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Farid Zamani Che Rose, Mohd Tahir Ismail, Nur Aqilah Khadijah Rosili

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Structural breaks detection using step-indicator saturation technique in state-space model

Farid Zamani Che Rose*

Department of Mathematics and Statistics,
Faculty of Science,
Universiti Putra Malaysia,
43400 UPM Serdang, Selangor Darul Ehsan, Malaysia
Email: farid6908@gmail.com
*Corresponding author

Mohd Tahir Ismail

School of Mathematical Sciences,
Universiti Sains Malaysia,
11800 USM Penang, Malaysia
Email: m.tahir@usm.my

Nur Aqilah Khadijah Rosili

Faculty of Computing and Engineering,
Quest International University,
30250 Ipoh, Perak, Malaysia
Email: nuraqilahkhadijah.rosili@qiup.edu.my

Abstract: Recently, there has been a lot of interest in identifying structural breaks in economic time series. Failing to capture any structural breaks may have a pernicious effect on model estimation due to significant forecast errors after such breaks and inappropriate tests. Therefore, this study proposed a step-indicator saturation (SIS) technique as an extension of the general-to-specific (GETS) modelling framework for detecting any structural changes in time series. Monte Carlo simulations assessed the performance of the SIS in the local level model based on potency and gauge metrics using the 'gets' package in the R programming language. Sequential selection outperformed the non-sequential approach in the automatic GETS model selection procedure. Accordingly, this study applied the SIS technique to the Financial Times Stock Exchange (FTSE) Bursa Malaysia Hijrah Shariah and FTSE USA Shariah using a split-half approach and sequential selection. The retained indicators in the terminal model were selected based on the sequential and non-sequential algorithms. It was found that the retained indicators in both indices collided with the financial crises in 2008–2009. Overall, the proposed technique offers an effective approach to detect unknown locations, magnitudes, and structural break signs in a structural times series framework.

Keywords: structural breaks; step-indicator saturation; SIS; Monte Carlo; model selection; state-space model; general-to-specific; GETS.

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Biographical notes: Farid Zamani Che Rose is a Senior Lecturer at the Department of Mathematics and Statistics, Faculty of Science, Universiti Putra Malaysia. Prior to his current appointment, he rendered his invaluable expertise and services as a research officer at the Department of Veterinary Services Malaysia. He obtained his doctorate degree from the Universiti Sains Malaysia. His current research includes automatic model selection, predictive model in machine learning algorithm, time series analysis and forecasting.

Mohd Tahir Ismail is an Associate Professor at the School of Mathematical Sciences, Universiti Sains Malaysia. His research interests are financial time series, econometrics, categorical data analysis, and applied statistics. He has published more than 150 publications in reviewed journals and proceedings (some of them are listed in ISI, Scopus, Zentralblatt, MathSciNet, and other indices). Currently, he is an Exco member of the Malaysian Mathematical Sciences Society and an active member of other scientific and professional bodies.

Nur Aqilah Khadijah Rosili is a Lecturer at the Faculty of Science and Technology, Quest International University. Her researches are mainly about simulations, data mining and application of machine learning algorithm in legal issues.

1 Introduction

When the mean and variance of a time series are constantly changing over time, the series is considered non-stationary, which is a norm to most economic data. Certain occurrences like wars, the COVID-19 pandemic, and economic recessions can result in prolonged means and variance fluctuations, leading to non-stationary time series. According to Castle and Hendry (2019), evolution and sudden shifts are the two crucial sources that caused series to be non-stationary. The former is defined as gradual changes or the cumulation of past shocks and the latter is defined as a sudden shift called structural breaks. Failing to tackle non-stationarity will result in a distortion of the empirical model's parameter estimation or forecast failure. Hendry and Mizon (2011) documented that unmodelled structural breaks lead to improbable regressor coefficients. Furthermore, unmodelled structural breaks may detrimentally affect forecast performance (Hendry, 1999). These are the most frequently encountered problems when managing structural breaks. Hence, it is imperative to have a better understanding of the algorithm for detecting structural breaks.

The typical approaches mainly used in studies are the Chow (1960) test, Quandt likelihood ratio (QLR) test, an extension from Chow test proposed by Quandt (1960), and Bai and Perron (1998, 2003) test. Meanwhile, Andrews (1993) focused on a methodology to test for a change in single parameter with unknown break point in nonlinear models. Recent studies by Rashedi et al. (2020), Dadakas (2022) and Dadakas and Fargher (2021) presented alternative procedures for the detection of structural breaks. However, there are several downsides to the existing detection methods. The Chow test is less effective in detecting several structural breaks in time series data. Besides, the QLR test is computationally expensive, hence time-consuming. Additionally, Antoshin et al. (2008) highlighted that when there are more than two structural breaks, Bai and Perron test's sequential algorithm might incorrectly estimate and assess their statistical significance. An iterative process is necessary for the detection procedure by Rashedi et al. (2020) when combined with the Tukey method and Maximal-overlap discrete wavelet transform (MODWT). This method may not yield its full potential when there is insufficient number of observations to reach the level of wavelet transform. While Dadakas and Fargher (2021) and Dadakas (2022) only focused on the methodology to examine the stationarity under the presence of endogenous structural breaks. Hence, there is a mounting need to study an approach for detecting the location, magnitude, duration, and sign of multiple breaks in time series data.

In recent years, general-to-specific (GETS) modelling has seen an increase in the use of indicator saturation (IS) approaches. Santos et al. (2008) and Johansen and Nielsen (2009) demonstrated that the IS algorithm currently performed in *Autometrics* is highly effective in a regression framework. It is used to determine the unascertained number of breaks occurring at unascertained locations, magnitude, duration, and signs of structural breaks in time series data. The recent advances in IS literature motivated this study. Marczak and Proietti (2016) were the first and only to apply IS to a structural time series framework using a basic structural model. There had been no known studies or publications on the application of IS in the local level model (one of the structural time series model). Moreover, no study had attempted to assess the effectiveness of IS integration in the state-space model using the R programming language's 'gets' package, which consists of facilities for automated GETS modelling and IS techniques for the detection and modelling of outliers and structural breaks. Hence, this study aimed to close this methodological gap by incorporating step indicators into the model at the local level.

