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Outliers Detection using Impulse Indicator Saturation approach: Monte Carlo Simulations and Empirical Applications in Shariah Compliant Stock Indices

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Abstract: The existence of outliers in time series may have a pernicious effect on the estimation of economic and financial signals. Structural changes caused by outliers may reduce the estimated time series model's accuracy and result in forecast failure. The procedure for detecting outliers has been the most crucial issue in this study. We apply a general-to-specific modelling to detect the outlier via indicator saturation in the local level model framework using *gets* a package embodied in R programming language. Focusing on impulse indicator saturation, we assess its performance by using Monte Carlo simulations. The Monte Carlo experiments revealed that the effectiveness of impulse indicator saturation relies heavily on the size of additive outliers, level of significance, and locations of an outlier in the series. Furthermore, we apply impulse indicator saturations to the detection of outliers in FTSE Bursa Malaysia Hijrah Shariah and FTSE All-World Shariah stock indices.

Keywords: Monte Carlo, indicator saturation, outliers, local level, general-to-specific, model selection

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1. INTRODUCTION

Time series are mostly observational in nature. Any structural changes in time series may affect the model estimation, primarily for economic and financial indicators. The existence of outlying observations and structural changes always raises a big question on the accuracy and efficiency of the estimated parameter in the model. Outliers are known as substantial values of the irregular disturbance at a specific time point in the series examined. Failing to model the outliers leads to mis-specify the distribution to be fat-tailed distributions when it is thin-tailed. Besides, [1] demonstrated that the interval forecast is hopelessly too wide when the model ignored the existing outliers. In machine learning literature, a data cleaning process is essential in modelling the data using a data mining algorithm. Thus, outlier detection is considered as part of the data cleaning process. Several recent studies used the indicator saturation technique through general-to-specific (GETS) approach in model selection to detect outliers and structural breaks [2]–[6].

The classical way of performing model selection is using a specific-to-general approach. The method consists of excessive model reduction with inadequate diagnostic testing. On the other hand, the GETS approach postulates a general unrestricted model (GUM) then progressively reduced to a simple model through a sequence of tests. David F. Hendry advocated the GETS procedure for model selection in the econometric model. See the collection of his papers in [7] about GETS procedure. Reference [8] revisited [9] work on data mining experiments using Monte Carlo experiments. Their work started with the GUM to be congruent, then simplify the model by eliminating any variable that satisfies the selection until no variables are to be eliminated. The study improved the automated multipath general-to-specific modelling using MATLAB code in simulations. Reference [10] also proved that the algorithm can be modified and works using cross-sectional data. A further improvement was made by [11] in *Autometrics* by adding indicator variables to identify outliers and structural breaks in the fully saturated regressions.

Impulse indicator saturation (IIS) performed well in the basic structural time series, although the work has only been done by [12]. However, the full potential of the approach has not yet been proven, and hence we focus on the local level model (LLM), which consists of a random disturbance around an underlying level that fluctuates without any specific direction [13]. LLM is known as the simplest model in the state space family and can be presented in state space forms. We refer to the work of [14] for a detailed analysis of state space methods. Here we briefly give an overview about the functional of state space methods. All the components in state model are permitted to vary over the time and explicitly modelled in state space approach. If all the components are deterministic, then the model can be treated as linear regression model. However, the state space models are much superior than linear regression model in fitting the data. In addition, the treatment in state space model is not necessarily require the time series data to be stationary. Furthermore, the state space methods also effortlessly handled missing data and time-varying regressions coefficients.

We conducted this study in response to detect outliers in a series immediately to avoid the misspecification of estimation and distortion of forecast accuracy. Specifically, the IIS is used to detect the outlier when it is near to the forecast origin. The solution is to apply the IIS proposed by [15] to identify the unknown amount, location, and magnitude of outliers in the series examined. IIS works by annexing a set of dummy variables as an intervention for each observation in the series. A plethora of studies on this approach has been found in [6],[11],[12],[16],[17], and [18] using *Autometrics* embodied in *OxMetrics* as a computational tool to perform GETS algorithm.

The most recent development in the GETS algorithm is in R package made available by [19] named *AutoSearch*. Then, [20] introduced *gets* package as a successor from *AutoSearch*. The *gets* package's key strength is that it is the only free, open-source software available to provide GETS modelling of the mean of a regression, GETS modelling of a conditional variance regression, and indicator saturation methods using *isat* function. Furthermore, the *isat* function provides IIS, step indicator saturation (SIS), and trend indicator saturation (TIS) to detect and model the outlier and structural breaks in time series data. The *gets* package proven to increase the computational speed substantially with *turbo = TRUE* and *max.paths = NULL* arguments in *isat* function [20].

This study investigates several questions related to how IIS integrates and performs in the local level model. Besides, it is of interest to investigate the performance of the GETS algorithm in R package instead of *Autometrics*. Hence, this study has been one of the first attempts to thoroughly examine the performance of IIS in the context of the local level model by assessing the potency and gauge values. To our knowledge, the performance of IIS integrated with the local level model has not been scrutinized yet. Therefore, we aim to fill this methodological gap using *gets* a package in R. Further; we apply the IIS to detect additive outliers (AO) in the shariah compliant stock price series, specifically FTSE All World Shariah and FTSE Bursa Malaysia Hijrah Shariah.

