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Short-Term Insurance Claims Payments Forecasting with Holt-Winter Filtering and Residual Analysis

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Abstract
Time series are essential for anticipating various claims payment applications. For insurance firms to prevent significant losses brought on by potential future claims, the future values of predicted claims are crucial. Additionally, the ideal parameter is chosen artificially. By using a genuine application, the proposed model's utility is demonstrated. Additionally, the ideal parameter is chosen artificially. By using a genuine application, the proposed model utility is demonstrated. Also, the single exponential smoothing model is used for prediction under the Holt-Winters' additive algorithm.

Key Words: : Exponential smoothing; Claims data; Cullen-Frey; Holt-Winters' additive algorithm; Insurance data; Residuals analysis; Forecasting.

Mathematical Subject Classification: 60E05; 62H05; 62E10; 62F10; 62F15; 62P05.

1.Introduction

The autoregressive integrated moving average (ARIMA) models have beee developed by Box and Jenkins (1970) for prediction of time series data. The Box-Jenkins method is based on inputs from a specific time series and is used to forecast data. It can perform forecasting using a variety of time series data analyses. This methodology evaluates discrepancies between time series data points to determine findings. In order to create future projections, it is possible to discover patterns utilising the autoregressive models, moving averages models, and seasonal differencing. The primary implementation of Box-Jenkins approach uses ARIMA models. Sometimes people will use the two names for these cars interchangeably. For the time series analysis with forecasting and control, see Box et al. (2015).

On the other hand, research based on ARIMA models became widely published in the actuarial literature, see Cummins and Griepentrog (1985) for forecasting automobile insurance paid claim costs using econometric and ARIMA models, Jang et al. (1991) for analysing some medical insurance program for employees by ARIMA model, Venezian and Leng (2006) for some applications of spectral and ARIMA analysis to combined-ratio patterns, Mohammadi and Rich (2013) for the dynamics of unemployment insurance claims with an application of ARIMA model, Hafiz et al. (2021) for projecting insurance penetration rate in Nigeria, and Kumar et al. (2020) for forecasting motor insurance claim amount using ARIMA model. In the area of applied mathematical modelling, the autoregressive (AR) and ARIMA models have drawn the attention of numerous authors. For example, forecasting the electricity price (Jakaša et al. (2011)), modelling and forecasting of area, production, yield and total seeds of rice and wheat (Sahu et al. (2015)), producing wheat output predictions (Iqbal et al. (2016)), forecasting the oil seeds prices in India (Darekar and Reddy (2017)), predicting India's wheat production (Nath et al. (2019)), identification of paddy crop phenological parameters (Palakuru et al. (2019)), and Shrahili et al. (2021) for modeling the negatively skewed insurance claim-size asymmetric data using a new Chen model and the AR model.

The future insurance-claims forecasting is very important for insurance companies to avoid uncertainty about big losses that may be produced from future claims. Recently, Shrahili et al. (2021) introduced a flexible claim-size Chen density for modeling asymmetric data (negative and positive) with different types of kurtosis (mesokurtic, leptokurtic and platykurtic). Since the insurance-claims data (Charpentier (2014)) are a quarterly time series dataset, Shrahili et al. (2021) analyzed these data using the AR model. A useful comparison is provided between the results of the Chen model and the autoregressive regression model. Many Chen densities were studied, see, for example, Ibrahim et al. (2022) for a novel test statistic for right censored validity under a new Chen extension with some applications in reliability and medicine, Yousof et al. (2022) for another Chen extension with characterizations and different estimation methods, and Korkmaz et al. (2022) for a new unit-Chen model with associated quantile regression.

Following Shrahili et al. (2021), Mohamed et al. (2022) define a new size-of-loss synthetic autoregressive model for the left skewed insurance claims datasets. In order to choose the optimal model, the technique essentially involves examining the insurance claims using all feasible ARIMA models. The suitability for the insurance claims will therefore dictate this choice. Statistics are used to evaluate the parameter model's importance. It is advisable to choose a model with fewer significant parameters. Finding out if the time series is stationary and whether there is any substantial seasonality that has to be modelled is the first stage in creating a specific Box-Jenkins model for the time series insurance claims. The autoregressive model is selected following the identification of the Box-Jenkins model. The synthetic autoregressive model is used to model the insurance claims. Through a few simulation studies, its suitability is evaluated, the artificial means are used to determine the ideal parameter.

In some cases, we need to make quick, short-term and low-cost forecasts. In those cases, the Box-Jenkins methodology is not the optimal choice although it may be the best under the regular cases. so, some other models such as the single exponential smoothing (SES) model can be recommended for forecasting. The SES model was proposedby Brown (1959), Holt (1957) and Winters (1960). Forecasts made with the aid of SES techniques are weighted averages of earlier observations, with the weights degrading exponentially with time. In other words, the associated weight is higher when the observation is more recent. This framework quickly and accurately creates projections for a variety of time series, which is a significant benefit for applications in industry.

There are two versions of Holt-Winters' method, and the seasonal component in each one is different. When seasonal fluctuations are essentially constant throughout the series, the additive method is recommended; when they change proportionally to the level of the series, the multiplicative method is favoured. The seasonal component is stated in absolute terms in the scale of the observed series using the additive approach, and the level equation adjusts the series for the season by deducting the seasonal component. The seasonal component will roughly equal zero within each year.

In this paper, the SES model is considered for modeling and forecasting historical insurance real data used for prediction under the Holt-Winters' additive algorithm. The SES model is can be compared with the size-of-loss synthetic autoregressive model (SAR) firstly proposed by Mohamed et al. (2022) under the sum squares of errors (SSE) criteria. The integrity of the model residues is one of the most important indicators of the integrity of the model, so, for the two models, we numerically and graphically analyze the residuals. The exponential window function is a general method for smoothing time series data known as exponential smoothing. In contrast to the ordinary moving average, which weights previous data equally, exponential functions use weights that decrease exponentially with time. It is a simple process that can be understood and used right away to make a decision based on the user's existing assumptions, like seasonality. Time-series data analysis frequently employs exponential smoothing. The SES and moving average approaches are equivalent to first-order infinite-impulse response filters and finite impulse response filters, respectively, with equal weighting factors in the signal processing literature. Non-causal (symmetric) filters are frequently used, and the exponential window function is widely used in this way.

By extending straightforward exponential smoothing, Holt (1957) made it possible to forecast data that had a trend. A forecast equation and two smoothing equations ,one for the level and one for the trend, are used in this approach. Indefinitely into the future, the forecasts produced by Holt's linear technique show a steady trend (growing or decreasing). According to empirical data, these approaches frequently overpredict, especially for forecast horizons that are longer (see Holt (1957) and Hyndman and Athanasopoulos (2018)).