The remainder of this paper is organised as follows: Section 2 highlights IS-based past research and the establishment of GETS modelling; Section 3 describes the step indicators structure and structural breaks detection procedure; Section 4 elaborates the Monte Carlo experiment simulation settings and reports the simulations' performance on the detection power of step-indicator saturation (SIS) approach; Section 5 presents the SIS approach applied to the actual stock price; Section 6 provides the conclusions and potential future work.

2 Literature review

Numerous research has been conducted in recent years employing IS methods to meticulously examine structural change modelling (Johansen and Nielsen, 2009; Castle et al., 2012, 2015, 2020; Pretis et al., 2016b; Marczak and Proietti, 2016; Doornik et al., 2020). Hendry (1999) first introduced impulse IS (IIS) as a component of the GETS approach when modelling the US real per-capita annual food demand from 1929–1952. Furthermore, impulse indicators were included at each observation for testing an unknown number of breaks happening at uncertain dates, durations, and magnitudes. Besides that, various studies on economic applications have been conducted (Ericsson, 2012, 2017; Hendry and Mizon, 2011; Marczak and Proietti, 2016). Continuous development led to another extension of IS called SIS, by Doornik et al. (2013) to model structural breaks based on step interventions. Computations of IIS and SIS were made available in *Autometrics* by Doornik (2009) and the *gets* package in R by Pretis et al. (2016a). As highlighted earlier, the performance of IS in a structural time series model framework has only been investigated by Marczak and Proietti (2016), who utilised basic structural time series as a reference model and the GETS approach to identify outliers and level shifts; this was the inspiration and starting point for this study.

Much of the early works in the development of data mining algorithms in GETS modelling began with Hoover and Perez (1999), who revisited Lovell (1983) works in data mining experiments using limited *MATLAB* code, called HP1999. The essential ingredients of the HP1999 algorithm were the formulation of a general unrestricted model (GUM), multiple paths searching strategies, encompassing tests, diagnostic tests, and info criterion as a tiebreaker. Krolzig and Hendry (2001) improved this algorithm in *PcGets*, an Ox package, which offers an extension from HP1999 with additional pre-search, iterative multiple paths searching strategies and theoretical aspects in model selection. Further, Doornik (2009) accomplished tremendous advances in GETS algorithm via *Autometrics* embodied in *OxMetrics*. The *Autometrics* algorithm systematically improved the multiple paths using a tree-search method and increased the computational speed by avoiding the same model estimation and delayed diagnostic testing.

On the other hand, the most recent development in the GETS algorithm is in the R Package made available by Sucarrat and Escribano (2012), *AutoSearch*. Later, Pretis et al. (2018) introduced the *gets* package as the *AutoSearch* successor. The key strength of the *gets* package is that it is the only free and open-source software available that provides GETS modelling for conditional variance regression and the mean of a regression, as well as IS methods using the *isat* function. Furthermore, the *isat* function provides the impulse, step, and trend indicators for detecting and estimating the outlier and structural breaks in time series data. Pretis et al. (2018) demonstrated that the *gets* package could increase the computational speed substantially with *turbo* = *TRUE* and *max.paths* = *NULL* arguments in the *isat* function.

In this study, a new perspective was taken to investigate the SIS performance in the local level model and combined with the GETS approach. The goal was to integrate SIS into the local level model and assess the SIS performance to capture multiple structural breaks using Monte Carlo simulations. This is a novel area of research, and the reliability of SIS in the local level model is not yet sufficiently studied. No assessment of SIS in the local level model had been published before, and this study aimed to fill this gap. This study utilised the *gets* package in R to employ SIS in the local level model. Then, SIS empirical application was provided to financial data: Financial Times Stock Exchange (FTSE) Bursa Malaysia Hijrah Shariah Index and FTSE USA Shariah. The main interest was to evaluate the capability of SIS to capture structural breaks in the stock indices corresponding to the 2008 financial crisis.

3 Research methodology

Non-stationary data is typically handled by econometricians using a differencing approach that decreases integration order. Nevertheless, long-run equilibrium, such as data relationships, could not be modelled using this method. Since IS can handle non-stationary data, this study proposed integrating it into the state-space model framework. Regression coefficients that change over time, missing or incomplete data and multivariate extensions are also supported by the proposed framework. The state-space model's simplest level is the local model. The level component of this model fluctuates with time and may be thought of as the intercept in a conventional regression model. The level component can also change from a time point to another in a state-space model. The following represents the local level model:

$$y_t = \mu_t + \varepsilon_t \quad \varepsilon_t \sim NID\left(0, \sigma_\varepsilon^2\right) \tag{1}$$

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

For t = 1, 2, …,T where ε_t = observation disturbance or irregular component at time t, μ_t = unobserved level at time t, and ω_t = level disturbance at time t. All observations and level disturbances are assumed to be mutually and serially independent, and normally distributed with zero means (ε_t) and variances (ω_t). Equation (1) is referred to as the observation equation, whereas equation (2) is referred to as the state equation. Based on a random walk, the transition equation illustrates the fundamental values. In addition, ε_t is defined as noise originating from the fundamentals, assumed to be unrelated to the state innovations to μ_t. The signal-to-noise ratio of variances, $q = \frac{\sigma_\varepsilon^2}{\sigma_\omega^2}$, measures the signal strength in the fundamental value relative to random deviation. Hence, the local level model is also known as the *random walk plus noise* model (Commandeur and Koopman, 2007). Additionally, the model can be expressed as ARIMA (0,1,1). The first difference of equation (1) is as follows:

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

From equation (2), $\omega_t = \mu_{t-1} - \mu_t$ is substituted into equation (3), yielding:

$$\Delta y_t = y_t - y_{t-1} = \omega_t + \varepsilon_t - \varepsilon_{t-1}. \tag{4}$$

It is evident that equation (4) is a stationary process and has the same correlogram as in ARIMA (0,1,1). Furthermore, the general state-space form of the local level model in equation (1) and equation (2) can be represented as $\alpha_t = \mu_t$, $\xi_t = \eta_t$, $z_t = \boldsymbol{S_t} = \boldsymbol{R_t} = 1$, and $\boldsymbol{W_t} = \sigma_\eta^2$, where $\boldsymbol{z_t}$: design vector of size $m \times 1$, $\boldsymbol{\alpha_t}$: state vector of $m \times 1$, $\boldsymbol{S_t}$: $m \times m$ transition matrix, $\boldsymbol{m}$: number of elements in the state vector, and $\boldsymbol{R_t}$: an identity matrix of order $m \times m$. Furthermore, $\boldsymbol{W_t}$ encompasses the m state disturbances with zero means and variances that are unknown.