The direction of this study is structured as follows. Section 2 elaborates on the framework for the local level model in outlier detection and presents the indicator saturation concepts in the local level model framework. Section 3 begins with a description of the simulation settings for the Monte Carlo experiment. Section 4 summarizes the performance of Monte Carlo simulations on the detection power of IIS. IIS is then applied to the real stock price data for detecting outliers in Section 5. Finally, concludes the paper.

2. Detection method in state space model

A. *Local level model*

The simplest form of state space model is local level model. The model consist of level component which varies over time. The level component act as an intercept in the classical regression model. The local level model can be formulated as

$$y_t = \mu_t + \varepsilon_t \qquad \varepsilon_t \sim NID(0, \sigma_\varepsilon^2) \qquad (1)$$

$$\mu_{t+1} = \mu_t + \omega_t \qquad \omega_t \sim NID(0, \sigma_\omega^2) \qquad (2)$$

for $t = 1,2,\dots,T$ where μ_t is the unobserved level component at time *t*, $\varepsilon_t$is the irregular component at time *t*, and $\omega_t$is the level disturbance at time *t*. The μ_t and ε_t are all assumed to be independent and identically distributed with zero mean and variances ε_t and ω_t , respectively. Equation (1) is defined as the observation equation and the equation (2) is defined as the transition state equation. The transition equation shows the fundamental values based on a random walk. The component ε_t is defined as noise and are assumed to be independent and identically distributed. In this study,we define the signal-to-noise ratio as $q = \sigma_\varepsilon^2/\sigma_\xi^2$. Thus, the local level model also can be referred to as the *random walk plus noise* model [21]. Besides, the local level model also can be written as ARIMA(0,1,1). The first difference of equation (1) resulting as

$$\Delta y_t = y_t - y_{t-1} = \mu_t - \mu_{t-1} + \varepsilon_t - \varepsilon_{t-1} \qquad (3)$$

From equation (2), we substitute $\omega_t = \mu_t - \mu_{t-1}$ into (3) yields

$$\Delta y_t = y_t - y_{t-1} = \omega_t + \varepsilon_t - \varepsilon_{t-1} \qquad (4)$$

It is evident that (4) is stationary process and has same correlogram as in ARIMA(0,1,1).

B. *Indicator saturation*

The classical approach of handling any outlier in the sample data is to discard any outlier in the sample because it 'looks different' or consider as 'bad data'. However, another alternative method is to use indicator saturation approach introduced by David F. Hendry in [15] when he modelled the whole available sample of the US food expenditure data. Hendry believed that there is no need to discard the data because a good economic model should be able to portray the whole features including any structural changes in the data. In practical, the information about the number of outliers, magnitude, location and durations are unknown. Indicator saturation approach is proven efficicent to capture all these informations at any location of sample observations. There are few types of indicator saturations namely impulse indicator saturations, step indicator saturations [18], and design-break indicator saturation [22] can be utilized to identify any forms of deterministic location shifts in time series data [1]. We discuss impulse indicator saturation extensively in this section. IIS approach annexed a set of *T* indicator variables based on *T* observations. The indicator variables act as regressors in GETS modelling process. However, annexing indicator variables in GETS modelling had caused the number of regressors exceeding the number of observations leading to lack of degree of freedom. In order to overcome the potential effect of this problem, [3] proposed a block-splitting estimation in GETS modelling procedure. Hence, not all the indicators are certainly included in estimation of regressors. The key idea of block-splitting is to ensure the number of regressor is always lower than the number of observations. In this process, the indicator variables are partitioned into *m* partitions of s_i regressors resulting to $\sum_{i=1}^{m} s_i = N$. We denote the impulse indicators as $\{1_{\{j=t\}}\}$ where $\{1_{\{j=t\}}\}$ correspond to one when $j = t$ and equal to zero otherwise for $j = 1, \dots, T$. Assume *m* equal to 2 to demonstrate the process of split-half approach in GETS modelling. First, the first half of the sample $T/2$ impulse indicators are added to the model resulting in the model becoming

$$y_t = \mu + \sum_{k=1}^{\frac{T}{2}} \beta_{lk} I_t(k) + \varepsilon_t \; for \; t = 1, \dots, T \qquad (5)$$

The chosen indicators at the significance value, α are determined using the t-statistics value in the first half of the sample. The information about location of significant indicators will be recorded. Then, $T/2$ impulse indicators are added to the second half of the sample, $T - T/2$ and the selection procedure is repeated until significant indicators are chosen under the null hypothesis of no outliers. Finally, a terminal model is obtained from combined significant indicators retained in the two blocks. The selection of retained indicators is regulated by the absolute value of t-statistics $|t_j|$ greater than critical value, c_α. This approach is always feasible if the amount of indicators is the same as the number of observations. However, if the total number of regressors are greater than the number of observations available, we consider a block-splitting algorithm. This approach was also employed by [12] in the context of local linear trend with seasonal component using *Autometrics* algorithm. Inspired by their work, we integrated the IS approach in the local level model using *gets* package in R as follows. We have defined *m* as the number of blocks after the indicators are partitioned. Assume that the blocks are equal in size. Hence, the observation equation in (1) is extended to

$$y_t = \mu + \sum_{k=\left(\frac{T}{m}\right)(i+1)+1}^{\left(\frac{T}{m}\right)i} \beta_{lk}\, I_t(k) + \varepsilon_t,\ t = 1, \dots, T \quad (6)$$

which denotes impulse indicator saturation (IIS). Equation (6) is then put in state space form along with Equation (2).