The rest of the paper is organized as follows: Section 2 presents SES model along with its main statistical results. An assessment, comparison and application to historical insurance real data under the Holt-Winters' additive algorithm are addressed in Section 3. Finally, some concluding remakes are offered in Section 4.

2. The SES model

For time series data, short-term forecasts can be created using exponential smoothing. If your time series data can be accurately predicted by an additive model with constant level and no seasonality, making short-term projections is possible using straightforward exponential smoothing. This approach is appropriate for predicting data without a distinct trend or seasonal pattern. One method for determining the level at the present time point is the straightforward SES method. For the estimate of the level at the current time pointThe alpha parameter governs the SES model. It is worth mentioning that, alpha's value ranges from 0 to 1. When forecasting future values, alpha values near to 0 indicate that the most recent observations are not given much weight and alpha values near to 1 indicate that the most recent observations are given much weight. It can make sense to give more weight to recent observations compared to older observations. The idea behind straightforward exponential smoothing is just this.

According to the naive technique, all future predictions are equal to the most recent value of the series seen where

$$\hat{y}_{T+h|T} = y_T | h = 1,2,\ldots, \tag{1}$$

all future predictions made using the average approach equal a simple average of the observed data, where

$$\hat{y}_{T+h|T} = \frac{1}{T}(y_1 + y_2 + \ldots + y_T) | h = 1,2,\ldots, \tag{2}$$

as a result, the average approach bases its forecasting on the premise that all observations are equally important and should be given similar weights. We frequently seek a middle ground between these two extremes. For instance, it might make sense to give more weight to current findings than to those made in the distant past. The idea behind straightforward exponential smoothing is just this. According to the SES model, The forecast at time $T + 1$ is equal to a weighted average between the most recent observation y_T and the previous forecast $\hat{y}_{T|T-1}$ where

$$\hat{y}_{T+1|T} = \alpha y_T + (1 + \alpha)\hat{y}_{T|T-1} | T = 1,2,\ldots, \tag{3}$$

where $0 \leq \alpha \leq 1$ is the smoothing parameter. The fitted values can be expressed similarly as

$$\hat{y}_{t+1|t} = \alpha y_t + (1 + \alpha)\hat{y}_{t|t-1} | T = 1,2,\ldots, \tag{4}$$

Since the process must begin somewhere, we'll use I_0 to represent the first fitted value (which we will have to estimate) at time 1. Then,

$$\hat{y}_{2|1} = \alpha y_1 + (1 + \alpha)I_0, \tag{5}$$

$$\hat{y}_{3|2} = \alpha y_2 + (1 + \alpha)\hat{y}_{2|1}, \tag{6}$$

$$\hat{y}_{T|T-1} = \alpha y_{T-1} + (1+\alpha)\hat{y}_{T-1|T-2} \quad (7)$$

$$\hat{y}_{T+1|T} = \alpha y_T + (1+\alpha)\hat{y}_{T|T-1} \quad (8)$$

For large T, the term $(1+\alpha)I_0$ shrinks. Consequently, the prediction model is the same using the weighted average version as

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1+\alpha)y_{T-1} + \alpha(1+\alpha)^2 y_{T-2} + \ldots |0 \le \alpha \le 1. \quad (9)$$

The weights $\alpha, \alpha(1+\alpha), \alpha(1+\alpha)^2, \ldots$ are exponentially decreasing and this the weighting logic of the SES model. The prediction error can be expressed by

$$e_t = y_T - \hat{y}_{t|t-1}. \quad (10)$$

The selection of the smoothing parameter α and the initial value I_0 is a prerequisite for applying any exponential smoothing approach. In particular, for simple exponential smoothing, we need to select the values of α and I_0 . Once we are aware of these numbers, we can generate all forecasts using the data. There are typically multiple smoothing parameters and multiple starting components available for the algorithms that follow. Consequently, we identify the unknown parameter values and the starting points that minimize the SSE. This includes a non-linear minimization problem, and we need to employ an optimization tool to solve it, unlike the regression situation where we have formulas that provide the values of the regression coefficients that minimize the SSE.

3. Application and forecasting under the Holt-Winters' additive algorithm

A formal request for compensation for damages covered by your insurance policy is known as an insurance claim. An insurance policy is a contract between you and your insurer. You are required to pay a set premium. In return, the insurance company provides financial protection against losses in accordance with the conditions of the policy. A claim must be made after the occurrence of the insured event. The intent is to inform the insurance provider that the occurrence of the event for which you selected coverage has occurred and that the provider should pay the claim amount.

A financial safety net is provided by an insurance claim. Unexpected costs from things like accidents, medical emergencies, and life's uncertainties can have a severe negative impact on your finances. Such terrible situations may be relieved by insurance claims. A formal request for coverage or payment for a covered loss or other policy event made by a policyholder to an insurance company is known as an insurance claim. The insurance provider confirms the claim (or denies the claim). If it is accepted, the insurance provider will pay the insured or a recognised interested party on their behalf. Given the importance of studying, analyzing, modeling and evaluating insurance claims for companies and insured individuals, we found ourselves motivated to present this application.

Time series data can display many different patterns, hence it is frequently useful to divide a time series into numerous components, each of which represents a different type of underlying pattern. Typically, we combine the trend and cycle into a single trend-cycle component when we dissect a time series into its constituent parts (sometimes called the trend for simplicity). Thus we think of a time series as comprising three components: a trend-cycle component, a seasonal component, and a remainder component (containing anything else in the time series). The seasonal component is presumed to reoccur every year by traditional decomposition techniques. This is a valid assumption for many series, but it is incorrect for some longer series.

For instance, as the use of air conditioning has increased, patterns of electricity demand have evolved. In particular, the seasonal consumption pattern from a few decades ago had its peak demand in many regions during the winter (due to heating), whereas the current seasonal pattern has its peak demand during the summer (due to air conditioning). These seasonal changes over time cannot be captured by the traditional decomposition techniques. On occasion, the values of the time series in a select few periods might be particularly out of the ordinary. For instance, a labour disagreement may have an impact on the monthly air passenger flow, causing the traffic during the conflict to be different from typical. These kinds of odd values are not resistant to the classical procedure.

The temporal growth of claims through time for each appropriate exposure (or origin) period is frequently shown in the historical insurance actual data in the form of a triangle presentation. The year the insurance policy was purchased or the time period during which the loss occurred may be regarded as the exposure period. It is obvious that the origin period need not be annual. For instance, it may be monthly or quarterly origin periods. The development period of an origin period is known as the "claim age" or "claim lag". Data from separate insurance is frequently combined to represent uniform company lines, division levels, or risks.