3.1 SIS

SIS is a structural break extension of the IIS literature introduced by Doornik et al. (2013). *Autometrics* define step indicators as $1_{\{t \leq j\}}$, j = 1, …, T where $1_{\{t \leq j\}}$ = 1 for observation up to j and zero otherwise. In contrast, R's *gets* package introduced step indicators as $1_{\{t \geq j\}}$, j = 1, …, T. SIS works similarly to IIS in that the indicators act as additional variables for each observation. Hence, additional T indicators will be added to the model for a univariate local level data series that has T observations.

In detail, a unity value will take place from $j = t$ until $t = T$. Besides, SIS can be expressed in vector form as $I_1' = (1, 1, 1, ..., 1), I_2' = (0, 1, 1, ..., 1), ..., I_T' = (0, 0, 0, ..., 1)$, where I_1' denotes the intercept dummy. The GETS modelling process requires that the indicators be in the GUM as regressors and pass the *gets* package standard diagnostics tests (Pretis et al., 2018). Any regressor with a *p*-value greater than the selected significance level (α) will be omitted one by one from the GUM. Each non-significant regressor will pass through sets of diagnostic tests in *gets*, which are autoregressive conditional heteroscedasticity (ARCH) in standardised residuals and test for serial correlation. Finally, using an information criterion, a final model is selected among terminal models. Since SIS acts as a regressor in the GUM, the regression model fits perfectly. This happens when the model has a greater number of regressors (N) than observations (T). Santos et al. (2008) proposed a partition of m blocks estimation in a fully saturated regression model to address the problem of having more regressors than observations. Consider a split-half approach where $m = 2$ blocks and $T/2$ indicators are added for the first half block of observations as follows:

$$y_t = \mu + \sum_{j=1}^{T/2} \delta_j 1_{\{t \geq j\}} + \varepsilon_t \quad t = 1, 2, ..., T \tag{5}$$

Significant indicators will be selected at α, followed by the addition of $T - T/2$ in the second block, and the procedure will be repeated to select significant indicators. From these two partitions, a final terminal model can be constructed, which includes only the most important indicators. A significant indicator is chosen sequentially based on the absolute value of t-statistics, $|t_j|$ greater than the critical value of t-distribution, and c_α at the selected α. In the absence of structural breaks in a time series data set, it is expected that αT indicators would be retained by chance in the model. By setting $\alpha - 1/T$, it is expected that, on average, the model would retain a misclassification of only one indicator. The following illustrates the data generating process (DGP) for a univariate local level model with step indicators:

$$y_t = \mu + \sum_{j\left(\frac{T}{m}\right)(i-1)+1}^{\left(\frac{T}{m}\right)i} S_j \delta_{\{t \geq j\}} + \varepsilon_t, \quad j = 1, ..., T \tag{6}$$

where $\varepsilon_t \sim IID\ N(0, \sigma_\varepsilon)$, m is the number of partitions assuming the blocks are equal size, S_j is the coefficient of SIS. The matrix notation of DGP in equation (6) can be represented as:

$$\boldsymbol{y} = \boldsymbol{S\delta} + \boldsymbol{\varepsilon} \tag{7}$$

where $\boldsymbol{\varepsilon}$ and $\boldsymbol{y}$ are vectors corresponding to $T \times 1$, δ is the matrix coefficient with dimension $T \times 1$, and $\boldsymbol{S}$ is the SIS in matrix form with dimension $T \times T$. For univariate time series, the SIS matrix can be expressed as follows:

$$
\begin{aligned}
\boldsymbol{S} &= \delta_{1,t}, \delta_{2,t}, \delta_{3,t}, \ldots, \delta_{T,t} \\
\delta_{1,t} &= (\delta(1), \delta(2), \delta(3), \ldots, \delta(T))^T \\
\delta_{2,t} &= (0, \delta(2), \delta(3), \ldots, \delta(T))^T \\
\delta_{3,t} &= (0, 0, \delta(3), \ldots, \delta(T))^T \\
&\vdots \quad \vdots \\
&\vdots \quad \vdots \\
\delta_{T,t} &= (0, 0, 0, \ldots, \delta(T))^T
\end{aligned} \tag{8}
$$

Since the function of SIS, $\delta(t)$ is equal to unity, equation (8) can be represented as:

$$
\begin{aligned}
\boldsymbol{S} &= \delta_{1,t}, \delta_{2,t}, \delta_{3,t}, \ldots, \delta_{T,t} \\
\delta_{1,t} &= (1, 1, 1, \ldots, 1)^T \\
\delta_{2,t} &= (0, 1, 1, \ldots, 1)^T \\
\delta_{3,t} &= (0, 0, 1, \ldots, 1)^T \\
&\vdots \quad \vdots \\
&\vdots \quad \vdots \\
\delta_{T,t} &= (0, 0, 0, \ldots, 1)^T
\end{aligned} \tag{9}
$$

Notably, the problem of regressors exceeding observations persists in the SIS mechanism. Thus, like the SIS procedure, the block-splitting method is utilised. The general structure of step indicators discussed thus far is based on the *gets* package introduced by Pretis et al. (2016a). Nevertheless, the general structure of SIS offered by *Autometrics* and embodied in *OxMetrics* slightly differs but remains consistent with the GETS framework. Specifically, *Autometrics* presents the indicators as $S = 1_{\{t \leq j\}}$, $j = 1, \ldots, T$, whereas the *gets* package uses $S = 1_{\{t \geq j\}}$, $j = 1, \ldots, T$, as shown in equation (9).