We apply 1-cut selection and multi-path selection method in selecting the significant indicators. The former has been discussed so far. Meanwhile the latter works by eliminating non-significant indicators one by one starting with the least significant indicator variable in every partition. The iterative procedure continues until the significant indicators are retained in the model. We developed the selection methods algorithm in R language to compare the performance of GETS procedure in terms of potency and gauge. The multi-path selection has been proven to reduce the variance of estimators resulting in a higher power of test as shown in [18].

3. MONTE CARLO SIMULATIONS

A. Experimental design

The Monte Carlo experiments measure the performance of the indicator saturation approach. A time series is generated from local level model given in Equation (1) with initial values of components $\sigma_\eta^2 = 0.0563$ and $\sigma_\varepsilon^2 = 1$. We contaminate the series with an additive outlier, hereafter AO in the generated series. Firstly, we design a benchmark simulation setting for the outlier detection procedure. Then, we consider various alternative settings to investigate the robustness of the procedure. Every experiment involves M = 1000 replications. The following are specifications for the simulation settings for a reference data generating process (DGP):

- Sample size T = 120 and T = 360 observations reflecting 10- and 30-years monthly data.
- A single AO is located at the middle of the sample. Meanwhile, double AO were predetermined at the [0.25, 0.75] as a proportion of observations, T.
- Target size or significance level, α = 0.001, 0.01 and 0.025. According to [23], these values will determine the statistical tolerance of the procedure. For example, a target of 0.01 for IIS indicates that on average, we accept 1 impulse dummy that may not be in the data generating process for every 100 observations.
- We labelled the magnitude of an AO as *z*σ where *z* is a positive integer. Meanwhile, σ is the prediction error standard deviation (PESD) of the series. The magnitude of AO varies between 3σ, 5σ, 7σ, 9σ, and 12σ.
- We apply the block-splitting algorithm by partitioned the indicator variables into two, four, and six blocks to lower the variance of estimates.
- The location of AO also varies based on the share of the sample.

We decided to follow [12] to determine the appropriate size of AO in our Monte Carlo experiments since we deal with multiple sources of disturbances in structural time series. We formulated σ as

$$v_t = y_t - E(y_t|Y_{t-1}) = \mu_t - E(\mu_t|Y_{t-1}) + \varepsilon_t \quad (7)$$

with $Y_t = \{y_t, y_{t-1}, \dots, y_1\}$. Moreover, this approach is also consistent with [24] and [25]. Overall, we measure the robustness of the model based on a few aspects: the number of observations, T, number of AO added, values of target size, magnitude and of AO, number of blocks estimation, and locations of the AO in the series.

B. Assessing the performance of the Monte Carlo experiment

We apply the concepts of potency and gauge to assess the efficiency of the outlier detection procedure. Potency can be defined as the proportion of relevant indicators that remain in the final model, while gauge is the proportion of irrelevant indicators that remain in the final model. Both potency and gauge are computed based on the retention rate formulated as

$$\tilde{r} = \frac{1}{M}\sum_{i=1}^{M} 1\left[\widetilde{\beta_{lj}} \neq 0\right],\ j = 1, \dots, T \quad (8)$$

$$potency = \frac{1}{n}\sum_j \tilde{r}_j,\ j \epsilon R_n \quad (9)$$

$$gauge = \frac{1}{T-n}\sum_j \tilde{r}_j,\ j \epsilon R_{T-n} \quad (10)$$

where M denotes the number of replications and *n* the number of true outliers in the time series of length T. Hence, let R_n and R_{T-n} as sets of time indices for relevant and irrelevant indicators retained in the model, respectively. Meanwhile, $\widetilde{\beta_{lk}}$ denotes the estimated coefficient in the impulse indicator and if $I_t(k)$ is selected, then the variable $1\left[\widetilde{\beta_{lk}} \neq 0\right]$ will take a value of one indicating that the argument is true and zero otherwise. We follow the rule of thumb suggested by [20] to determine the value of target size $\alpha = \min\left[0.05, {}^{1}/_{T}\right]$. This will ensure a low gauge value below 5% of the sample, T or only one irrelevant indicator variable retained in the final model.

The concept of potency and gauge used in this study can also be illustrated as a confusion matrix adapted from [12]. However, the confusion matrix presented only summarises the outcome of one Monte Carlo experiment. We defined W and Z as a true positive and true negative, respectively.

