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Change Points Analysis for the Trendof Count Data

Taghreed M. Jawa[1], David Young[2], Chris Robertson[3]
[1]*Department of Mathematics and Statistics, Faculty of Sciences, P.O.Box 11099,Taif University, Taif 21944, Saudi Arabia*
[2]*Department of Mathematics and Statistics, University of Strathclyde, Glasgow, Scotland*
[3]*Health Protection Scotland, Glasgow, Scotland*

Abstract:** Introduction: Change point analysis is a technique for detecting change in trend over time. Seg- mented regression analysis and joinpoint analysis are used to try to determine the most important interventions which impact rates of healthcare associated infections (HAIs). Aims: Use change point analysis to determine which interventions reduce rates of HAIs. Data and Methods: The data on HAIs was monitored by Health Protection Scotland (HPS) and includes staphylococcus aureus bacteraemia (SAB) and clostridium difficile infection (CDI). Since 2004, several interventions were implemented by NHS to reduce the rates and these were reported by Health Protection Scotland (HPS). Segmented regression and joinpoint models are investigated and developed to detect times when the indection rates changed significantly. Profile likelihood and bootstrapping are used to construct confidence intervals for the joinpoints. Results: Interventions which took place from April-June 2006, July-September 2008 and January-March 2011 appear to be associated with a significantly decreasing trend in MRSA. Joinpoint analysis suggested that from July-September 2007 and January-March 2012 there was a significant change in the trend of MRSA bacteraemia. The trend of MSSA bacteraemia did change significantly from January-March 2011, however, joinpoint analysis did not indicate any change in MSSA bacteraemia. A segmented model suggested interventions around October-December 2009 had an impact on the rates of CDI in patients over 65 years and joinpoint analysis showed from April-June 2008 and January-March 2011 the rates changed. Conclusion: Segmented regression analysis detects changes in rates associated with specific interventions. It appears from this that training of hospital staff in dealing with infection outbreaks and the implementation of an antibiotic policy are associated with an observed reduction in the rates of SAB and CDI in healthcare settings. Joinpoint analysis gives the most robust modelling to estimate significant change. Keywords: Segmented regression; joinpoint analysis; seasonal effect; bootstrap confidence interval; profile likelihood confidence interval; healthcare associated infections; MRSA; MSSA; CDI.

I. INTRODUCTION

Everything in the world tends to change over time such as the economy, education and epidemi-ology. It is of interest to know when changes happened to determine the cause. Change point analysis aims to detect a time point when a trend in data changes. A trend in data may havemultiple change points. The change point analysis addresses two aspects in the analysis of a trend - a hypothesis testing approach to decide if there are any change points and an estimation approach to locate the change. Detecting change points was investigated using different methods.Segmented regression analysis was used to discover change points where the rates changesignificantly after a specific intervention and thereby help improve the quality of the interventions [Wagner et al. (2002)].

Joinpoint analysis was used to identify change points at unknown times and to estimate the location of them. Using a joinpoint statistical software package [NCISR (2020)] the simplest joinpoint model (which in includes only a time variable) is fitted to the data. The minimum and maximum number of joinpoints is determined. The program starts with the minimum number ofjoinpoints and tests whether additional joinpoints are statistically significant using a permutationmethod. These are added to the model up to the maximum number. A grid search method hasa discrete number of locations that are tested to find the best fitted model and joinpoints occur exactly at one or more of these locations (observed rate) [Kim (2001)].

A. Healthcare Associated Infections

Healthcare associated infections (HAIs) are a major contributor to morbidity and mortality[Tong et al. (2009)]. These include staphylococcus aureus bloodstream (SAB) infections and clostridium difficile infection (CDI). SAB includes methicillin resistant staphylococcus aureus (MRSA) bacteraemia and methicillin sensitive staphylococcus aureus (MSSA) bacteraemia. The treatment of MRSA bacteraemia can be challenging because MRSA is resistant to the mostantibiotics. Bacteraemia is a bloodstream infection associated with high risk of morbidity and mortality [(Wertheim, 2005)].

The surveillance programme in Scotland reported the occurrence of HAIs up to March 2017 which included data on staphylococcus aureus from January 2003 for MRSA bacteraemia and from April 2005 for MSSA bacteraemia [HPS (2017)].

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CDI data was reported from October 2006 inpatients aged over 65 years and from April 2009 for patients aged 15-64 years [HPS (2017)]. Data was collected every three months and records the number of patients with MRSA bacteraemia, MSSA bacteraemia, CDI. The number of acute occupied bed days (AOBDs) in Scotland are based on the daily counts of occupied beds that are undertaken in every hospital at midnight [HPS (2007)]. Rates of infections are presented per 100,000 AOBDs and this gives an indication of the number of cases relative to the size of the population at risk (Notice: due to updated data from April 2017 was recorded for SAB generally and for CDI generally, data until March 2017 was usedin this paper [HPS (2020)]).