3.2 Structural break detection procedure using SIS

As a convenience, assume that the detection procedure for a single structural break occurs at the local level framework, with the first and second halves of the partition denoted by b_1 and b_2, respectively. Additionally, assume that there is one structural break in local level DGP that occurs between $t = H_1$ and $t = T$ with a magnitude λ, such that $\lambda \neq 0$. The DGP is denoted by the matrix notation:

$$\mathbf{y} = \boldsymbol{\delta}_{\boldsymbol{H}_1} + \boldsymbol{\varepsilon} \tag{10}$$

where the vector $\mathbf{y}$ represents $y_t - \mu_t$, $\boldsymbol{\delta}_{\boldsymbol{H}_1}$ is a vector with dimension $T \times 1$ with value equal to unity for $t \geq H_1$, zero for $t < H_1$ and ε is distributed identically and independently, with zero mean and variance, σ_ε^2. Suppose the matrix notation of equation (7) in the first block (b_1), the expression can be re-written as follows:

$$\mathbf{y} = \mathbf{S}_{b_1} \boldsymbol{\delta}_{b_1} + \mathbf{v} \tag{11}$$

where $\boldsymbol{\delta}_{b_1}$ is the SIS vector consisting of step indicators $\delta_{1,t}$ to $\delta_{T/2,t}$. Substituting equation (10) into equation (11) results in the least square estimator of the SIS vector, $\hat{\delta}_{b_1}$ as follows:

$$\hat{\delta}_{b_1} = \left(\mathbf{S}_{b_1}^T \mathbf{S}_{b_1}\right)^{-1} \mathbf{S}_{b_1}^T \mathbf{y} \tag{12}$$

The vector $\mathbf{S}_{b_1}^T \mathbf{S}_{b_1}$ in the first block can be represented as:

$$\begin{bmatrix} \delta_{1,t} \\ \delta_{2,t} \\ \vdots \\ \delta_{T/2,t} \end{bmatrix} \begin{bmatrix} \delta_{1,t} & \delta_{2,t} & \cdots & \delta_{T/2,t} \end{bmatrix} = \begin{bmatrix} T/2 & T/2-1 & T/2-2 & \cdots & 3 & 2 & 1 \\ T/2-1 & T/2-1 & T/2-2 & \cdots & 3 & 2 & 1 \\ T/2-2 & T/2-1 & T/2-3 & \cdots & 3 & 2 & 1 \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots & \vdots \\ 3 & 3 & 3 & \cdots & 3 & 2 & 1 \\ 2 & 2 & 2 & \cdots & 2 & 2 & 1 \\ 1 & 1 & 1 & \cdots & 1 & 1 & 1 \end{bmatrix} \tag{13}$$

Then, as the second difference matrix, the inverse of $\mathbf{S}_{b_1}^T \mathbf{S}_{b_1}$ is obtained:

$$\left(\mathbf{S}_{b_1}^T \mathbf{S}_{b_1}\right)^{-1} = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ -1 & 2 & -1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 2 & -1 & 0 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & 2 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & -1 & 2 & -1 \\ 0 & 0 & 0 & 0 & 0 & \cdots & 0 & -1 & 2 \end{bmatrix} \tag{14}$$

The expression $\left(\mathbf{S}_{b_1}^T \mathbf{S}_{b_1}\right)^{-1} \mathbf{S}_{b_1}^T$ can be computed to obtain:

$$\left(\mathbf{S}_{b_1}^T \mathbf{S}_{b_1}\right)^{-1} \mathbf{S}_{b_1}^T = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ -1 & 1 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & 0 & -1 & 1 \end{bmatrix} \tag{15}$$

The forward-difference matrix obtained in equation (15) is in line with Doornik et al. (2013) and Castle et al. (2015) even though the SIS structure is different. Next, equation (12) can be solved to obtain the least square estimator:

$$\begin{aligned} \hat{\delta}_{b_1} &= \lambda\left(\mathbf{S}_{b_1}^T \mathbf{S}_{b_1}\right)^{-1} \mathbf{S}_{b_1}^T \delta_{H_1} + \left(\mathbf{S}_{b_1}^T \mathbf{S}_{b_1}\right)^{-1} \mathbf{S}_{b_1}^T \boldsymbol{\varepsilon} \\ &= \lambda \mathbf{s} + \nabla \varepsilon_{b_1} \end{aligned} \tag{16}$$

where s is a vector with dimension $\frac{T}{2}\times 1,$ consisting of value unity at the location of candidate structural break's starting point, $t = H_1$. The vector $\nabla\varepsilon_{b_1}$ is equal to $\varepsilon_{t+1} - \varepsilon_t$ in which the vector element is $(\varepsilon_1, \nabla\varepsilon_1, \nabla\varepsilon_2, \cdots, \nabla\varepsilon_{T/2})^T$. Equation (16) can be rearranged to obtain:

$$\nabla\varepsilon_{b_1} = \hat{\delta}_{b_1} - \lambda\mathbf{s} \tag{17}$$

Hence, all the elements of $\hat{\delta}_{b_1}$ should be distributed around mean-zero following $\nabla\varepsilon_{b_1}$, except the element at $t = H_1$ takes the value λ. The element at $t = H_1$ in $\hat{\delta}_{b_1}$ can be presented as $\hat{\delta}_{t=H_1} = \lambda_{b_1} + \nabla\varepsilon_{H_1}$. On the other hand, the elements at $t \neq H_1$ in $\hat{\delta}_{b_1}$ are denoted as $\hat{\delta}_{t=H_1} = \nabla\varepsilon_t$. Referring to Doornik et al. (2013) and Castle et al. (2015), $E\left[\nabla\varepsilon_{b_1}\nabla\varepsilon_{b_1}^T\right]$ is equal to $\sigma_\varepsilon^2\left[S_{b_1}^t S_{b_1}\right]^{-1}$. Then, the least square estimator distribution in the first block b_1 is given as follows:

$$\left(\hat{\delta}_{b_1} - \lambda\mathbf{s}\right) \sim N\left(0, \sigma_{b_1}^2\left(\mathbf{S}_{b_1}^T\mathbf{S}_{b_1}\right)^{-1}\right) \tag{18}$$

Finally, the significance testing in GETS modelling can eliminate non-significant indicators at the chosen α. The procedure discussed above assumes that the structural break is present in the first block. Thus, the SIS in the second block is not able to catch any breaks. The least square estimator obtained for the second block is given as follows:

$$\hat{\delta}_{b_2} = \lambda\left(S_{b_2}^T S_{b_2}\right)^{-1} S_{b_2}^T\delta_{H_1} + \left(S_{b_2}^T S_{b_2}\right)^{-1} S_{b_2}^T\varepsilon \tag{19}$$