True	**Predicted**		
	Outlier not exist	Outlier exist	
Outlier not exist	W	X	M(T – n)
Outlier exist	Y	Z	Mn
Total	W+Y	X+Z	MT

According to machine learning literature, X and Y are also known as false positives and false negatives. Hence, the potency is known as the ratio of Z/Mn. Meanwhile, the gauge is defined as the ratio of X/[M(T-n)]. All computations are done using *gets* package in R programming language offered by [26].

4. RESULTS AND DISCUSSION

As mentioned in the previous section, we assess the effectiveness of IIS based on potency and gauge values. Overall, the IIS performed well to detect almost 100% for a value of *z* greater than 7. As we increased the target size value, the potency reached almost 100%. We split the sample up to *m* = 6 blocks to estimate the model. A similar approach has been used in [12] also shows that any additional number of blocks exceeding ten did not efficicent to capture the AO in the data.

Based on the Monte Carlo results shown in Table 1-8 below, obviously the performance of IIS relies heavily on the magnitude of outliers even though with different target sizes. The potency when *z* = 3 is relatively low with a satisfactory gauge value. However, when the size of *z* increases to 7, the probability of the first detection is almost 100%.

In 1-cut selection, the number of blocks was a critical aspect that affected the performance of IIS in outlier detection. Thus, we decided to generate the results using two, four, and six blocks for both series. A minimum number of blocks would minimise the risk of missing any essential structural changes when there are too many blocks. The Monte Carlo results for T =120 observations using different blocks are summarised in Table 1. The potency achieved 100% when the size of AO is at least *z* = 7. Similarly, for T = 360 (See Table 2), the potency achieved is above 90%, which is still an excellent result with a low false retention rate. This means that the number of blocks plays a vital role in outlier detection using IIS as the number of T increases. As examined closely, we found the average gauge values in multi-path selection are much lower than in 1-cut selection. In fact, the gauge values for 1-cut selection exceeding but still clustered around the significance level, α in most settings. Thus, multi-path selection approach plays a crucial role in eliminating the indicator that spuriously retained in the model.

Table 9 and 10 show the Monte Carlo results for single AO and double AO at different locations using 4 blocks estimation. The target size was chosen as $\alpha = {}^{1}/_{T}$ and magnitude of AO as 7σ. The Monte Carlo results for a single AO with different locations are summarised in Table 9. We found a more satisfactory potency values when the AO located in the middle of the sample as compared to the location of AO near the end of the sample. These results are consistent with [12] findings computed using *Autometrics* algorithm.

TABLE 1. POTENCY AND GAUGE VALUES WHEN CONTAMINATED WITH SINGLE AO, VARIOUS SIGNIFICANCE VALUES, 1-CUT SELECTION

T=120		2 blocks					4 blocks					6 blocks				
	α	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ
Potency (%)	0.001	19.7	75.6	97.6	99.8	100	22.2	77.5	97.1	99.7	100	18.7	77.7	97.8	99.6	100
	0.01	50.1	92.5	99.7	99.9	100	47.4	91.9	99.7	100	100	47.2	92.4	99.9	100	100
	0.025	64.2	96.7	100	100	100	60.6	96.3	100	100	100	57.9	97.3	99.9	100	100
Gauge (%)	0.001	0.05	0.10	0.03	0.04	0.02	0.20	0.05	0.04	0.01	0.01	0.16	0.04	0.01	0.02	0.00
	0.01	0.87	0.73	0.70	0.59	0.56	0.79	0.56	0.41	0.24	0.18	0.80	0.54	0.34	0.20	0.12
	0.025	3.12	2.64	2.28	2.02	1.90	2.52	1.92	1.32	0.92	0.58	2.34	1.72	1.21	0.71	0.43

TABLE 2. POTENCY AND GAUGE VALUES WHEN CONTAMINATED WITH SINGLE AO, VARIOUS SIGNIFICANCE VALUES, 1-CUT SELECTION

T=360		2 blocks estimation					4 blocks estimation					6 blocks estimation				
	α	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ
Potency (%)	0.1	8.9	45.6	75.1	92.8	98.8	7.7	43.6	77.8	90.3	98.8	7.9	41.9	78.7	91.6	99.0
	1	23.1	66.8	90.8	99.9	100	23.8	65.8	89.4	97.9	99.9	23.5	68.6	89.8	97.8	100
	2.5	40.7	78.5	95.0	99.5	100	35.5	74.6	94.9	99.9	100	33.8	74.6	94.9	99.8	100
Gauge (%)	0.1	0.04	0.09	0.03	0.04	0.13	0.35	0.24	0.16	0.20	0.09	0.24	0.17	0.09	0.12	0.08
	1	1.18	0.99	0.95	0.93	0.78	1.05	0.87	0.81	0.70	0.44	0.94	0.88	0.76	0.52	0.43
	2.5	4.46	4.51	4.42	3.91	3.17	3.36	3.21	2.75	2.35	1.89	2.75	2.65	2.37	2.05	1.66