In this article, we examine a U.K. Motor Non-Comprehensive account's insurance claims payment. For convenience, we set the origin period from 2007 to 2013 (see Charpentier (2014) and Shrahili et al. (2021)). The insurance claims payment data frame displays the claims data in the manner in which a database would normally keep it. The first column holds the origin year (from 2007 to 2013), the second column is the development year, and the third column has the incremental payments. It's important to note that this data on insurance claims was initially examined using a probability-based distribution.

First of all, we need to explore the insurance claims data. Exploring real data can be done using both numerical and graphical methods. We consider a variety of graphical methods such as the skewness-kurtosis diagram (or the Cullen and Frey diagram) for exploring initial fits of theoretical distributions such as normal, logistic, uniform, exponential, beta, lognormal and Weibull. Bootstrapping is applied and also plotted for more accuracy. Cullen and Frey's graphic, while a decent summary of the distribution properties, only compares distributions in the space of (the squared skewness, kurtosis). The "nonparametric Kernel density estimation (NKDE)" approach for examining the initial shape of the empirical hazard rate function (HRF), the "Quantile-Quantile (Q-Q)" diagram for examining the "normality" of the current data, the "total time on test (TTT)" diagram for examining the initial shape of the empirical hazard rate function (HRF), and the "box diagram" for identifying the extreme claims are among the other graphical tools. We offer the ACF, which shows how the correlation between any two signal values changes as their separation changes. The theoretical ACF does not provide any insight into the frequency content of the process; rather, it is a time domain measure of the stochastic process memory. It provides some information about the distribution of hills and valleys across the surface with lag$=k=1$.

Figure 1 displays the box plot, Cullen and Frey diagram, Q-Q diagram, Scattergram, fitted scattergram, ACF (under lag$=k=1$), partial ACF (under lag$=k=1$), TTT diagram and NKDE plot for the original insurance claims data, respectively. Figure 2 displays the box plot, Cullen and Frey diagram, Q-Q diagram, Scattergram, fitted scattergram, ACF (under lag$=k=1$), partial ACF (under lag$=k=1$), TTT diagram and NKDE plot for the converted insurance claims data, respectively.

Based one Figure 1 (top right diagram), no extreme observations are spotted due to the original and the insurance claims data. Based one Figure 2 (top right diagram), no extreme observations are spotted due to the converted and the insurance claims data. Based one Figure 1 (top middle diagram), the original and the insurance claims data do not follow any of the theoretical distributions including normal, logistic, uniform, exponential, beta, lognormal and Weibull. Based one Figure 2 (top middle diagram), the converted and the insurance claims data do not follow any of the theoretical distributions including normal, logistic, uniform, exponential, beta, lognormal and Weibull. Based one Figure 1 (top left diagram), no extreme observations are spotted due to the original and the insurance claims data. Based one Figure 2 (top left diagram), no extreme observations are spotted due to the converted and the insurance claims data. Based one Figure 1 (middle left and middle middle diagrams), the original and the insurance claims data scattered randomly with no pattern. Based one Figure 2 (middle left and middle middle diagrams), the converted and the insurance claims data scattered randomly with no pattern.

Based one Figure 1 (middle right and bottom left diagrams), the ACF (under lag$=k=1$) and the partial ACF (under lag$=k=1$) of the original and the insurance claims dataare exponentially vanishing. Based one Figure 2 (middle right and bottom left diagrams), the ACF (under lag$=k=1$) and the partial ACF (under lag$=k=1$) of the original and the insurance claims dataare exponentially vanishing. Also Figure 1 (middle right and bottom left diagrams), Figure 2 (middle right and bottom left diagrams) shows that the first lag value is statistically significant, whereas the other autocorrelation coefficients and partial autocorrelation coefficients for all other lags are not statistically significant.

Figure 1 (bottom middle plot) indicates that the hazard rate function for the original insurance claims data is monotonically increasing. Figure 2 (bottom middle diagram) indicates that the hazard rate function for the converted insurance claims data is also monotonically increasing. Figure 1 (bottom right diagram) indicates that the density function for the original insurance claims data is bimodal. Figure 1 (bottom right diagram) indicates that the density function for the converted insurance claims data is left skewed.

Figure 3 presents the initial plots for the original (right) and converted (left) insurance claims payments data. It indicates that the two data sets have a seasonally pattern. When an additive model can adequately explain a seasonal time series, the time series can be seasonally adjusted by estimating the seasonal component and deducting the estimated seasonal component from the original time series. The estimate of the seasonal component generated by the "decompose()" function can be used for this. So, decomposition process of additive insurance claims time series will be considered.