To control infections, some healthcare interventions were implemented in Scottish hospitals from 2004 to 2011 (see Table 3 in Appendix) [HPS (2015)]. It is important in developing healthcarepolicy to know whether any of these interventions had an impact on reducing the rates of HAIs. This research uses different methods to detect changes in infection rates and identifies the numberand location of change points.

II. CHANGE POINT DETECTION METHODS

Change points analysis uses several different models to find statistically significant change pointsassociated with a rate change and identifies how many change points can be estimated [Chen andGupta (2011)].

A. Segmented Regression Analysis

Segmented regression analysis is used to discover change points where the rates change after a specific intervention [Wagner et al. (2002)]. By using Poisson and quasi-Poisson distributions, the general segmented regression model for the rates of MRSA bacteraemia, MSSA bacteraemia, CDIin patients over 65 years and CDI in patients aged 15-64 years was obtained as:

$$\log(\text{Cases}(t)) \sim \text{offset}(\log(\text{AOBDs}(t))) + \alpha_0 + \beta_0 t(i) + \gamma Qu(t) + \beta_1 t^*(i), \quad (1)$$

where i is an indicator of the quarter when the intervention took place. Cases(t) is the number of patients at time t, log(AOBDs(t)) accounts for different population sizes in each period of time and t is the year. $t^*(i)$ is a continuous variable counting the time after the intervention at quarter i, which is coded 0 before the intervention at quarter i and $(t - t(i))$ after the intervention. The coefficient α_0 estimates the intercept (baseline level). The coefficient β_0 estimates the change in therate before the intervention at quarter i (baseline slope). The coefficient β_1 estimates the change inthe slope where the estimate of the slope after the intervention at quarter i is $\beta_0 + \beta_1$. Finally, the coefficient γ estimates the seasonal effect $Qu(t)$.

Two different selections of data points were used to fit segmented regression models. Specific change points were investigated at time points when interventions took place. The first method used all data points before and after each intervention at quarter i and looked for one or more interventions associated with rate changes. The residual deviance is used as a measure of goodness of fit. Change in deviance can be used to compare models since the same number of datapoints were used around each intervention to fit the model. Model (1) is fitted with all possible interventions and the model with least residual deviance (the biggest effect) is chosen. Evidence of additional significan interventions can then be considered until the final number of change points is chosen.

The second method considers four years of data (8 data points before and 8 after eachintervention at quarter i). For example, when the intervention took place at Qu4, October- December 2007, data from Qu1, January-March 2006 to Qu4, October-December 2009 is used to fit the segmented model. Using the same number of data points avoids bias but residual deviance cannot be used to compare models. Here percentage of deviance explained (PDE) is used to measure the goodness of fit where the best fitted model has the biggest PDE. PDE is calculated as:(1 - (deviance of the segmented model / deviance of the null model))× 100, where the null model is obtained as log(rate) = 1.

Segmented regression detects the times when specific interventions took place. There may wellbe a lag period for an effect to be seen as the intervention was rolled out over a period of time across various health boards. The next method looks for the significant changes at all possible time points within the rate data.

B. Joinpioint Analysis

Joinpoint analysis is used to estimate the number and location of change points. The joinpoint regression model describes changes in the rate by connecting linear trends. Using similar ideas to [Kim et al. (2000)], a joinpoint analysis based on the Poisson distribution which incorporates seasonality was developed and confidence intervals estimated. The joinpoint function was writtenin R [R Core Team (2014)] as the standard joinpoint software [NCISR (2020)] did not allow for a seasonal factor.

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1) Joinpoint estimation

The algorithm for the analysis is as follows:

a) Set minimum (min) and maximum (max) number of joinpoints which satisfy max-min ≥ 2.

b) Use Equation 1 to fit null models with the minimum number of joinpoints and alternativemodels with the maximum number of joinpoints to the data.

c) Find the best fitted model of both (null and alternative) models by using a grid searchmethod considering one time point of data between every possible joinpoint.

d) Permute the residuals from the chosen null model (100 times) and use them to get permutedcounts.

e) The permuted counts are calculated using Pearson residuals and are obtained as: permuted counts = expected values of null model + Pearson residuals $\times \sqrt{}$ expected values of null model.

f) Use permuted counts to fit an alternative model and find the smallest permuted deviances.

g) The permutation test is calculated to find the p-value for accepting or rejecting the nullmodel.