Note that a few irrelevant indicators may inadvertently retain in during parameter estimation in each partition. For example, Doornik et al. (2013) demonstrated that any step indicators near the location of structural break have higher potential to retain in the model by chance. These spuriously retained indicators and correctly matched indicators from both blocks are combined to re-estimate the final terminal model. Then, the DGP of the final terminal model is given as follows:

$$\mathbf{y} = \mathbf{S}_{\boldsymbol{b}_3}\delta_{b_3} + \mathbf{v} \tag{20}$$

where $\boldsymbol{\delta}_{\boldsymbol{b}_3}$ denotes the vector of combined retained SIS from both blocks (b_1 and b_2). Hence, the least square estimator $(\hat{\delta}_{b_3})$ for the final terminal model in matrix form is given as follows:

$$\begin{aligned}\hat{\delta}_{b_3} &= \lambda\left(\mathbf{S}_{b_3}^T\mathbf{S}_{b_3}\right)^{-1}\mathbf{S}_{b_3}^T\delta_{H_1} + \left(\mathbf{S}_{b_3}^T\mathbf{S}_{b_3}\right)^{-1}\mathbf{S}_{b_3}^T\boldsymbol{\varepsilon}\\ &= \lambda\mathbf{s} + \left(\mathbf{S}_{b_3}^T\mathbf{S}_{b_3}\right)^{-1}\mathbf{S}_{b_3}^T\varepsilon\end{aligned} \tag{21}$$

Finally, the estimated DGP distribution in equation (18) can be expressed as:

$$\left(\hat{\delta}_{b_3} - \lambda\mathbf{s}\right) \sim N\left(0, \sigma_\varepsilon^2\left(\mathbf{S}_{b_3}^T\mathbf{S}_{b_3}\right)^{-1}\right) \tag{22}$$

Until this point, it is vital to highlight that the SIS detection mechanism's efficiency is unaffected by any irrelevant indicators retained from any partition, as long as all significant indicators are combined in the final terminal model for estimation. Finally, it is noteworthy that the main contribution of this section is the results produced in equations (20)–(22), which demonstrated that the SIS in the *gets* package could detect structural breaks at unknown locations even though the SIS structure in the *gets* package and *Autometrics* differs. Furthermore, the least square estimator $(\hat{\delta})$ and its normal error terms distribution are unaffected.

4 Monte Carlo simulations

This study conducted Monte Carlo simulations to measure the performance of step indicators in the local level framework through potency and gauge. Furthermore, SIS performance to detect structural breaks in the local level model was assessed through the Monte Carlo experiments, initiated by producing a time series from the local level model as in equation (1) for $T = 120$, $T = 240$, and $T = 360$ observations, reflecting ten years, 20 years, and 30 years of monthly time series data. The variance of parameters was $\sigma_E = 1$ and $\sigma_\omega = 0.0005$. Replications of experiments were set at $M = 1{,}000$ replications. This study first considered a benchmark specification, followed by alternative settings to examine the SIS procedure's robustness. Since the local level model consisted of multiple sources of disturbances, the approach by Marczak and Proietti (2016) was adopted for designing the appropriate structural breaks size. The expression *k*.PESD represents the shift's magnitude (*k*: an integer; PESD: prediction error standard deviation of steady-state innovation). Then, these structural breaks were contaminated in the reference DGP.

The benchmark specification for simulation settings are as follows:

a Number of observations, $T = 240$.

b Number of blocks, $m = 2$, indicating a split-half approach.

c Significance level, $\alpha = 1/T$.

d Structural breaks magnitude of five times PESD.

e A single structural break occurs in the centre of the sample, but double structural breaks occur at [0.25, 0.75] as a percentage of length *T*.

f Length of structural breaks, $\lambda = 10$.

g Selection of significant indicators via non-sequential and sequential algorithms.

Alternatively, the simulation settings were set in several directions:

a $T = 120$ and $T = 360$ observations.

b Partitions of 4, 6, 8, and 10 blocks to assess the effect of further splits in structural breaks detection.

c Varying significance levels of 0.1%, 1%, and 2.5%.

d Structural breaks magnitude with $k = 3, 5, 7$.

e Location of structural breaks at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 as a share of length *T*.

f Varying structural breaks length of $\lambda = 5, 10, 15$.

g Application of sequential selection for selecting significant indicators.

The sequential selection procedure works by iteratively removing the least significant indicators in every partition until only the vital ones are preserved. Doornik et al. (2013) and Castle et al. (2015) demonstrated that the sequential selection strategy can improve the test power compared with the non-sequential approach by reducing the variance of the coefficients.

4.1 Monte Carlo experiments performance evaluation

The Monte Carlo experiments performance was evaluated based on potency and gauge values. *Potency* is the proportion of relevant indicators retained in the final terminal model, whereas *gauge* is the proportion of irrelevant indicator variables retained. The gauge is also known as false detection rate that can be controlled by reducing α. This study followed the general rule of thumb by Pretis et al. (2018) to ensure a low false detection rate by setting $\alpha = \min\left[0.05, {}^{1}\!/_{T}\right]$, aiming only one irrelevant indicator retained by chance in a large sample *T* or gauge value less than 5% for a small sample. Potency and gauge computations depended on the retention rate $(\tilde{r}_j)$. Assume that *M* denotes the number of replications of Monte Carlo experiments, *n* denotes the number of relevant indicators, and R_n and R_{T-n} are the sets of time indices for the model's relevant and irrelevant indicators, respectively.

$$\tilde{r}_j = \frac{1}{M}\sum_{j=1}^{M} 1[\tilde{\beta}_{lj} \neq 0], \quad j = 1, ..., T \tag{23}$$

$$potency = \frac{1}{n}\sum_{j} \tilde{r}_j, \quad j \epsilon R \tag{24}$$

$$gauge = \frac{1}{T-n}\sum_{j} \tilde{r}_j, \quad j \epsilon R_{T-n} \tag{25}$$

Meanwhile, $\tilde{\beta}_{lk}$ signifies the impulse indicator's estimated coefficient, and if $I_t(k)$ is chosen, the variable $1[\tilde{\beta}_{lk} \neq 0]$ will take a value of one if the argument is true, and zero if false. The concepts of potency and gauge can also be explained using the confusion matrix, which is widely used in the machine learning literature. The matrix presents a concise summary of the results of a Monte Carlo experiment, as depicted in Table 1.