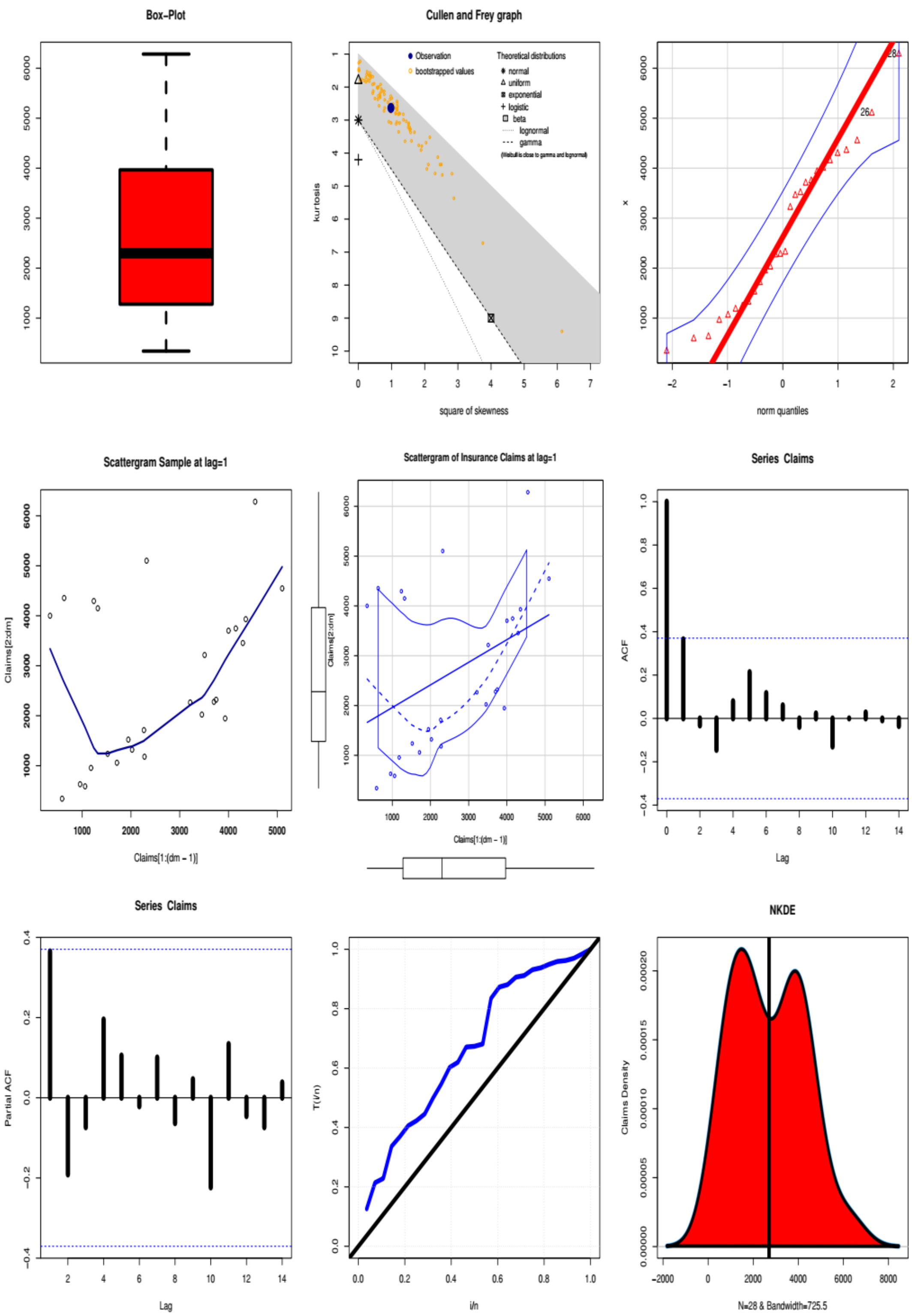

Figure 1: Describing the original insurance claims payments data.

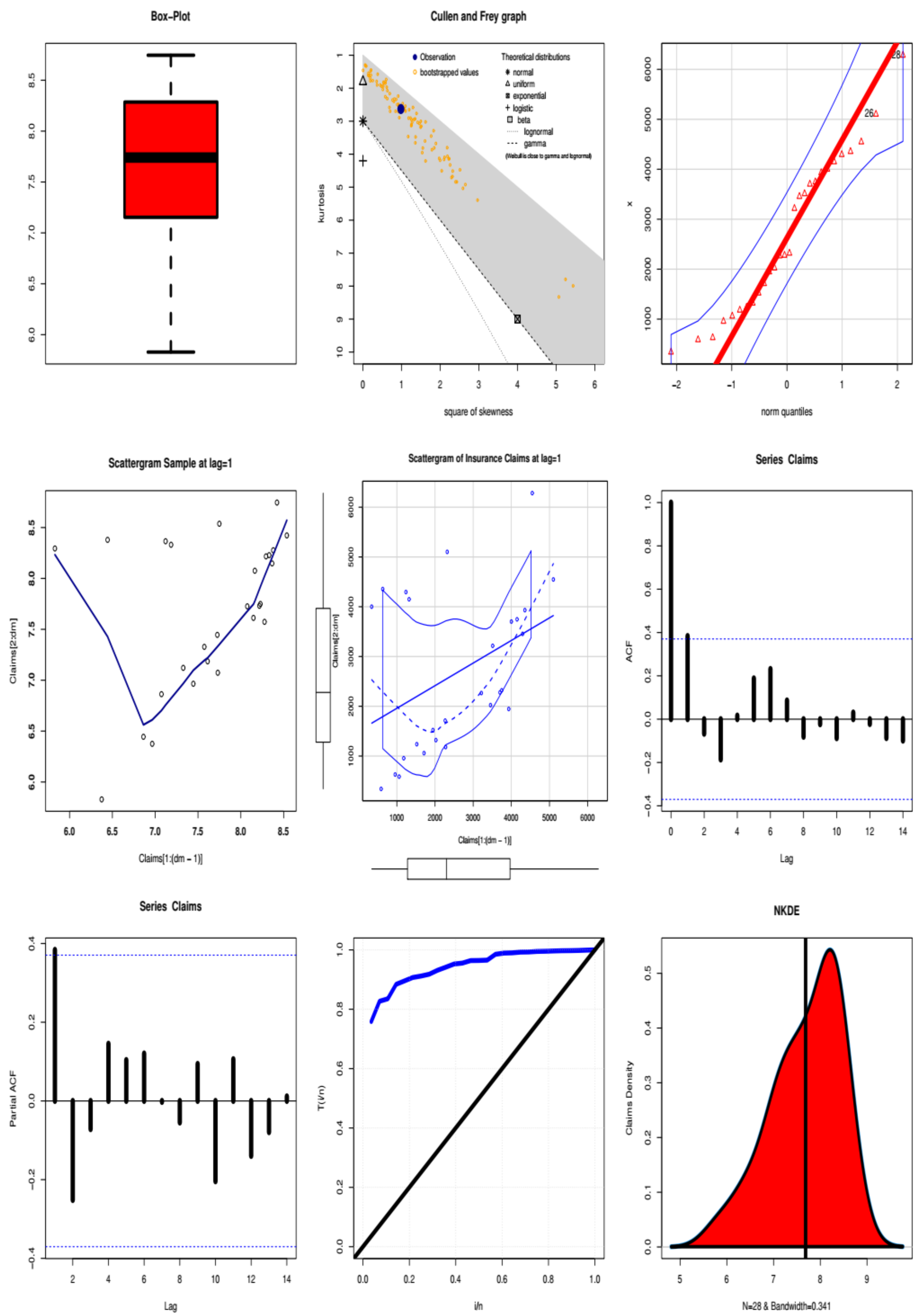

Figure 2: Describing the converted insurance claims payments data.

Figure 3: Initial plots for the original (right) and converted (left) insurance claims payments data.

For the purpose of decomposition process, we present Tables 1, Table 2 and Table 3. Also, Figure 4 and Figure 5. Table 1 lists the separated seasonal components for both original and converted insurance claims payments data sets. Table 2 lists the separated trend components for both original and converted insurance claims payments data sets. Table 3 lists the separated random components for both original and converted insurance claims payments data sets. Figure 4 gives the decomposition plots for the original insurance claims payments data. Figure 5 shows the decomposition plots for the converted insurance claims payments data. Figure 6 gives the seasonally adjusted plots for the original (right) and converted (left) insurance claims payments data. Figure 7 provides the Holt-Winters filtering plots for the original (right) and converted (left) insurance claims payments data.