- Find the change in deviance from original data (X= deviance of null model - devianceof alternative model).
- Find the change in deviance from permuted data (Y= deviance of null model - permuteddeviances of alternative model).
- Calculate p-value of permutation test as $\sum I(Y > X)/(\text{length}(Y) + 1)$, $I(Y > X) = 1$; $Y > X$ and 0; otherwise.

h) If p < 0.05/(max-min), reject the null model and accept the alternative model then perform the same analysis using the same alternative model and set the null model as (minimum number of joinpoint +1). See Bonferroni correction in Kim et al. (2000).

i) If p > 0.05/(max-min), accept the null model and reject the alternative model then perform the same analysis using the same null model and set the alternative model as (maximum number of joinpoint -1).

j) Repeat the analysis until the distance between the null and alternative models becomes 1.

k) The number of joinpoints and their locations can be then known from the last accepted model.

C. Confidence Intervals for joinpoint

Confidence intervals for joinpoints are constructed using a Profile likelihood method and boot-strapping.

1) Profile Likelihood Confidence Interval

The profile likelihood confidence interval is based on the asymptotic chi-square distribution of the log-likelihood ratio test statistic. The confidence interval for one joinpoint can be computed by adding $\chi^2_{(0.95,1)} = 3.84$ to the minimum value of the deviance function which was calculated from each joinpoint model. The deviance is -2 multiplied by the log-likelihood value of null model minus the log-likelihood value of the saturated model [Royston et al. (2007)]. The residual deviances from joinpoint models were calculated and the curve of deviance function was plotted.This is U-shaped where deviances start to decrease and at the minimum deviance start to increase. A horizontal line based on the minimum deviance plus 3.84 was plotted and two points of intersection with the deviance function curve were obtained. These two points are the lower and upper confidence level of the estimated joinpoint. The deviance function of models with two or more joinpoints cannot be used to find confidence intervals so bootstrap confidence interval wereproduced.

2) Bootstrap confidence interval

The algorithm for constructing bootstrap confidence intervals is as follows:

a) Use original data sample to fit a joinpoint model of the rate of infection.

b) Obtain the fitted values $\hat{y}_i$ and Pearson residuals $\hat{\varepsilon}_i$Re-sample the residuals to get a new response variable y_i^* by adding re-sampled residuals tothe fitted values as $y_i^* = \hat{y}_i + \hat{\varepsilon}_i \times \sqrt{\hat{y}_i}$.

c) Round y_i^* to integer values.

d) Use the new responses (bootstrap data) to fit joinpoint models which have the same number of joinpoints as in the original model.

e) Save the location of joinpoints from the best fitted model.

f) Repeat steps 3 to 6 B times (say 1000 times) to obtain bootstrap estimates of joinpoints.

g) Calculate the 95% confidence interval for joinpoint by using the bootstrapped joinpointswith the function **quantile** at 0.025 and 0.975 in R

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III. RESULTS

Change points for MRSA bacteraemia, MSSA bacteraemia, CDI in patients aged over 65 years andCDI in patients aged 15- 64 years were estimated. Firstly, segmented regression analysis was usedto detect change points when the specific interventions took place. Secondly, joinpoint analysis was used to estimate the number of change points and their locations.

A. Segmented Regression Analysis

Segmented regression uses the data to fit linear trends in log rates and interventions are assumedto have taken place at specific times when the trend changes.

B. MRSA Bacteraemia

Using all data before and after an intervention at quarter *i*, and assuming that only one significantintervention affects the rate, the Poisson fitted model (1) of MRSA bacteraemia with intervention at Qu2, 2006 gave least deviance (105.65 on 51 degrees of freedom). Assuming the time when the first intervention took place is Qu2, 2006, a second intervention at Qu3, 2008 gave a significantly improved model with two interventions. Given these two interventions, a third intervention at Qu1, 2011 gave a significantly better with residual deviance is 64.76 on 49 degrees of freedom. This implies three significant change points at which interventions affected the rates of MRSA. Using 8 points of data before and 8 after each intervention, the Poisson fitted model (1) on MRSAbacteraemia with intervention at Qu2, 2006 has the largest PDE= 0.6538, see Figure 1 and Table 1.

Table 1: *Change points by segmented regression analysis*

Infection	Segmented points All data	Segmented point 2 years B and A
MRSA bacteraemia	Qu2, 2006 Qu3, 2008 Qu1, 2011 DV:64.76, DF:49	Qu2, 2006 PDE=0.6538
MSSA bacteraemia	Qu1, 2011 DV:105.66, DF:42	Qu2, 2008 PDE=0.1862
CDI in patients aged over 65 years	Qu4, 2009 DV:1405.52, DF:36	Qu4, 2009 PDE=0.9889
CDI in patients aged 15-64 years	Qu4, 2009 DV:94.05, DF:26	Qu4, 2009 PDE=0.8629

Qu: Quarter, Qu1: January- March, Qu2: April- June, Qu3: July- September, Qu4: October- December, DV: Residual Deviance, DF: Degree of freedom, A: After, B: Before.