TABLE 3. POTENCY AND GAUGE VALUES WHEN CONTAMINATED WITH DOUBLE AO, VARIOUS SIGNIFICANCE VALUES, 1-CUT SELECTION

T = 120		2 blocks estimation					4 blocks estimation					6 blocks estimation				
	α	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ
Potency (%)	0.1	18.1	72.2	93.1	99.6	100	19.7	72.6	94.7	99.6	100	18.7	77.9	97.4	99.7	100
	1	48.7	89.9	99.3	99.8	100	49.3	89.3	98.7	99.9	100	47.2	92.6	100	100	100
	2.5	61.5	94.4	99.4	100	100	63.0	93.8	99.6	100	100	57.9	97.6	99.5	100	100
Gauge (%)	0.1	0.05	0.02	0.01	0.00	0.00	0.11	0.02	0.03	0.00	0.00	0.16	0.04	0.01	0.02	0.00
	1	0.82	0.46	0.25	0.11	0.02	0.72	0.38	0.21	0.06	0.02	0.80	0.54	0.34	0.20	0.12
	2.5	2.98	1.84	1.10	0.52	0.14	2.21	1.35	0.71	0.32	0.08	2.34	1.72	1.21	0.71	0.43

TABLE 4. POTENCY AND GAUGE VALUES WHEN CONTAMINATED WITH DOUBLE AO, VARIOUS SIGNIFICANCE VALUES, 1-CUT SELECTION

T = 360		2 blocks estimation					4 blocks estimation					6 blocks estimation				
	α	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ
Potency (%)	0.1	8.46	41.5	73.7	90.1	98.5	8.5	43.1	76.2	90.4	98.0	7.9	42.7	75.6	90.8	97.4
	1	25.1	68.5	89.8	96.3	99.3	25.9	66.5	86.8	96.6	99.9	25.0	66.0	87.6	95.7	99.4
	2.5	44.5	75.9	92.0	97.8	99.8	39.9	76.0	94.1	97.5	99.7	38.8	76.0	92.2	97.3	99.9
Gauge (%)	0.1	0.04	0.03	0.03	0.02	0.01	0.32	0.12	0.04	0.06	0.01	0.23	0.20	0.14	0.08	0.02
	1	1.02	0.91	0.87	0.67	0.52	0.79	0.73	0.68	0.54	0.26	0.82	0.72	0.57	0.35	0.20
	2.5	4.28	3.74	3.13	2.74	2.00	3.04	2.91	2.52	2.03	1.34	2.63	2.33	1.84	1.45	0.97

TABLE 5. POTENCY AND GAUGE VALUES WHEN CONTAMINATED WITH SINGLE AO, VARIOUS SIGNIFICANCE VALUES, MULTI-PATH SELECTION

T = 120		2 blocks estimation					4 blocks estimation					6 blocks estimation				
	A	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ
Potency (%)	0.1	19.7	75.6	97.6	99.8	100	19.7	73.9	97.6	99.8	100	21.0	77.8	98.0	99.6	100
	1	50.1	92.5	99.7	99.9	100	47.0	92.4	99.7	100	100	48.0	92.7	99.5	100	100
	2.5	64.2	96.7	100	100	100	59.5	95.5	99.9	100	100	60.9	96.4	99.9	100	100
Gauge (%)	0.1	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
	0.1	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00
	2.5	0.02	0.02	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.02	0.01	0.00	0.00	0.00

TABLE 6. POTENCY AND GAUGE VALUES WHEN CONTAMINATED WITH DOUBLE AO, VARIOUS SIGNIFICANCE VALUES MULTI-PATH SELECTION

T = 120		2 blocks estimation					4 blocks estimation					6 blocks estimation				
	A	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ
Potency (%)	0.1	20.2	71.8	95.0	98.8	100	19.1	70.3	94.6	99.5	100	19.6	71.6	95.1	99.3	100
	1	48.7	90.1	98.7	100	100	47.3	89.0	98.8	99.9	100	47.1	90.6	98.6	99.9	100
	2.5	64.0	94.5	99.3	99.9	100	61.7	93.3	99.4	99.9	100	60.5	93.1	99.5	100	100
Gauge (%)	0.1	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.09	0.0	0.00	0.00	0.00
	1	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.02	0.02	0.01	0.00	0.00
	2.5	0.02	0.02	0.01	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.00

TABLE 7. POTENCY AND GAUGE VALUES WHEN CONTAMINATED WITH SINGLE AO, VARIOUS SIGNIFICANCE VALUES, MULTI-PATH SELECTION.

		2 blocks estimation					4 blocks estimation					6 blocks estimation				
T=360	A	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ
Potency (%)	0.1	19.7	75.6	97.6	99.8	100	21.1	73.9	97.6	99.8	100	23.4	77.8	98.0	99.6	100
	1	50.1	92.5	99.7	99.9	100	47.0	92.4	99.7	100	100	48.0	92.7	99.5	100	100
	2.5	64.2	96.7	100	100	100	59.5	95.5	99.9	100	100	60.9	96.4	99.9	100	100
Gauge (%)	0.1	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	1	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00
	2.5	0.02	0.02	0.00	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00