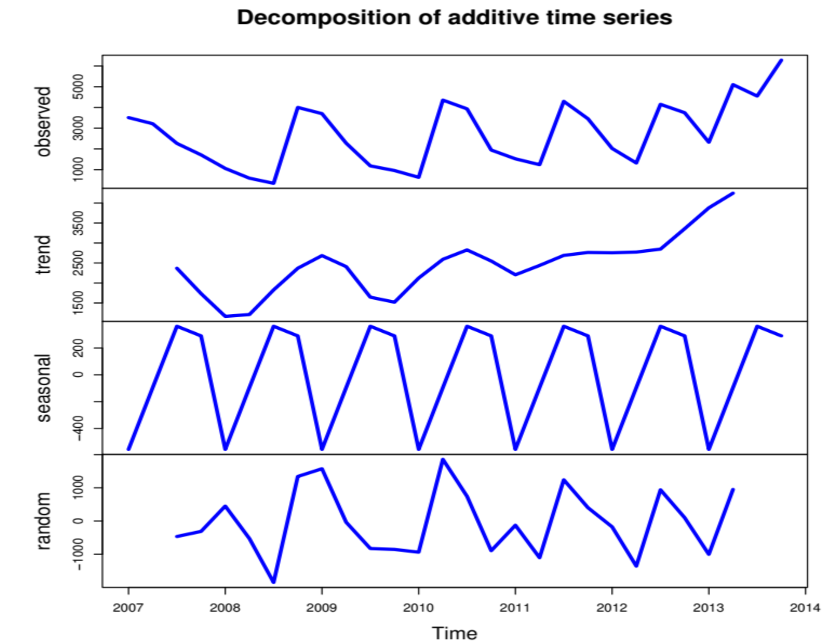

Figure 4: Decomposing plots for the original insurance claims payments data.

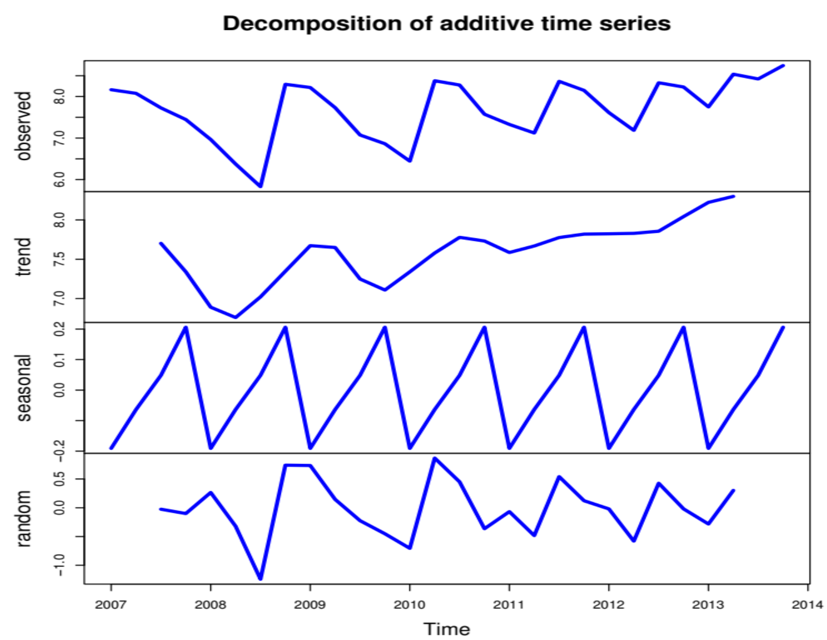

Figure 5: Decomposing plots for the converted insurance claims payments data.

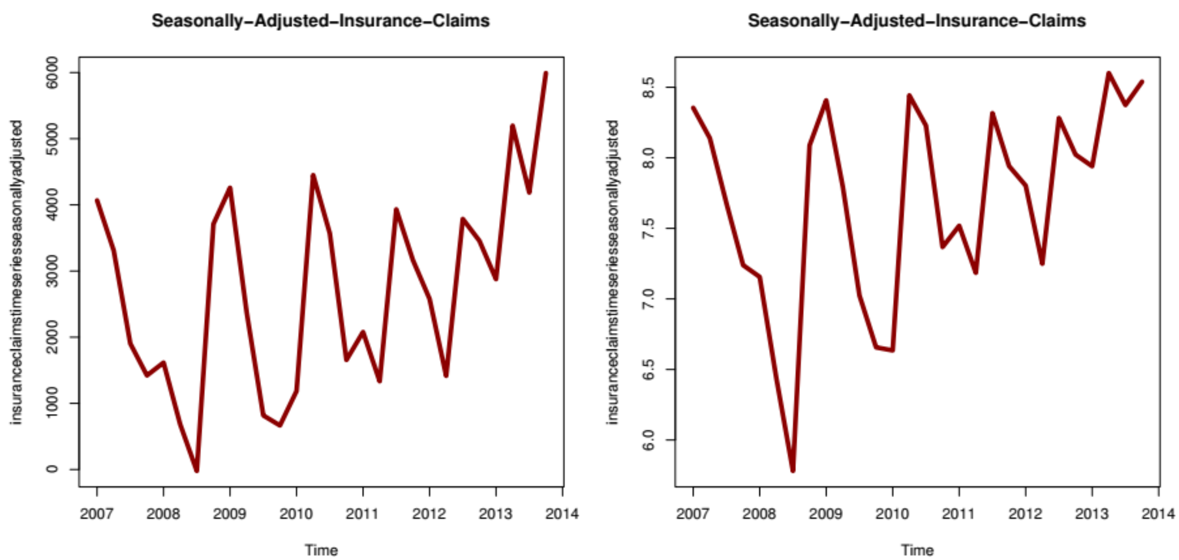

Figure 6: Seasonally adjusted plots for the original (right) and converted (left) insurance claims payments data.

Figure 7: Holt-Winters filtering plots for the original (right) and converted (left) insurance claims payments data.