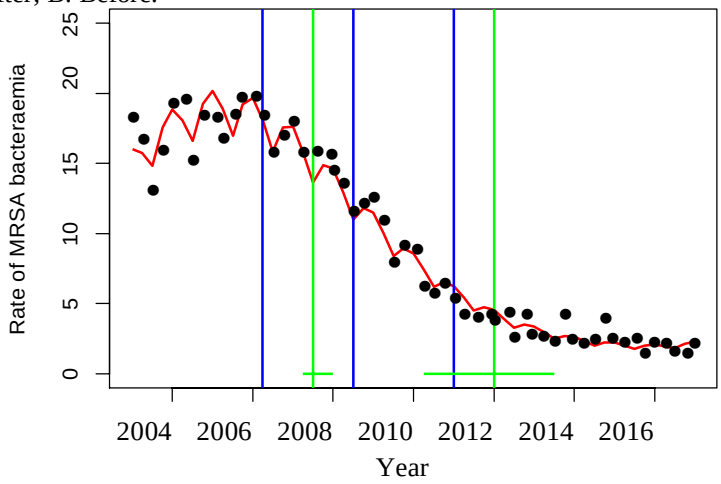

Figure 1: Change points in MRSA bacteraemia. Black circles are the observed rates, red line is the expected rates, the change points by segmented regression from all data observed at blue lines and the change points by joinpointanalysis with bootstrap confidence interval observed at green lines.

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C. MSSA Bacteraemia

Fitting segmented regression models using all data on MSSA rates before and after each inter- vention at quarter *i* and fitting quasi-Poisson regression suggested one change point at Qu1, 2011 giving the smallest residual deviance of 105.66 on 42 degrees of freedom. However, by using two years of data before and two years after each intervention at quarter *i* and using Poisson regression, the significant change in the slope was observed at Qu2, 2008 with PDE= 0.1862, see Figure 2 and Table 1.

D. CDI in Patients Aged over 65 Years

For CDI in patients over 65 years, using all data before and after each intervention at quarter *i* and fitting segmented models with quasi-Poisson gave one significant change point at Qu4, 2009 with residual deviance of 1405.52 on 36 degrees of freedom. Segmented models with one change pointand two years of data before and after each intervention at quarter *i* showed Qu4, 2009 had PDE=0.9889 with a significant change in the slope, see Figure 3 and Table 1.

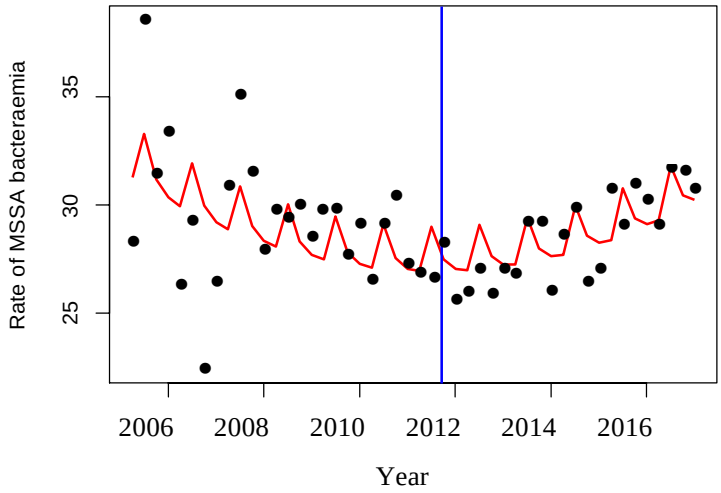

Figure 2: Change points in MSSA bacteraemia. Black circles are the observed rates, red line is the expected rates andthe change point by segmented regression from all data observed at blue line.

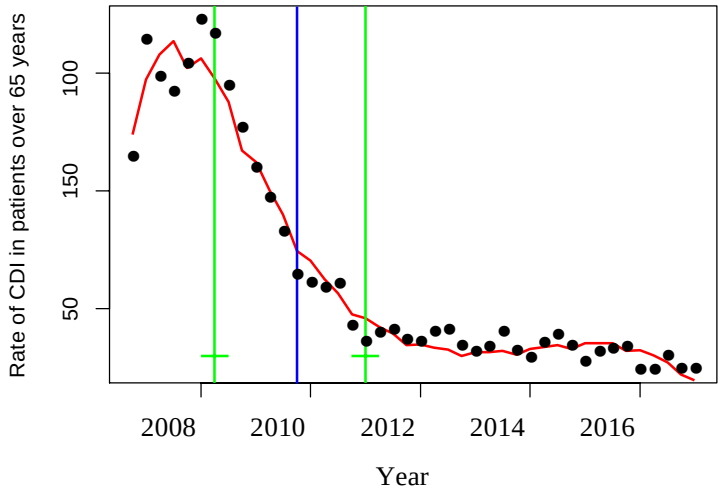

Figure 3: Change points in CDI in patients over 65 years. Black circles are the observed rates, red line is the expected rates, the change points by segmented regression from all data observed at blue line and the change points byjoinpoint analysis with bootstrap confidence interval observed at green lines.

