karakozova (2004) indicated that univariate models can produce reasonably accurate modelling and forecasting results using smaller data-sets. Nevertheless, for the purpose of this study, the IPD index is extended by chain-linking it with Scott's (1996) rental series. The combination is produced following RICS' (1999) empirical evidences that both series are highly compatible. The combination of both IPD and Scott's series extended the rental series for 13 years for the 1963-2010 period, what as a result gives 48 data points (Figure 1).

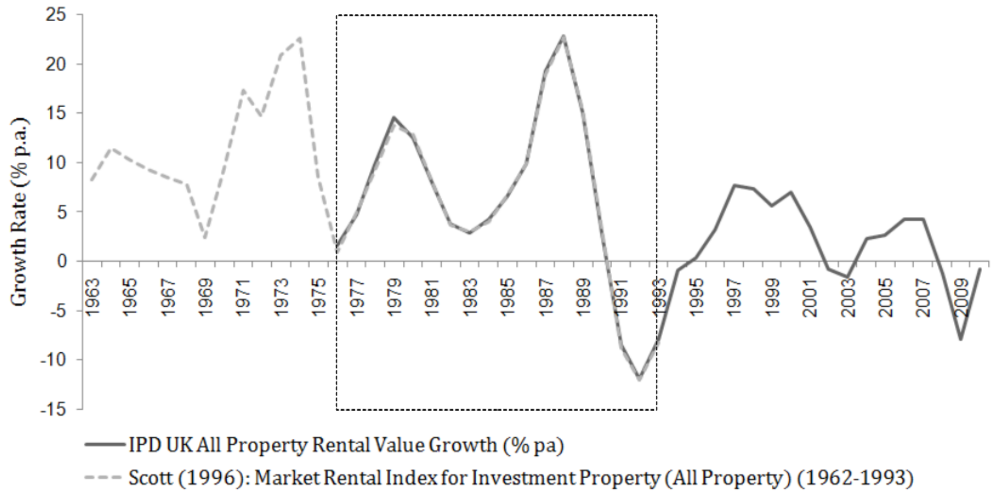

Figure 1. IPD and Scott's (1996) Combined UK Property Rental Series (1963-2010) (Source: IPD, 2011; Scott, 1996)

MODEL PARAMETERISATION AND EVALUATION

The forecasting performance is estimated for sixteen ARIMA specifications ranging from ARMA (1,1) to ARMA (4,4) and four SESMA specifications ranging from SESMA (1) to SESMA (4). All twenty models are estimated over the initialisation period from 1963 to 2008. Then, their forecasting adequacy is evaluated over the holdout period of the final two years of the sample 2009-2010.

The assessment of the relative goodness of fit of alternative specifications is assessed by computing Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) accuracy measures and two so called *"information criteria"* including Akaike Information Criterion (*AIC*) and Bayesian Information Criterion (*BIC*). Researchers including Chaplin (1998; 1999), Stevenson and McGarth (2003), and Karakozova (2004), suggest that *"information criteria"* are superior model selection measures. According to Chaplin (1999) and Brooks and Tsolacos (2010), both *AIC* and *BIC* contains a *"penalty"* for adding extra variables into a model. As a result, both information criteria select the most parsimonious model. The *AIC* selection criterion is calculated as follows:

$$AIC = n * \ln(RSS/n) + 2 * K \tag{6}$$

Where *K* is the number of free parameters in the model, *n* is the length of time-series, and *RSS* is Residual Sum of Squares obtained from the regression. In the situation, when the sample size is relatively small, i.e. $n/K<40$, *AIC* requires a bias-adjustment. The bias adjusted *AICc* is calculated as follows:

$$AICc = AIC + 2K(K+1)/(n-K-1) \tag{7}$$

The principle equation of Bayesian Information Criterion (*BIC*) is as follows:

$$BIC = n * \ln(RSS/n) + (K + 1) * ln(n) \quad (8)$$

Table 1 reports in-sample model fit and likelihood ratio test statistics. As the empirical results suggest, there is no uniformity between model fit statistical measures. The MAE identifies ARIMA (4,0,3) as the best fitting model, while MAPE suggest that ARIMA (3,0,1) has the best goodness of fit to historical data, although the most correlated model is ARIMA (4,0,4). However, both *AICc* and *BIC* indicates ARIMA (1,0,2) to be the best parameterised specification of all sample models. Amongst alternative SESMA models, SESMA (3) is indicated as the best parameterised specification.