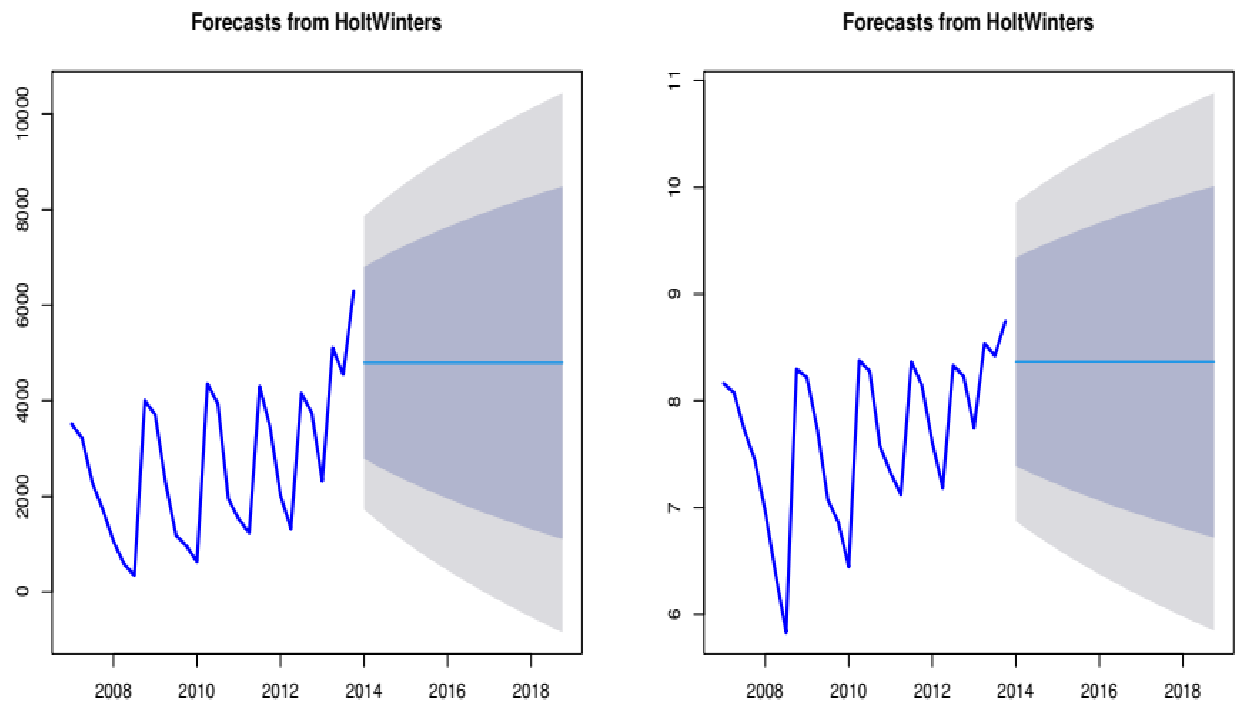

Figure 8: Holt-Winters forecasting plots for the original (right) and converted (left) insurance claims payments data.

The SES model can be used to generate short-term forecasts for time series that fit an additive model with constant level and no seasonality. One method for determining the level at the present time point is the straightforward exponential smoothing method. The parameter alpha, which estimates the level at the current time point, controls the smoothing. Alpha's value ranges from 0 to 1. When forecasting future values, alpha values near to 0 indicate that the most recent observations are not given much weight. Table 4 lists the predicted values for assessing the SES model. The estimated parameter is $\hat{\alpha} = 0.3542739$ for original data and $\hat{\alpha} = 0.3117948$ for the coverted data. The SSE is 17.9783 for original data and. the SSE is 17.9783 for coverted data, based on this, it is better to use the coverted data. Figure 7 is used for assessing the SES model.

Using the Holt-Winters' additive algorithm, we can fit a SES predictive model and create forecasts using this method. The forecast HoltWinters() function provides you with the forecast for a year, an interval of prediction of 80%, and an interval of prediction of 95%. Table 5 lists the predicted values for assessing the SES model for two future years. However, Figure 8 gives the Holt-Winters forecasting plots for the original (right) and converted (left) insurance claims payments data up to 2022. Residual analysis for the converted insurance claims payments data in igure Figure 9. Residual analysis for the converted insurance claims payments data in igure Figure10.

It is also a good idea to see if the forecast errors are regularly distributed with a mean zero and constant variance to ensure that the predictive model cannot be improved. We can create a temporal plot of the in-sample forecast errors to determine whether the forecast errors have constant variance, for this we presented Figure Figure 10, This graphic demonstrates that the variance of the in-sample forecast errors appears to be essentially consistent throughout time. For the original insurance claims payments data, since the p-value is 0.621 and the Ljung-Box test statistic is 13.444, there is minimal proof that the in-sample forecast errors at lags 1–20 have non–zero autocorrelations. For the converted insurance claims payments data, since the p-value is 0.565 and the Ljung-Box test statistic is 11.812, there is minimal proof that the in-sample forecast errors at lags 1–20 have non–zero autocorrelations. Table 5 lists 95% confidence intervals (95% CI) for two years. Due to results of Table 5, it is noted that $\hat{y}_{T+h|T}|_{h=1,2,...,8}$ ≅4794.753 for the orignal insurance claims payments data, this means that $Q_1(2014) \cong ... \cong Q_4(2014) \cong Q_1(2015) \cong ... \cong Q_4(2015)$, $\hat{y}_{T+h|T}|_{h=1,2,...,8}$ =8.365536 for the converted insurance claims payments data, this means that $Q_1(2014) \cong ... \cong Q_4(2014) \cong Q_1(2015) \cong ... \cong Q_4(2015)$. This stability in predictive values does not always occur. For the converted insurance claims payments data, the corresponding predictive value of 8.365536 is 4296.414. Hence, $\hat{y}_{T+h|T}|_{h=1,2,...,8}$ =4794.753 for the orignal insurance claims payments data $>$ $\hat{y}_{T+h|T}|_{h=1,2,...,8}$ =4296.414 for the converted insurance claims payments data

Table 1: Seasonal components

Time	Q_1	Q_2	Q_3	Q_4
	Original time series			
2007	-556.98438	-95.58854	362.36979	290.20312
2008	-556.98438	-95.58854	362.36979	290.20312
2009	-556.98438	-95.58854	362.36979	290.20312
2010	-556.98438	-95.58854	362.36979	290.20312
2011	-556.98438	-95.58854	362.36979	290.20312
2012	-556.98438	-95.58854	362.36979	290.20312
2013	-556.98438	-95.58854	362.36979	290.20312
	Converted time series			
2007	-0.19093962	-0.06355648	0.04846463	0.20603148
2008	-0.19093962	-0.06355648	0.04846463	0.20603148
2009	-0.19093962	-0.06355648	0.04846463	0.20603148
2010	-0.19093962	-0.06355648	0.04846463	0.20603148
2011	-0.19093962	-0.06355648	0.04846463	0.20603148
2012	-0.19093962	-0.06355648	0.04846463	0.20603148
2013	-0.19093962	-0.06355648	0.04846463	0.20603148

Table 2: Trend components

	Original time series				Converted time series			
	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4
2007	-	-	2369.500	1734.500	-	-	7.702785	7.340393
2008	1165.250	1210.625	1827.125	2368.875	6.890720	6.759728	7.022281	7.348228
2009	2685.250	2409.625	1644.875	1520.375	7.673272	7.649870	7.249365	7.108806
2010	2124.000	2591.750	2827.125	2549.125	7.340264	7.579565	7.778868	7.732095
2011	2204.875	2438.875	2690.125	2763.000	7.585905	7.668699	7.776024	7.819610
2012	2755.125	2773.500	2847.125	3357.000	7.823334	7.829183	7.856448	8.042571
2013	3879.500	4246.250	-	-	8.223019	8.299077	-	-