A is referred to as true positive while *D* is known as true negative, indicating the number of right decisions made. In comparison, *B* and *C* signify incorrect decisions in the absence and presence of an outlier, respectively. *B* is also called false positive, while *C* is known as false negative in the machine learning literature. Thus, the potency is denoted by the *D*/Mn ratio. On the other hand, the gauge is denoted by the *B*/[M(T-n)] ratio. All computations were performed utilising the R's *gets* package offered by Pretis et al. (2016a).

Table 1 Confusion matrix for the one outcome of Monte Carlo experiment

Actual	*Predicted*		*Total*
	No outlier	*Outlier*	
No outlier	A	B	M(T – n)
Outlier	C	D	Mn
Total	A+C	B+D	MT

The simulations began by contaminating each series with a single structural breaks size k = 5 and λ = 10. The significance level varies at 0.1%, 1%, and 2.5% with a split-half approach according to the general rule of thumb by Pretis et al. (2018) to control the false detection rate. The *isat* function in the *gets* package performed excellently in non-sequential and sequential path selection with potency above 90% for all observations. Close observations on Table 2–Table 5 revealed that the overall potency in the sequential selection was consistently higher than non-sequential selection. As expected, the sequential selection increased the retention rate, thus improving the test power, as proven by Doornik et al. (2013). The findings of this study were also aligned with those of Castle et al. (2011, 2015), proving that the sequential selection using *Autometrics* yields higher potency even though the structure of step indicators is different in the *gets* package.

Table 2 shows the simulation results when the magnitude of structural breaks varies with k times PESD. Besides, different values of α were also implemented to measure the procedure's robustness. As expected, a higher α value leads to a higher potency value, indicating more tolerant to the probability of the first detection. Hendry and Santos (2005) stated that potency relies heavily on the length of a single break in the series examined. As shown in Table 3, SIS performed satisfactorily above 90% in both non-sequential and sequential selections. Doornik et al. (2013) and Santos et al. (2008) demonstrated that partitioning the series into m blocks did not affect the gauge values. However, a significant finding of this study was that the potency was consistently between 60% and 70% when the observations were split into four and eight blocks. As mentioned in Section 3, the DGP in partitioned m blocks was assumed to be of equal size; hence the first step indicator was exactly located at the block partitioned. This finding was consistent with Marczak and Proietti (2016), who obtained less than 4% potency in non-sequential and sequential selections. Additionally, the symmetrical pattern was notable in potency at different locations with potency values beyond 90%.

Table 2 Potency of single structural break, split-half approach, λ = 10, k.PESD, and different α values

	T = 120			*T = 240*			*T = 360*		
Size	*0.1%*	*1%*	*2.5%*	*0.1%*	*1%*	*2.5%*	*0.1%*	*1%*	*2.5%*
3	44.0	54.2	57.3	55.4	69.3	74.8	61.1	74.1	79.6
5	89.3	92.9	93.3	90.5	93.3	94.4	95.3	94.9	91.8
7	98.7	98.3	100	98.8	100	100	99.9	100	100

Table 3 Potency of single structural break, split-half approach, $k = 5$, and different lengths in non-sequential and sequential selections

	Non-sequential			*Sequential*		
Length, λ	*T = 120*	*T = 240*	*T = 360*	*T = 120*	*T = 240*	*T = 360*
5	93.9	97.4	96.2	92.9	97.8	93.2
10	99.8	93.3	94.5	99.7	95.9	94.1
15	97.9	92.5	91.2	98.1	94.7	93.8

Table 4 Potency of two opposite signs of structural breaks located at [0.25, 0.75], $k = 5$, $\lambda = 10$, with *m* splits in non-sequential and sequential selections

	Non-sequential			*Sequential*		
Splits, m	*T = 120*	*T = 240*	*T = 360*	*T = 120*	*T = 240*	*T = 360*
2	87.6	94.6	88.0	88.2	96.3	90.9
4	61.5	73.4	60.7	63.8	67.3	65.9
6	91.6	92.3	88.1	92.1	93.0	90.2
8	62.0	73.7	61.8	66.2	67.5	64.3
10	83.1	94.4	87.7	91.7	96.3	92.2

Table 5 Potency of single structural break, $k = 5$, $\lambda = 10$, split-half approach, and different locations in non-sequential and sequential selections

	Non-sequential			*Sequential*		
Locations	*T = 120*	*T = 240*	*T = 360*	*T = 120*	*T = 240*	*T = 360*
0.1	91.5	87.8	90.3	91.1	93.7	92.8
0.2	91.2	91.8	92.0	93.0	93.6	93.7
0.3	90.9	91.1	91.3	91.8	91.2	92.3
0.4	92.9	91.0	90.3	93.8	94.6	92.9
0.5	93.5	93.8	92.9	96.4	97.9	97.2
0.6	92.0	92.3	87.3	94.9	94.2	93.9
0.7	91.8	92.0	87.5	92.4	91.6	90.4
0.8	91.1	91.5	89.8	92.0	90.9	91.8
0.9	90.3	89.7	87.2	94.0	93.1	90.4

Furthermore, it was found that the significance level (α) plays a vital role in ensuring a low false detection rate. Overall, the gauge values were clustered around the chosen α, as shown in Table 6. This study decided to tighten α below 2.5% to ensure the gauge approximated the same magnitude. However, a tight α will reduce the potency for estimators with small non-centralities. Setting a looser α, for example, 10%, will lead to overfitting. Details of potency and gauge in GETS modelling are further discussed in Hendry and Doornik (2014). As expected, the gauge values were consistently lower in the sequential selection as compared to non-sequential. Doornik et al. (2013) proved that the sequential selection is beneficial to rapidly converge the estimator's variance and drastically improve the outcome of SIS in *Autometrics*. In addition, the sequential selection outperformed non-sequential selection in non-orthogonal problems when non-sequential is inappropriate.