		Model Fit statistics		Likelihood Ratio Tests	
Model Specification	**MAE**	**MAPE**	**Correlation**	**AICc**	**BIC**
ARIMA (1,0,1)	3.200	215.396	0.598	136.779	143.006
ARIMA (1,0,2)	2.705	182.418	0.697	**129.252**	**136.747**
ARIMA (1,0,3)	2.690	153.016	0.706	130.768	139.398
ARIMA (1,0,4)	2.660	140.928	0.707	133.527	143.146
ARIMA (2,0,1)	2.845	118.392	0.681	131.176	138.671
ARIMA (2,0,2)	2.590	135.390	0.712	129.996	138.625
ARIMA (2,0,3)	2.629	140.216	0.724	131.223	140.842
ARIMA (2,0,4)	2.700	136.786	0.741	131.871	142.324
ARIMA (3,0,1)	2.824	**112.160**	0.681	133.851	142.480
ARIMA (3,0,2)	2.606	163.391	0.722	131.546	141.166
ARIMA (3,0,3)	2.526	143.753	0.739	132.145	142.598
ARIMA (3,0,4)	2.686	130.643	0.744	134.519	145.637
ARIMA (4,0,1)	2.708	180.910	0.723	131.364	140.984
ARIMA (4,0,2)	2.444	140.922	0.755	129.620	140.073
ARIMA (4,0,3)	**2.369**	123.175	0.759	132.162	143.280
ARIMA (4,0,4)	2.425	126.066	**0.766**	134.287	145.883
SESMA(1)	3.242	199.467	0.560	139.729	145.955
SESMA(2)	3.187	199.479	0.559	142.341	149.836
SESMA(3)	2.623	134.068	0.701	131.438	140.068
SESMA(4)	2.635	128.308	0.699	134.512	144.131

*Table 1.*In-Sample Model Fit and Likelihood Ratio Test Statistics (1964-2008)

Model	**K**	**RSS**	**AICc**	**Δi**
SESMA(1)	4	822.00	65.775	0.653
SESMA(2)	5	823.35	68.345	3.223
SESMA(3)	6	608.94	65.122	**0.000**
SESMA(4)	7	612.43	68.050	2.928

Table 2. The Distance of Truth for SESMA specifications

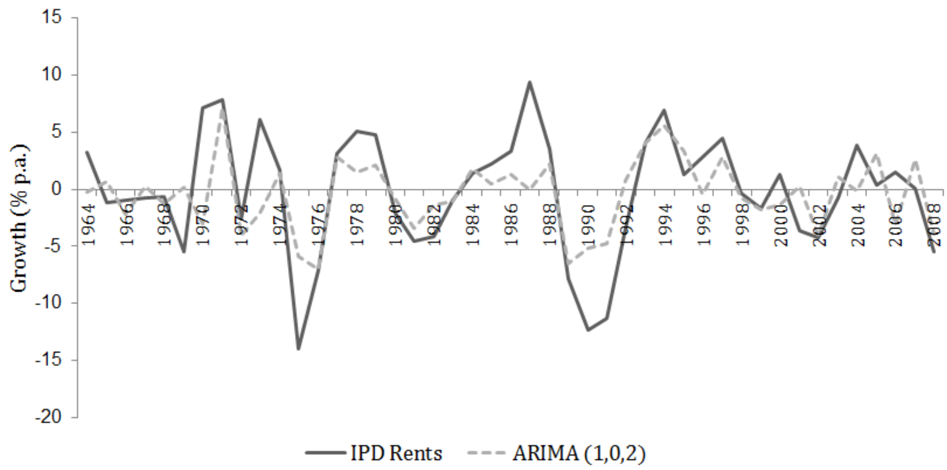

Figure 2. ARIMA (1,0,2) Model Fit (1964-2008) (1st.dif)