Table 3: Random components

Time	Q_1	Q_2	Q_3	Q_4
Original time series				
2007	-	-	-465.86979	-312.70312
2008	450.73438	-528.03646	-1849.4948	1341.9219
2009	1573.73438	-36.03646	-827.24479	-854.57812
2010	-938.01562	1858.83854	742.50521	-893.32812
2011	-125.89062	-1105.2865	1242.50521	401.79688
2012	-175.14062	-1357.9115	940.50521	99.79688
2013	-1002.5156	951.33854	-	-
Converted time series				
2007	-	-	-0.02547863	-0.1010067
2008	0.26529925	-0.3211460	-1.24179988	0.74004027
2009	0.73429538	0.14473948	-0.22455975	-0.4520799
2010	-0.70519325	0.86307185	0.44957088	-0.3645957
2011	-0.06718412	-0.4838902	0.54071838	0.12193615
2012	-0.02005775	-0.5802397	0.42595150	-0.0198916
2013	-0.28275700	0.30186698	-	-

Table 4: Assessing the SES model

	Q	Original	Converted
2007	Q_1	-	-
	Q_2	3511.000	8.163656
	Q_3	3406.135	8.136195
	Q_4	3002.215	8.008227
2008	Q_1	2545.125	7.832746
	Q_2	2018.630	7.562212
	Q_3	1511.441	7.192053
	Q_4	1096.430	6.767044
2009	Q_1	2125.443	7.243234
	Q_2	2683.976	7.546733
	Q_3	2540.149	7.604203
	Q_4	2058.284	7.438661
2010	Q_1	1667.774	7.259097
	Q_2	1299.763	7.004995
	Q_3	2382.154	7.433428
	Q_4	2931.224	7.696419
2011	Q_1	2582.185	7.658103
	Q_2	2206.589	7.555110
	Q_3	1863.443	7.419836
	Q_4	2724.880	7.714598
2012	Q_1	2983.543	7.849599
	Q_2	2643.247	7.775622
	Q_3	2174.455	7.591590
	Q_4	2874.339	7.82209
2013	Q_1	3183.500	7.948873
	Q_2	2877.585	7.886654
	Q_3	3665.637	8.089550
	Q_4	3978.235	8.193344
$\hat{\alpha}$		0.3542739	0.3117948
		(8.475277)	(8.365536)
SSE		17.9783	**15.09381**

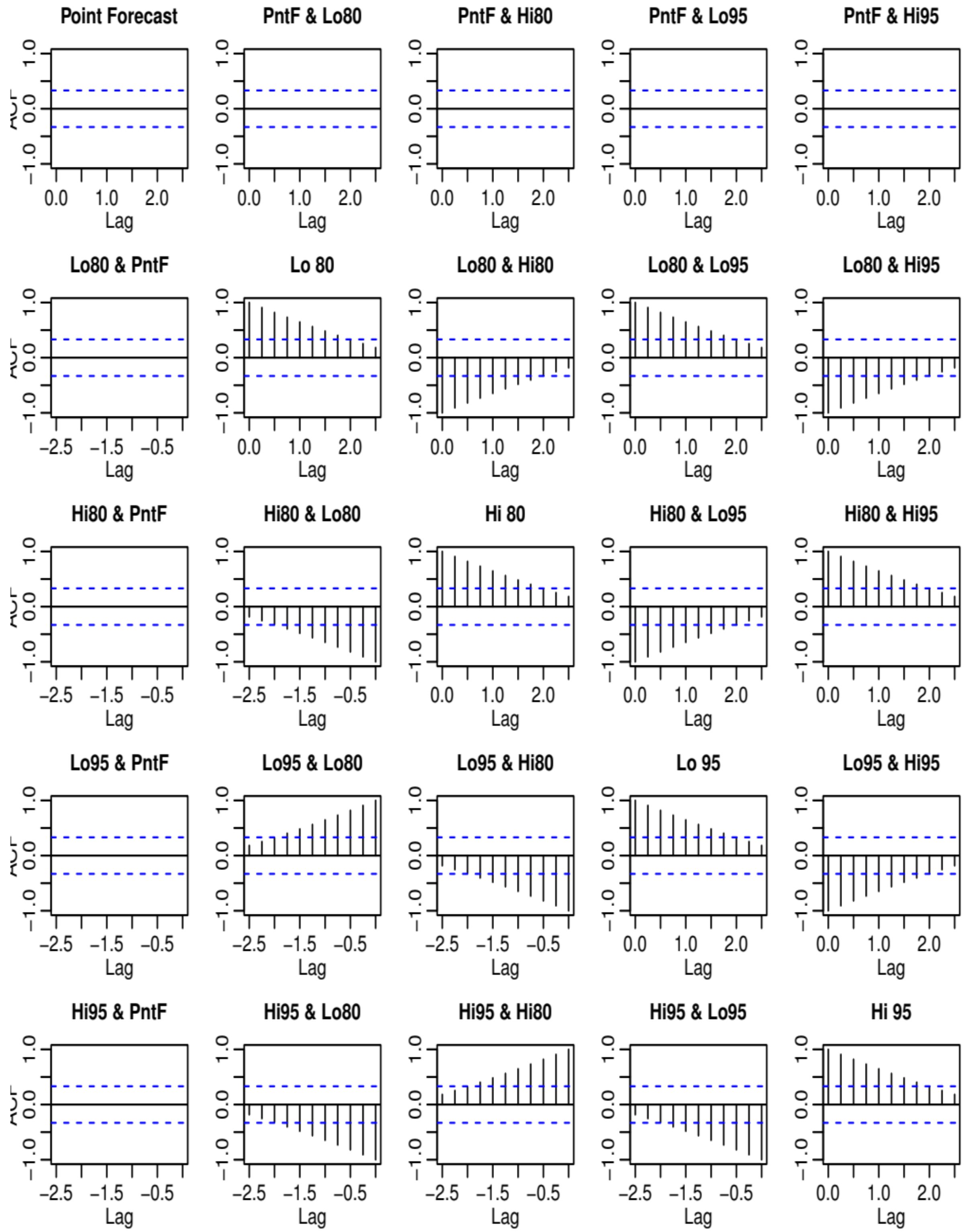

Figure 9: Residual analysis for the original insurance claims payments data.