Table 6 Gauge of single structural break, split-half approach, $\lambda = 10$, k.PESD and different α values

	T = 120			*T = 240*			*T = 360*		
Size	*0.1%*	*1%*	*2.5%*	*0.1%*	*1%*	*2.5%*	*0.1%*	*1%*	*2.5%*
3	0.97	1.11	4.76	0.51	1.50	3.49	0.38	1.72	4.18
5	1.01	1.22	3.21	0.50	1.53	3.29	0.19	1.84	4.10
7	1.00	1.21	3.19	0.53	1.56	3.02	0.04	1.49	4.19

Table 7 Gauge of single structural break, split-half approach, $k = 5$, and different lengths in non-sequential and sequential selections

	Non-sequential			*Sequential*		
Length, λ	*T = 120*	*T = 240*	*T = 360*	*T = 120*	*T = 240*	*T = 360*
5	0.27	0.23	0.31	0.08	0.10	0.10
10	0.34	0.27	0.13	0.01	0.01	0.09
15	0.26	0.27	0.26	0.02	0.01	0.09

Table 8 Gauge of two opposite signs of structural breaks located at [0.25, 0.75], $k = 5$, $\lambda = 10$, with m splits in non-sequential and sequential selections

	Non-sequential			*Sequential*		
Splits, m	*T = 120*	*T = 240*	*T = 360*	*T = 120*	*T = 240*	*T = 360*
2	0.55	0.17	0.33	0.04	0.01	0.03
4	1.51	0.48	0.56	0.02	0.07	0.05
6	0.36	0.13	0.23	0.02	0.01	0.02
8	1.45	0.47	0.52	0.10	0.07	0.03
10	0.69	0.12	0.22	0.01	0.09	0.02

Table 9 Gauge of single structural breaks, $k = 5$, $\lambda = 10$, split-half approach, and different locations in non-sequential and sequential selections

	Non-sequential			*Sequential*		
Locations	*T = 120*	*T = 240*	*T = 360*	*T = 120*	*T = 240*	*T = 360*
0.1	1.21	0.86	0.66	0.10	0.03	0.01
0.2	1.23	0.78	0.59	0.09	0.04	0.01
0.3	1.21	0.74	0.70	0.08	0.03	0.01
0.4	1.27	0.89	0.60	0.08	0.04	0.01
0.5	1.14	0.72	0.62	0.12	0.03	0.03
0.6	1.28	0.73	0.59	0.09	0.03	0.01
0.7	1.12	0.75	0.59	0.08	0.03	0.02
0.8	1.38	0.77	0.56	0.09	0.04	0.01
0.9	1.19	0.80	0.65	0.09	0.04	0.01

5 Empirical applications

This section discusses the performance of SIS to capture structural changes in FTSE USA Shariah and FTSE Bursa Malaysia Hijrah Shariah retrieved from *Datastream* using the *gets* package in R and *Autometrics*. The series has been approximately modelled by local level using *dlm* package in R and STAMP in *Oxmetrics 8*. The monthly data ranged from November 2007 to July 2019, with a total of T = 141 observations. The chosen significance level was determined by $\alpha = 1/T$, indicating that under the null of no outliers, less than one indicator is held spuriously on average. The split-half approach and sequential selection were applied to reduce the model's irrelevant indicator numbers.

The results of diagnostic tests conducted after applying the structural time series model to real data are shown in Table 10. To determine if the data matched the structural time series model, both Shariah-compliant stock indexes were first evaluated using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Both stock indices were chosen for the use of the IS technique to investigate the presence of outliers and structural breaks based on the AIC as a tiebreaker (Commandeur and Koopman, 2007). For the analysis, return values, r_t, of each data were determined from the log difference of monthly stock prices.

Table 10 Diagnostics tests for FTSE USA Shariah Index and FTSE Bursa Malaysia Hijrah Shariah Index

	Statistics	*FTSE USA Shariah*	*FTSE Bursa Malaysia Hijrah Shariah*
Independence	DW	1.7587	1.7997
	r(1)	0.1033	0.0952
Homoscedasticity	H(h)	H(52) 1.4705	H(60) 0.85517
Normality	N	13.621	7.102
Information criterion	AIC	8.9637	10.0671
	BIC	9.0023	10.1024

Table 11 Date of structural breaks detected by SIS in FTSE USA Shariah and FTSE Bursa Malaysia Hijrah Shariah

FTSE USA Shariah		*FTSE Bursa Malaysia Hijrah Shariah*	
gets package	*Autometrics*	*gets package*	*Autometrics*
2008 M9 (–0.29)	2008 M9 (0.29)	2008 M2 (–0.13)	2008 M2 (0.13)
2008 M10 (0.32)	2008 M10 (0.30)	2008 M3 (0.13)	2008 M3 (–0.10)
2010 M4 (–0.14)		2008 M6 (–0.08)	2008 M6 (0.08)
2010 M5 (0.14)		2008 M9 (–0.08)	2008 M10 (–0.13)
2011 M7 (–0.13)		2008 M10 (0.16)	2009 M7 (0.03)
2011 M8 (0.12)		2009 M7 (–0.05)	
		2011 M9 (0.12)	
		2011 M10 (–0.79)	

Note: *t-statistics value reported in parentheses.

Accordingly, residuals in the structural time series model are generally assumed to be independent and normally distributed, with the attribute of homoscedasticity. Therefore, the current study performed the following diagnostics tests to examine whether the residuals meet these respective properties:

1 Durbin-Watson test

2 homoscedasticity test

3 normality test.

Overall, the results diagnostic tests appear satisfactory for every model. It can be seen that most of the values of autocorrelations at lag 1 converge to zero indicating weak positive correlation among residuals. Moreover, the Durbin-Watsons statistics values are clustered around 2 indicating the same correlation between residuals. The H-statistics indicate that the variances of two consecutive and equal parts of the residuals are equal to one another. For instance, in Table 10, the test shows that the variance of the 52 elements of the residuals is unequal to the variance of the last 52 elements of the residuals. Summarising, the assumptions of independence, homoscedasticity and normality are all satisfied for each shariah index. When comparing the info criterion values, this study holds the rule of thumb: the smaller values denote better fitting models than larger ones. Overall, the AIC and BIC values are approximately the same for both shariah indices.