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E. CDI in patients aged 15-64 years

Segmented models with Poisson regression were fitted to the data on CDI in patients aged 15-64 years. Using all data before and after each intervention at quarter *i*, produced one significant change point where the model with Qu4, 2009 has the smallest residual deviance 94.05 on 26 degrees of freedom. However, Figure 4 shows that by using two years of data before and after each intervention at quarter *i*, Qu4, 2009 has PDE= 0.8629 with significant change in the slope. SeeTable 1.

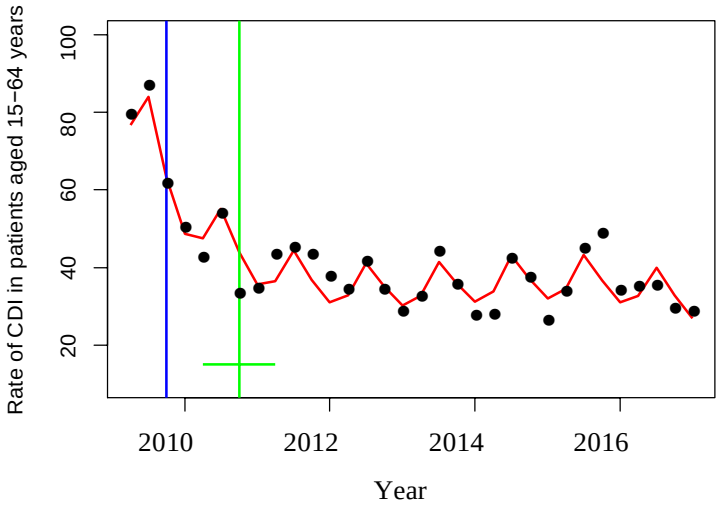

Figure 4: Change points in CDI in patients aged 15-64 years. Black circles are the observed rates, red line is the expected rates, the change points by segmented regression from all data observed at blue line and the changepoints by joinpoint analysis with bootstrap confidence interval observed at green lines.

F. Joinpoints and Their Confidence Intervals

Joinpoint analysis was to estimate change points at all possible data points. The joinpoint model is linear on the log rate and seasonality was considered to improve the model fit.

G. MRSA and MSSA Bacteraemias

There are two joinpoints detected on MRSA bacteraemia data using joinpoint software [NCISR (2020)] at Qu1, 2008 and Qu2, 2012, see Table 2. Adding a seasonal effect to the model gave two significant joinpoints at Qu3, 2007 and Qu1, 2012 with residual deviance 72.31 on 50 degrees of freedom, see Figure 1. 95% bootstrap confidence intervals for these joinpoints are (Qu2, 2007- Qu1, 2008) and (Qu2, 2010- Qu3, 2013), see Table 2. No significant joinpoint was identified for the

H. MSSA Data

Table 2: *Estimated change points by joinpoint analysis*

Infection	JPs by	JPs Profile likelihood	Confidence interval for joinpoint NCISR	Bootstrap
MRSA bacteraemia	Qu1,2008 Qu2, 2012	Qu3, 2007 Qu1, 2012	(Qu2, 2007 - Qu1, 2008) (Qu2, 2010 - Qu3, 2013)	
CDI in patients over 65 years	Qu4,2008 Qu2, 2011	Qu2, 2008 Qu1, 2011	(Qu1, 2008 - Qu3, 2008) (Qu4, 2010- Qu2, 2011)	
CDI in patients aged 15- 64 years	Qu2, 2011	Qu4, 2010	(Qu2, 2010 - Qu2, 2011)	(Qu2, 2010 - Qu1, 2011)

JPs: joinpoints, Qu:Quarter, Qu1: January- March, Qu2: April- June, Qu3: July- September, Qu4: October- December, DV: Residual deviance, DF: Degree of freedom.

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I. CDI in Patients Aged Over 65 Years

For the data on CDI in patients over 65 years, there are two joinpoints with model deviance 191.39 on 35 degrees of freedom. The first is at Qu2, 2008 with 95% bootstrap confidence interval (Qu1, 2008 - Qu3, 2008) and the second is at Qu1, 2011 with 95% bootstrap confidence interval (Qu4, 2010 - Qu2, 2011), see Figure 3 and Table 2. The joinpoint software [NCISR (2020)] detected the same number of joinpoints but at different locations, see Table 2.

J. CDI in Patients Aged 15-64 Years

Figure 4 shows there is one joinpoint in the data of CDI in patients aged 15-64 years in Qu4, 2010 with residual deviance 52.27 on 26 degrees of freedom. A 95% profile likelihood confidence interval is (30.45, 32.77) ≈ (Qu2, 2010 - Qu1, 2011) and a 95% bootstrap confidence interval is (Qu2, 2010 - Qu2, 2011), see Table 2. Joinpoint software [NCISR (2020)] detected the same number of joinpoint but at different locations, see Table 2.