TABLE 8. POTENCY AND GAUGE VALUES WHEN CONTAMINATED WITH DOUBLE AO, VARIOUS SIGNIFICANCE VALUES, MULTI-PATH SELECTION

		2 blocks estimation					4 blocks estimation					6 blocks estimation				
T=360	α	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ	3σ	5σ	7σ	9σ	12σ
Potency (%)	0.1	20.2	71.8	95.0	98.8	100	19.1	70.3	94.6	99.5	100	19.6	71.6	95.1	99.3	100
	1	48.7	90.1	98.7	100	100	47.3	89.0	98.8	99.9	100	47.1	90.6	98.6	99.9	100
	2.5	64.0	94.5	99.3	99.9	100	61.7	93.3	99.4	99.9	100	60.5	93.1	99.5	100	100
Gauge (%)	0.1	0.03	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.09	0.01	0.00	0.00	0.00
	1	0.01	0.01	0.01	0.00	0.00	0.08	0.01	0.01	0.01	0.01	0.04	0.01	0.01	0.00	0.00
	2.5	0.07	0.02	0.00	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.01	0..01	0.01	0.00

TABLE 9. POTENCY AND GAUGE VALUES FOR SINGLE AO AT DIFFERENT LOCATIONS.

No. of observations, T		Location of single AO				
		0.1	0.3	0.5	0.7	0.9
120	Potency (%)	97.9	98.9	99.5	98.9	97.9
	Gauge (%)	0.01	0.01	0.01	0.01	0.01
360	Potency (%)	88.2	90.6	88.6	82.6	81.5
	Gauge (%)	0.00	0.00	0.00	0.00	0.00

a. Location of AO is labelled based on proportion of observations, *T*

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TABLE 10. POTENCY AND GAUGE VALUES FOR DOUBLE AO AT DIFFERENT LOCATIONS.

No. of observations, T		Location of double AO				
		[0.1,0.2]	[0.3,0.4]	[0.5,0.6]	[0.7,0.8]	[0.9,1]
120	Potency (%)	99.5	99.05	99.65	98.25	97.35
	Gauge (%)	0.3525	0.1780	0.0805	0.1237	0.3576
360	Potency (%)	83.3	84.4	84.1	81.25	83.8
	Gauge (%)	0.1933	0.1869	0.2989	0.1115	0.1500

a. Location of AO is labelled based on proportion of observations, *T*

It appears that as we increased the number of samples to T = 360, the potency was reduced for both scenarios of single and double AO towards the end of the sample. However, a potency value of about 80% is consider acceptable when it is chained with a small value of false retention as obtained in [12]. Moreover, T = 120 shows a symmetry pattern with at least 97% potency values.

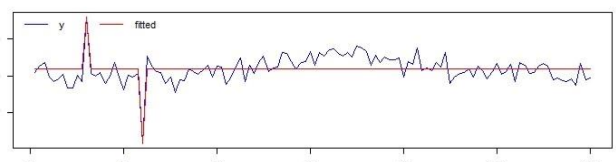

Figure 1. Fitted and actual values for step indicator saturations to AO generated by *Autometrics* for FTSE USA Shariah index.

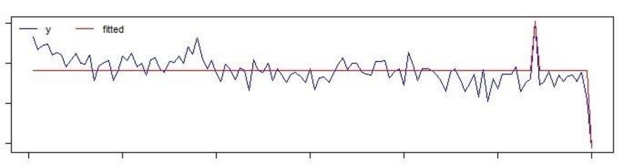

Figure 2. Example of series contaminated with additive outliers at the end of sample for 120 observations

5. EMPIRICAL APPLICATIONS

The detection of outlier has essential effects on economic time series data for parameter estimation and forecasting purposes. We apply the indicator saturation approach to the FTSE All World Shariah stock price index. The reference model framework for this application is the local level model. The data covers the period from February 2007 until July 2019, consisting of 150 observations, T. The data is transformed into log series and first difference. The selection of significant level is governed by $1/T = 0.0067$ which manifests that generally less than one indicator being remained spuriously under the null of no outliers. We split the blocks into two, four, and six with multi-path path indicator saturation. The objective of this application is to assess how indicator saturation, specifically IIS depicts recessionary events triggered by financial crises around the world, especially during the world financial crisis in 2008–2009. The outliers detected using IIS are tabulated in Table 11. As expected, the results show that outliers are detected during the years 2008 and 2009 for stock returns in Malaysia.

Interestingly, we find that the outliers detected in 2008 are negatively associated with the global economic recession occured. This result is consistent with previous occurrences of financial crises, which IIS interpret as recessions. However, there is only one positive AO detected by IIS in April 2009, and we conjecture that the change can be considered as the recovery process. Contrastingly, IIS manages to capture three negative AO in FTSE All World Shariah stock returns as reported in Table 11. Based on Figure 3, we find that the outlier detected is consistent with FBM Hijrah Shariah in September 2008, reflecting the global recession.