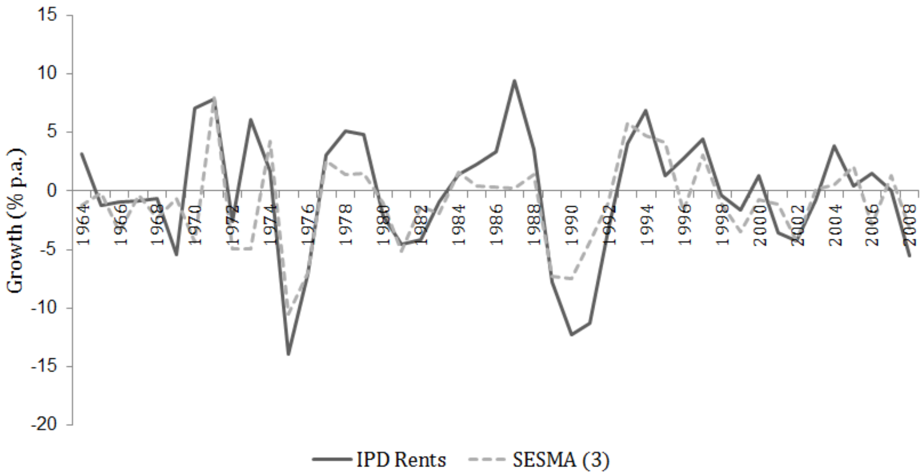

Figure 3. SESMA (3) Model Fit (1964-2008) (1st.dif)

The statistics above, however, describe only the goodness of fit of each of the models to historical data. As noted by Chaplin (1998; 1999) and Makridakis *et.al.* (1998), a good fit does not necessarily imply good forecasting ability. Therefore, the true forecasting accuracy of each of specification is measured for the out-of-sample period for 2009-2010. The predictive ability of each of the models is assessed by computing their standard accuracy measures, as well as Theil's second inequality coefficient *U*:

$$U = \sqrt{\frac{\sum_{t=1}^{n-1}(FPE_{t+1} - APE_{t+1})^2}{\sum_{t=1}^{n-1}(APE_{t+1})^2}} \tag{9}$$

Where FPE_{t+1} is forecast relative change and APE_{t+1} is actual relative change.

The subsequent assessment of the out-of-sample performance of all twenty models suggests that alternative SESMA (3) specification has greater statistical properties (Table 3). Both accuracy measures MAE and MAPE indicate that SESMA (3) fits the historic better than the best ARIMA (2,0,3) specification. In addition to that, the true forecasting accuracy of each specification (measured by *U* coefficient) also suggests that SESMA (3) has greater forecasting properties.

The results of this study indicate that the proposed SESMA framework produces better short-term forecasting results than the conventional ARIMA approach. The model correctly anticipated change in rental values in an out-of-sample period and it also has greater statistical out-of-sample properties. As with ARIMA, the SESMA model is easy to use and is not data intensive. It therefore can be suggested that there are benefits in using the SESMA modelling technique over a traditional ARIMA approach for short-term investment decision-making.

However, despite all the advantages of the proposed model, it does have some limitations. Whereas this model uses only current and past values of the dependent variable itself, it is unlikely that this specification would be able to correctly anticipate future market movements without incorporating additional supply and demand variables. It is also anticipated that SESMA may not generate accurate forecasts for longer-term decision-making; however, this has not been tested in this research.

			Model Fit statistics
Model Specification	**MAE**	**MAPE**	**Theil's U**
ARIMA (1,0,1)	5.964	84.228	0.720
ARIMA (1,0,2)	6.254	89.359	0.802
ARIMA (1,0,3)	5.601	79.759	0.667
ARIMA (1,0,4)	4.910	69.690	0.543
ARIMA (2,0,1)	5.576	78.443	0.649
ARIMA (2,0,2)	5.017	71.023	0.562
ARIMA (2,0,3)	**4.569**	**65.003**	**0.486**
ARIMA (2,0,4)	5.968	84.367	0.724
ARIMA (3,0,1)	5.438	76.542	0.628
ARIMA (3,0,2)	6.443	91.412	0.827
ARIMA (3,0,3)	5.895	83.455	0.716
ARIMA (3,0,4)	5.898	84.161	0.727
ARIMA (4,0,1)	5.039	70.818	0.566
ARIMA (4,0,2)	5.348	75.648	0.618
ARIMA (4,0,3)	5.066	71.544	0.570
ARIMA (4,0,4)	4.813	68.201	0.528
SESMA(1)	5.831	81.798	0.679
SESMA(2)	6.026	84.908	0.721
SESMA(3)	**4.274**	**60.484**	**0.445**
SESMA(4)	4.602	65.044	0.496

Table 3. Model Out-of-Sample Forecasting Accuracy Statistics (2008-2009)