IV. DISCUSSION

Change point analysis is necessary to detect significant interventions which impact rates of healthcare associated infections. Segmented regression with different sets of data was used to identify change points in HAIs (MRSA bacteraemia, MSSA bacteraemia, CDI in patients over 65 years and CDI in patients aged 15-64 years). Using all available data to fit segmented regression has some advantages.

Segmented models can be estimated more accurately when there is along period of time for analysis since the variance of the slope is then smaller. Since the same data was used each time when fitting different models, models with more than one interven- tion can be fitted and likelihood ratio test used to test the significance of nested models. The residual deviance can then be used to compare different models at different interventions.

The limitation of using all the data is that segmented regression is fitting linear trends before and after an intervention and the linear trend does not describe the date well over a long period of time.

Specifying the number of data points before and after each intervention to be two years of data (8 points) ensures there is enough residual degrees of freedom since each model has linear effect of time and a seasonal effect. This has the benefit that there are approximately equal variances of the slope before and after the intervention since the same number of data points are considered. The smallest variance then estimates the best fitting model. Also, since segmented regression is fitting linear trends before and after an intervention, the model is more likely to be linear and symmetric over this short period of time. On the other hand, the segmented model can be less accurate with lower power and precision because a short period of time was used. The residual deviance cannot then be used to compare fitted models so PDE was used to measure the goodnessof fit. This compares each model with its null model and the model with a significant change in the slope after the intervention and the largest PDE is best.

The trend of MSSA bacteraemia has one change over time but joinpoint analysis did not identify this. However, segmented regression of MSSA rates indicate one change where the rate starts to increase. It would appear that none of the interventions had a significant impact on the rates of MSSA.

Joinpoint software [NCISR (2020)] does not allow modelling the effect of seasonality. The soft- ware was modified to include seasonality allowing more flexibility. Adding seasonality to MRSA, CDI in patients over 65 years and CDI in patients aged 15- 64 years, did not change the number of joinpoints but did change the locations suggesting that seasonality does influence infection rates.

Confidence intervals for joinpoints can be constructed using the limiting distribution with large samples [Bai (1997)]. Profile likelihood and bootstrap are non-parametric approaches used to construct confidence intervals for joinpoints with unknown distributions. Using the profile likelihood method to construct confidence intervals for joinpoint does not work well, especially with small sample sizes. This is due to the residual deviance of joinpoint models being similar to each other. There can also be more than one minimum turning point or the horizontal line may not intersect with the curve. This can happen when the difference between the maximum and inimum points of deviances is less than $\chi 2_{(0.95,1)} = 3.84$. The profile likelihood cannot be applied when the model has more than one joinpoint because a single value of deviance describes these points and the curve of the deviance function cannot be plotted. As a result, profile likelihood confidence intervals do not perform well when the sample size is small or the model has more than one joinpoint. In such cases the bootstrap method can be used to construct confidence intervals, however, these intervals are wider and need much more computation than profile likelihood confidence intervals.

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The research aimed to detect the time point and the specific intervention which reduces the rates of HAIs. Segmented regression analysis showed that the change in the rate of MRSA bacteremia occurred in 2006 and the first of these was the initiation of standard infection control precautions [RCN (2005)]:

1) Cover all cuts with clean waterproof dressing.
2) Keep hand hygiene every time.
3) Shake off any waste safely.
4) Do not transfer unnecessary patient between wards.
5) Arranged time for patient to avoid crowding.
6) Isolate patients who have infection.

The second intervention was to introduce hand hygiene policy which includes [RCN (2005)]:

a) Hands should be cleaned before and after contact with patients.
b) Using soap and water for dirty hands and dried hands after that.
c) Using alcohol if hands are clean.

In addition, health improvement, efficiency, access and treatment (HEAT) was introduced with theexpectation of a 30% reduction in SAB by 2010 [HPS (2006)]. Finally, MRSA screening practices changed to include all patients at admission, discharge and transfer. Staff who test positive for MRSA are also screened [RCN (2005)].

Joinpoint analysis showed the changes in rates of MRSA in 2007 when the Scottish patient safety programme (SPSP) was declared. SPSP aimed to improve healthcare safety and reliability in all health care settings [SPSP (2005)].

The rates of CDI in patients over 65 years changed in 2009 when the first healthcare environ- ment inspectorate (HEI) was carried out across the NHS in Scotland [HIS (2009)]. The hospital infection incident assessment tool (HIIAT) also started in 2009. This provides all tools that are needed to know about hospital infection [HPS (2011)]. However, joinpoint analysis showed that the change occurred in 2008 when quality improvement Scotland (QIS) was launched. QIS coversthe issues relating to provision of patient-focused care and treatment [HIS (2008)]. Also in 2008, transmission based precautions(TBPs) commenced and was a requirement of staff. TBPs are control measures that should be implemented in addition to standard infection control precautionsto infected patients [ICT (2015)].