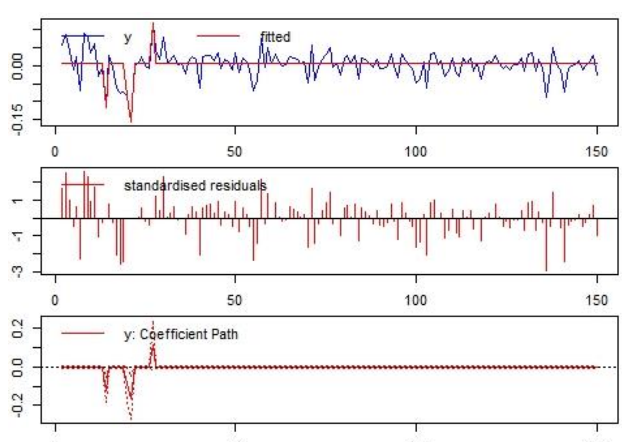

Figure 3. Stock returns of FTSE Bursa Malaysia Hijrah Shariah. The top plot present observed (blue) and fit (red). Middle plot present standardised residuals of stock returns and bottom plot present the coefficient approximate to 95% confidence interval.

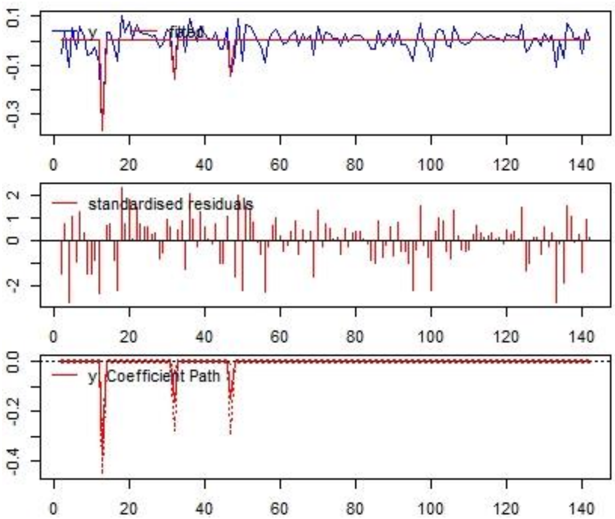

Figure 4. Stock returns of FTSE All World Shariah. The top plot presents observed (blue) and fit (red). Middle plot presents standardised residuals of stock returns and bottom plot presents the coefficient path approximate to 95% confidence interval.

TABLE 11. OUTLIER DETECTED FTSE ALL WORLD SHARIAH STOCK RETURNS.

Number of blocks, *m*					
2		4		6	
Apr-07	(-2.8059)	Jan-08	(-8.9606)	Jan-08	(-8.9606)
Jan-08	(-8.9606)	Aug-09	(-3.8616)	Aug-09	(-3.8616)
Aug-09	(-3.8616)	Nov-11	(-3.6905)	Nov-11	(-3.6905)
Nov-11	(-3.6905)				

a. t-statistics value reported in parentheses

6. CONCLUSIONS

Our study aimed to examine the ability of impulse indicator saturation in detecting outliers in a local level model using *gets* package in R language. To date, no study has investigated using indicator saturation integrated in a local level model and we aimed to contribute to body of knowlege in the literature. Interestingly, the state space model used in this study consist of level component that varied over time. Thus, stochastic changes will occur over the time as the trend component is driven by random disturbance. As mentioned earlier, the performance of IIS was measured by potency and gauge in an extensive Monte Carlo experiment. Hence, we conclude that IIS is very useful in detecting outliers.

We discovered a few aspects that can affect the performance of IIS. First, the size and magnitude of AO. IIS is very effective as the size of AO increases. Secondly, the target size chosen also affects the potency value as it determines the number of irrelevant indicators to be retained in the model. Next, the number of blocks is also an important factor in the performance of the IIS procedure. Reference [12] suggested that IIS approach works better if the AOs are in the same sample of blocks. Fourth, IIS performs better in detecting single AO than double AO in the series. Finally, the location of AO plays a vital role in the performance of IIS. We found that the potency achieved its maximum when the location of AO is in the middle of the sample. In the last part of the work, we applied IIS to the monthly stock returns for FTSE Bursa Malaysia Shariah and FTSE All World Shariah. We aimed to investigate the application of IIS to depict the global recession movement that affected the shariah compliant stock index. Overall, IIS is proven effective in detecting the outlier in the local level model. Eventhough, IIS is initially designed to detect outlier, it also capable to detect single location shift using split-half approach when a single location shift exists in the series. Finally, incorporating step indicator saturation (SIS) into the local level model is another direction of research to capture any structural change.

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REFERENCES

[1] J. L. Castle and D. F. Hendry, *Modelling our Changing World*. Palgrave Macmillan, 2019.

[2] D. F. Hendry and C. Santos, “Regression models with data-based indicator variables,” *Oxf. Bull. Econ. Stat.*, vol. 67, no. 5, pp. 571–595, 2005.

[3] C. Santos, D. F. Hendry, and S. Johansen, “Automatic selection of indicators in a fully saturated regression,” *Comput. Stat.*, vol. 23, no. 2, pp. 317–335, 2008, doi: 10.1007/s00180-007-0054-z.

[4] D. F. Hendry and H. Krolzig, “New Developments in Automatic General-to-Specific Modelling,” in *Econometrics and the Philosophy of Economics: Theory-Data Confrontations in Economics*, 2001, pp. 379–419.