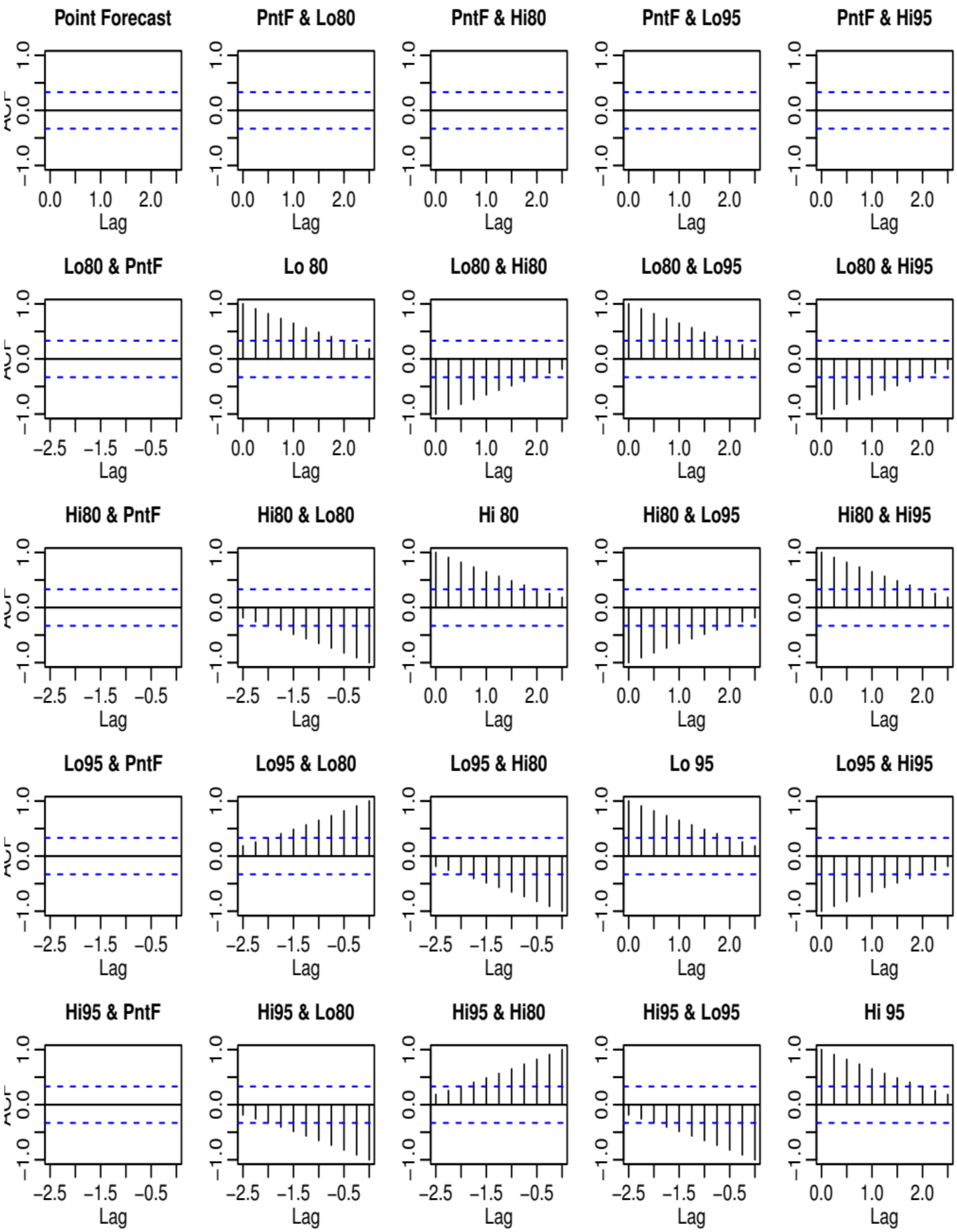

Figure 10: Residual analysis for the converted insurance claims payments data.

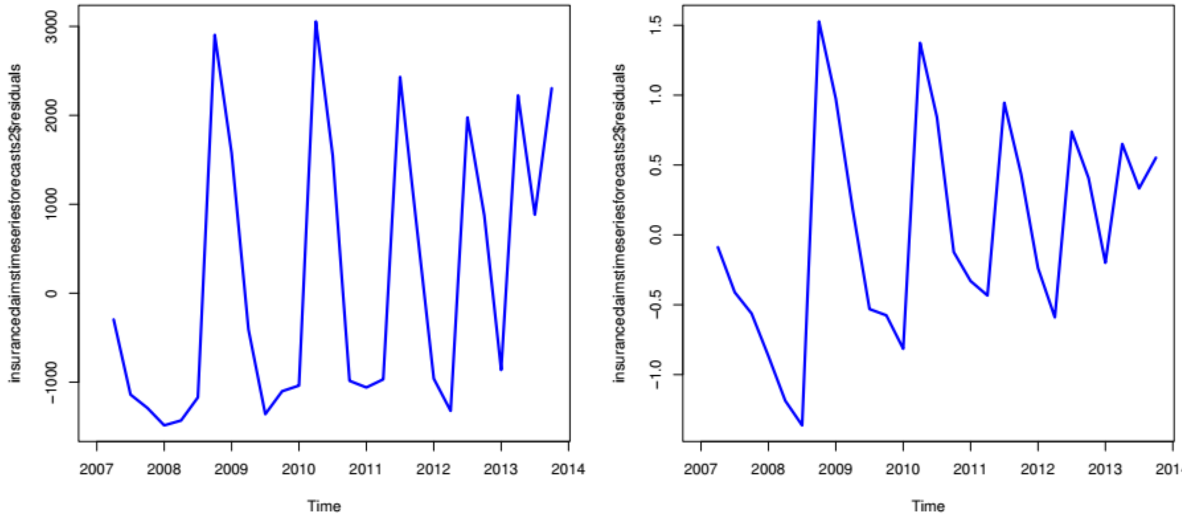

Figure 11: Residual plots for the original (right) and converted (left) insurance claims payments data.

4. Concluding remarks

Short-term forecasts can be made using simple exponential smoothing if your time series data can be successfully forecasted by an additive model with constant level and no seasonality. This method is suitable for forecasting data without a clear seasonal pattern or trend. The simple single exponential smoothing approach is one way to figure out the level at the current moment. For insurance firms to prevent significant losses brought on by potential future claims, the future values of predicted claims are crucial. For predicting various claims payment applications, time series are crucial. The future values of expected claims are essential in order for insurance companies to avoid major losses caused by potential future claims. For left skewed insurance claims, we consider the single exponential smoothing model. The usefulness of the proposed paradigm is illustrated using a real-world application iunder the Holt-Winters' additive algorithm. The optimum parameter is also picked arbitrarily. The usefulness of the proposed paradigm is shown using a real-world application. The Holt-Winters' additive algorithm is recommended for short term future perception in insurance and actuarial sciences.

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