In conclusion, the change point problem is an important analysis to detect the presence and locations of changes in trends of data. Segmented regression and joinpoint analysis have approx- imately similar results in terms of the location of such points. Segmented regression analysis depends on specific (known) time points, i.e. exact times when interventions took place. The process then looks at times when the pattern changes significantly after and intervention. Joinpoint analysis detects changes at unknown times and this approach looks for changes over a period of time and gives the most significant change points within all the data. It is more accurate than segmented regression because it is rare for an intervention to impact rates immediately - usually it takes time to affect the rates of HAIs. The joinpoint method detects the time not only at intervention points but also at points after interventions took place. The joinpoint analysis was also able to account for the impact of seasonality on rates.

The idea in this research was to detect the times and interventions that reduced the rate of healthcare associated infections. The work suggests that improving the implementation of some healthcare interventions such as hand hygiene, training courses for hospital staff in dealingwith infection, screening MRSA and MSSA in patients prior to hospital admission and applying antibiotic policy have helped to reduce and prevent infection in hospitals and healthcare systems.

REFERENCES

[1] Bai, J. (1997). Estimation of a change point in multiple regression models. Review of Economics andStatistics, 79(4):551–563.
[2] Chen, J. and Gupta, A. K. (2011). Parametric statistical change point analysis: with applications to genetics, medicine, and finance. Springer.
[3] HIS (2008). Healthcare associated infection (HAI) standards. Available at http: //www.healthcareimprovementscotland.org/previous_resources/standards/healthcare_ associated_infectio.aspx. [Accessed: 5-1-2015].
[4] HIS (2009). Healthcare environment inspectorate. Available at http://www. healthcareimprovementscotland.org/programmes/inspecting_and_regulating_care/ environment_inspectorate_hei.aspx. [Accessed: 5-1-2015].
[5] HPS (2006). HEAT targets due for delivery. Available at http://www.gov.scot/Resource/0046/ 00467027.pdf. [Accessed: 5-1-2015].
[6] HPS (2007). Protocol for the scottish mandatory surveillance programme for staphy- lococcus aureus bacteraemia. [Online] Health Protection Scotland. Available from: http://www.documents.hps.scot.nhs.uk/hai/sshaip/guidelines/s-aureus/ s-aureus-bacteramia-protocol-v3-2007-09.pdf. [Accessed: 30-10-2013].
[7] HPS (2011). Hospital infection incident assessment. Available at http://www.hps.scot.nhs.uk/ haiic/ic/publicationsdetail.aspx?id=43437. [Accessed: 5-1-2015]
[8] HPS (2015). National hand hygiene campaign. [Online] Health Protection Scotland. Available from: http://www.hps.scot.nhs.uk/haiic/ic/nationalhandhygienecampaign.aspx. [Accessed: 7-4-2014].

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[9] HPS (2017). Commentary on quarterly epidemiological data on clostridium difficile infection, escherichia coli bacteraemia, staphylococcus aureus bacteraemia and surgical site infection in Scotland. January to March (Q1) 2017. Available at http://www.hps.scot.nhs.uk/haiic/ sshaip/resourcedetail.aspx?id=3277. [Accessed: 1-10-2017].
[10] HPS (2020). Quarterly epidemiological data on clostridioides difficile infection, escherichia coli bacteraemia, staphylococcus aureus bacteraemia and surgical site infection in Scotland. Jan-uary to March (Q1) 2020. Available at https://www.hps.scot.nhs.uk/search?q=Quarterly+ epidemiological#searchForm. [Accessed: 14-7-2020].
[11] ICT, I. C. T. (2015). Transmission based precautions literature review: Definitions of trans- mission based precautions. Available at http://www.documents.hps.scot.nhs.uk/hai/ infection-control/ic-manual/tbp-lr-definitions-v1.0.pdf. [Accessed: 5-1-2015].
[12] Kim, H.-J. (2001). Permutation tests for joinpoint regression with applications to cancer rates. Statistics in Medicine, 20(4):655–655.
[13] Kim, H.-J., Fay, M. P., Feuer, E. J., and Midthune, D. N. (2000). Permutation tests for joinpoint regression with applications to cancer rates. Statistics in medicine, (19):335–51.
[14] NCISR (2020). Joinpoint regression program, statistical methodology and applications branch, surveillance research program, national cancer institute, version 4.8.0.1. https://surveillance. cancer.gov/joinpoint/. (Accessed: 13-12-2020).
[15] R Core Team (2014). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
[16] RCN, R. C. N. (2005). Methicillin-resistant staphylococcus aureus (mrsa). Available at http: //www.nhs.uk/conditions/mrsa/documents/rcn%20mrsa%20guidelines.pdf. [Accessed: 5-1-2015].
[17] Royston, P. et al. (2007). Profile likelihood for estimation and confidence intervals. Stata Journal, 7(3):376–387.
[18] SPSP (2005). Scottish patient safty programme. Available at http://www. healthcareimprovementscotland.org/our_work/patient_safety/spsp.aspx. [Accessed: 5-1-2015].
[19] Tong, E., Clements, A., Haynes, M., Jones, M., Morton, A., and Whitby, M. (2009). Improved hospital-level risk adjustment for surveillance of healthcare-associated bloodstream infections: aretrospective cohort study. BMC infectious diseases, 9(1):145.
[20] Wagner, A., Soumerai, S., Zhang, F., and Ross-Degnan, D. (2002). Segmented regression analysis of interrupted time series studies in medication use research. Journal of clinical pharmacy and therapeutics, 27(4):299–309.
[21] Wertheim, H. F. L. (2005). Staphylococcus aureus infections; Lead by the nose. PhD thesis, Erasmus MC: University Medical Center Rotterdam.