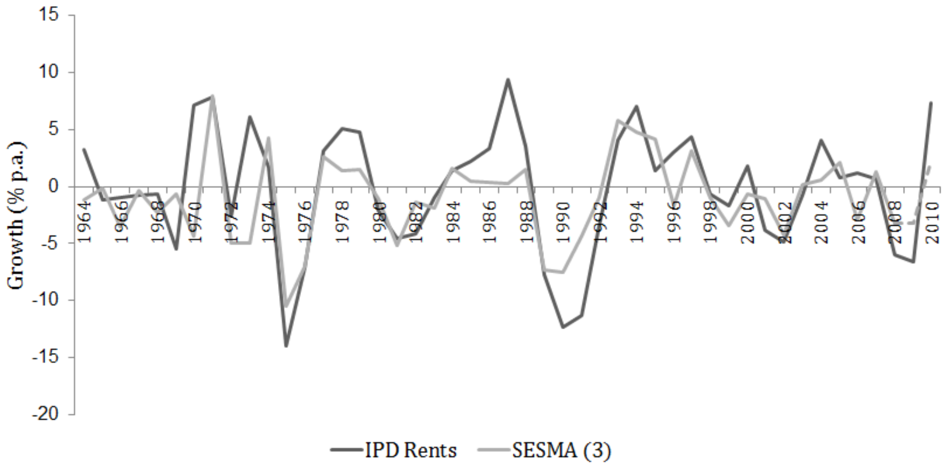

Figure 4. SESMA (3) (Model Fit and Forecasting Accuracy) (1st.dif)

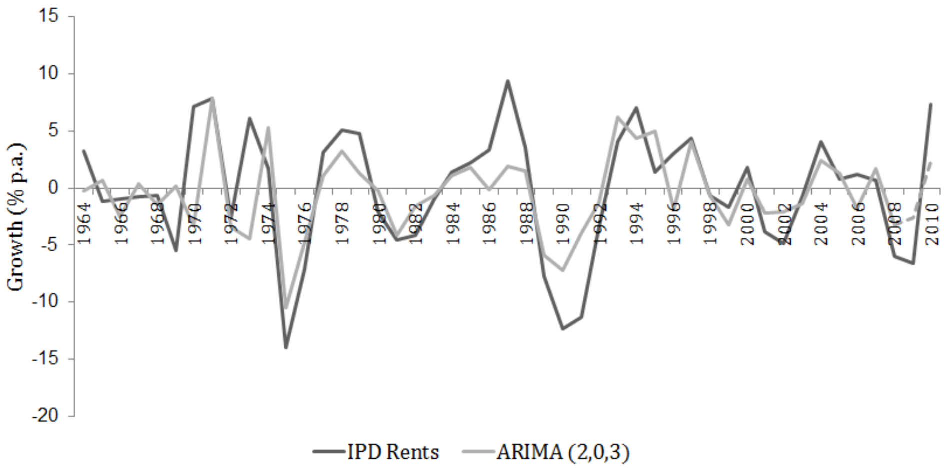

Figure 5. ARIMA (2,0,3) (Model Fit and Forecasting Accuracy) (1st.dif)

CONCLUSIONS AND IMPLICATIONS FOR FURTER RESEARCH

The issue of the property market modelling and forecasting has been a subject of extensive research and empirical analysis. Subsequently, it resulted in the development of forecasting models, ranging from simple single-equation methods to more advanced multi-equation with stationary data techniques, with the ARIMA modelling technique having been extensively used by property researchers. Although, the ARIMA modelling technique has been indicated as an applicable forecasting approach, and a source of useful information for short-term investment decision making, it was nevertheless suggested that this technique could be improved.

The purpose of the current research was, therefore, to propose an alternative ARIMA model specification which would yield greater forecasting accuracy. Certainly, previous attempts have been made to produce alternative ARIMA model specifications to help to achieve greater predictive adequacy. However, the current research re-examined the use of ARIMA approach strictly in a univariate time-series modelling context.

The paper has proposed replacing the AR part of equation with a SES element. As the modelling results indicated, this mathematical manipulation did improve out-of-sample forecasting performance. All statistical measures suggested that so called SESMA (3) model had better out-of-sample properties than the best specified ARIMA structure. Visual analysis also suggested SESMA (3) model's out-of-sample superiority. Although, it was indicated that this particular specification is not without limitations. Nevertheless, the results of the current study are positive. The study has shown that a SESMA univariate structure is applicable for time-series forecasting and therefore can be employed for short-term investment decision making.

All this can also lead to additional research in the current direction. Further research could assess model out-of-sample forecasting accuracy for a longer period of time. It could also examine whether by replacing AR with Holt's Linear Trend (HLT) or Brown's Linear Trend (BLT), which contain smaller errors and therefore produces more accurate extrapolations, would further improve forecasting accuracy.

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