Figure 1 Fitted and actual SIS values for a structural break generated by *Autometrics* for FTSE USA Shariah index (see online version for colours)

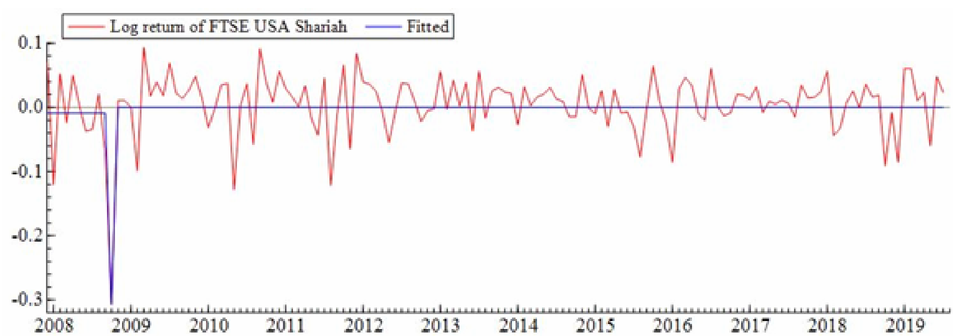

Figure 2 Fitted and actual SIS values for a structural break generated by *gets* package for FTSE USA Shariah index (see online version for colours)

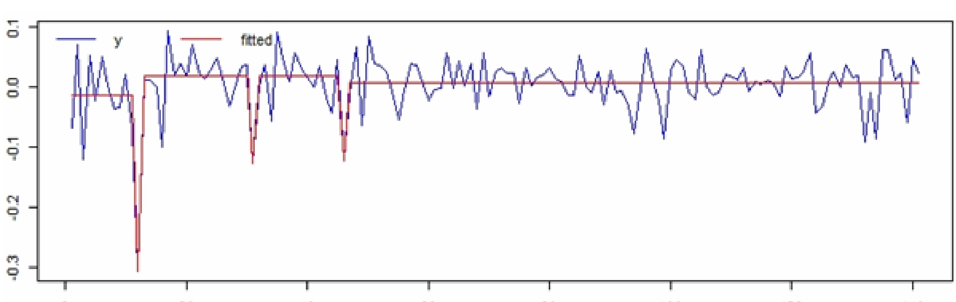

Figure 3 Fitted and actual SIS values for a structural break generated by *Autometrics* for FTSE Bursa Malaysia Hijrah Shariah index (see online version for colours)

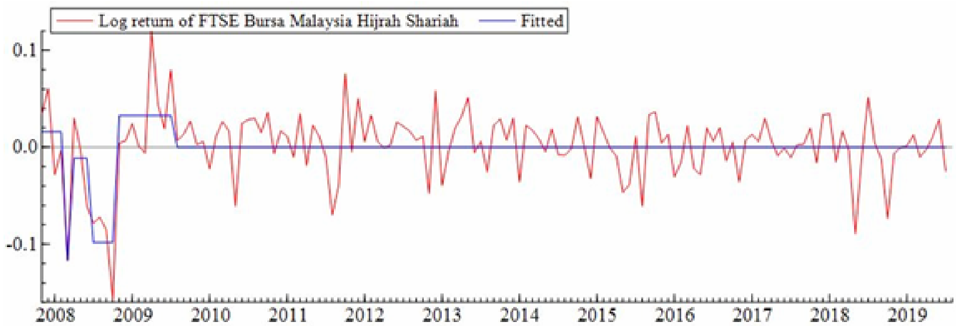

Figure 4 Fitted and actual SIS values for a structural break generated by *gets* package for FTSE Bursa Malaysia Hijrah Shariah index (see online version for colours)

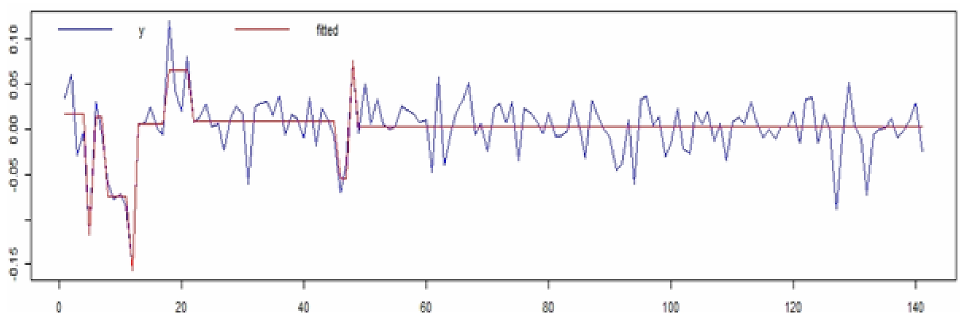

Table 11 compares the SIS performance between the *gets* package and *Autometrics*. Despite the difference in structural breaks detected in both algorithms, similar shifts dates were detected in September and October 2008 in FTSE USA Shariah, corresponding to the 2008 financial crisis. Note that the sign of t-statistics value in the *gets* package and *Autometrics* are opposite due to different approaches in handling the indicators. The former used forward steps for indicator function; hence, positive *t*-statistics values imply an upward step indicator, and negative t-statistics values imply a downward step. On the other hand, *Autometrics* relies on backward steps; hence, the interpretation of t-statistics values is opposite-signed as what has been reported. Besides, both algorithms captured similar structural breaks in FTSE Bursa Malaysia Hijrah Shariah for the 2008 financial crisis. Almost all indicators retained in *Autometrics* can be captured by the *gets* package, implying that there is an alternative algorithm to detect structural breaks using the GETS approach. The key strength of *gets* package over *Autometrics* is the ease with which user-specified GETS and ISAT techniques for particular issues may be implemented using generic functions and procedures. The *gets* package further provides users with appealing features and tools that let them to customise the model estimates, model diagnostics, and goodness of fit criteria.

6 Conclusions

Overall, the IS technique in GETS modelling effectively detects unknown locations, magnitudes, and signs of structural breaks when considering the local level model in a structural time series framework. This study's findings provided the first evidence demonstrating the application and effectiveness of the IS technique in a local level framework. The unobserved components constantly evolve over time driven by random disturbances. A key strength of SIS is that it can capture multiple breaks even though only one or two breaks are used in Monte Carlo simulations, as the potency exceeds 90% in most settings. The results revealed that SIS effectively detects structural breaks when combined with the sequential selection and split-half approach. Sequential selection has been proven to rapidly reduce estimator variances and is essential in reducing the terminal model's number of retained irrelevant indicators, although this algorithm is computationally expensive. Several factors that affect the potency and gauge were explored. First, the magnitude of shifts plays an important role in shifts detection. Evidently, it is easier for SIS to capture larger magnitudes of shifts. Second, the potency varies symmetrically, suggesting that detecting structural breaks that are present in the middle of a sample is much easier. Finally, the sample partitioning approach also affects SIS performance. However, there is still a great deal of work to be done in this area. For instance, other critical SIS analysis includes the trend components in the reference model since this study only considered level components.

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