[5] J. L. Castle, J. A. Doornik, and D. F. Hendry, “Model selection when there are multiple breaks,” *J. Econom.*, vol. 169, no. 2, pp. 239–246, 2012, doi: 10.1016/j.jeconom.2012.01.026.

[6] J. L. Castle, J. A. Doornik, and D. F. Hendry, “Evaluating Automatic Model Selection,” *J. Time Ser. Econom.*, vol. 3, no. 1, 2011, doi: 10.2202/1941-1928.1097.

[7] D. F. Hendry, *Econometrics Alchemy or Science?*, First. Oxford University Press, 2000.

[8] D. F. Hendry and H. Krolzig, “Improving on ‘Data mining reconsidered’ by K.D. Hoover and S.J. Perez,” *Econom. J.*, vol. 2, no. 2, pp. 202–219, 1999, doi: 10.1111/1368-423x.00027.

[9] M. C. Lovell, “Data Mining,” *Rev. Econ. Stat.*, vol. 65, no. 1, pp. 1–12, 1983.

[10] K. D. Hoover and S. J. Perez, “Truth and Robustness in Cross-country Growth Regressions,” *SSRN Electron. J.*, vol. 5, no. June 2001, pp. 6–9, 2005, doi: 10.2139/ssrn.258608.

[11] C. Santos, D. F. Hendry, and S. Johansen, “Automatic selection of indicators in a fully saturated regression,” *Comput. Stat.*, vol. 23, no. 2, pp. 317–335, 2008, doi: 10.1007/s00180-007-0054-z.

[12] M. Marczak and T. Proietti, “Outlier detection in structural time series models: The indicator saturation approach,” *Int. J. Forecast.*, vol. 32, no. 1, pp. 180–202, 2016, doi: 10.1016/j.ijforecast.2015.04.005.

[13] S. J. Commandeur, Jacques J. F. & Koopman, *An Introduction to State Space Time Series Analysis*, First. New York: Oxford University Press, 2007.

[14] J. Durbin and S. J. Koopman, *Time Series Analysis by State Space methods*, Second. Oxford: Oxford University Press, 2012.

[15] D. F. Hendry, “Department of Economics Discussion Paper Series Empirical Economic Model Discovery and Theory Evaluation,” *Society*, no. 529, 1999.

[16] S. Johansen and B. Nielsen, "An Analysis of the Indicator Saturation Estimator as a Robust Regression Estimator," *Methodol. Pract. Econom. A Festschrift Honour David F. Hendry*, 2009, doi: 10.1093/acprof:oso/9780199237197.003.0001.

[17] J. L. Castle, J. A. Doornik, and D. F. Hendry, "Model selection when there are multiple breaks," *J. Econom.*, vol. 169, no. 2, pp. 239–246, 2012, doi: 10.1016/j.jeconom.2012.01.026.

[18] J. L. Castle, J. a Doornik, D. F. Hendry, and F. Pretis, "Detecting Location Shifts by Step-indicator Saturation," *Econometrics*, vol. 3, no. 2, pp. 240–264, 2015, doi: 10.3390/econometrics03020240.

[19] G. Sucarrat and A. Escribano, "Automated model selection in finance: General-to-specific modelling of the mean and volatility specifications," *Oxf. Bull. Econ. Stat.*, vol. 74, no. 5, pp. 716–735, 2012, doi: 10.1111/j.1468-0084.2011.00669.x.

[20] F. Pretis, J. J. Reade, and G. Sucarrat, "Automated general-to-specific (GETS) regression modeling and indicator saturation for outliers and structural breaks," *J. Stat. Softw.*, vol. 86, no. 3, 2018, doi: 10.18637/jss.v086.i03.

[21] A. Harvey and S. J. Koopman, "Signal extraction and the formulation of unobserved components models," *Econom. J.*, vol. 3, no. 1, pp. 84–107, 2000, doi: 10.1111/1368-423x.00040.

[22] F. Pretis, L. Schneider, J. E. Smerdon, and D. F. Hendry, "Detecting Volcanic Eruptions in Temperature Reconstructions By Designed Break-Indicator Saturation," *J. Econ. Surv.*, vol. 30, no. 3, pp. 403–429, 2016, doi: 10.1111/joes.12148.

[23] R. Mariscal and A. Powell, "Commodity Price Booms and Breaks: Detection, Magnitude and Implications for Developing Countries," *Ssrn*, no. January, 2014, doi: 10.2139/ssrn.2384422.

[24] C. Chang, Ih, Tiao, George C. and Chen, "Estimation of time series parameters in the presence of outliers," *Technometrics*, vol. 30, no. 2, pp. 193–204, 1988.

[25] C. Chen and L.-M. Liu, "Joint Estimation of Model Parameters and Outlier Effects in Time Series," *J. Am. Stat. Assoc.*, vol. 88, no. 421, p. 284, 1993, doi: 10.2307/2290724.

[26] F. Pretis, J. Reade, and G. Sucarrat, "General-to-Specific (GETS) Modelling and Indicator Saturation with the R Package gets," *Discuss. Pap.*, no. 794, pp. 1–30, 2016.

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