APPENDIX: INTERVENTIONS PROVIDED BY HPS

Health protection Scotland (HPS) provided the information about when interventions took placefrom 2004 to 2011.

Table 3: Interventions provided By HPS

Month	Intervention
May 2004	NHS Scotland Code of Practice on HAI management published.February 2005 CNO letter on alcohol based handrubs and infection control.
March 2005	CNO requested that all G Grade Sisters/ Charge Nurses (Senior Charge Nurses) undertake the Cleanliness ChampionsCourse commenced.
July 2005	New IC structure in Boards, including ICM funding. August 2005 Antimicrobial Prescribing Policy and Practice in Scotland- Recommendations for good antimicrobial practice in acute hospitals.
January 2006	Hand hygiene national campaign announced/launched.
February 2006	Standard Infection Control Precaution model policiesfirst launched.
April 2006	HEAT targets introduced- target of 30% reduction in SAB by 2010asked of all boards.
April 2006	MRSA guidelines issued in Journal of Hospital Infection (although not Scottish initiative, widely recognised by infectioncontrol world)- screening practices changed.
March 2007	Scottish Patient Safety Programme (SPSP) announced-no intervention at this point.
December 2007	First national hand hygiene compliance report issued.
January 2008	HPS care bundles related to interventions first launched (SPSP).
March 2008	Launch of QIS standards (followed by visits to Boards related to these- from 2008).March 2008 HPS CDI bundle launched.
May 2008	Transmission Based Precaution model policies first launched.July 2008 SAPG guidance control of 4Cs antibiotic policy
July 2008	Cleanliness champions uptake at 2000 members of staff.
August 2008	Letter to CE in Scotland outlining roles and responsibilities for HAI(performance management push).
August 2008	National action plane for CDI.
October 2008	Credit card flyer issued (ABHR message).December 2008 National CDI guidance issued.
January 2009	Cab Sec announcement on zero tolerance tonon compliance with hand hygiene.
January 2009	HAIRT template introduce for hospital reporting atboards bi monthly.
March 2009	Second Wave of NHS staff materials (with mandate from SGHD forcompulsory placement).
April 2009	Revised HEAT targets announced- CDI one introduced.
April 2009	Public health act (inclusive of reporting SAB and CDI) implemented.

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Month	Intervention
September 2009	First HEI inspection carried out.
September 2009	Second Wave of NHS staff materials reissued.December 2009 HIIAT issued for managing outbreaks.
January 2010	SAB 90 day programme launched.
March 2010	MRSA Screening changes in all Boards- targeted universal in specialties interimpolicy.
March 2011	MRSA screening changes to CRA.

SAB: Staphylococcus aureus bacteraemia, **CDI:** Clostridium difficile infection,

NHS: National Health Service, **HAI:** Healthcare associated infection,

SAB: CNO: Chief nursing officer, **IC:** Infection control,

ICM: Intensive care medicine, **HEAT:** Health improvement, efficiency, access and treatment, **MRSA:** Methicillin-resistant staphylococcus aureus, **SPSP:** Scottish patients safety program,**HPS:** Health Protection Scotland, **QIS:** Quality improvement Scotland,
SAPG: Scottish antimicrobial prescribing group,

4Cs Antibiotic: Broad-spectrum antibacterials including clindamycin, co-amoxiclav, cephalosporins and fluoroquinolone,**CE:** Chief Executives, **ABHR:** Alcohol based hand rub, **HAIRT:** Healthcare Associated Infection Reporting Template, **SGHD:** Scottish Government Health Directorate, **HEI:** Healthcare environment inspectorate,
HIIAT: Hospital infection incident assessment tools, **CRA:** Clinical risk assessment.

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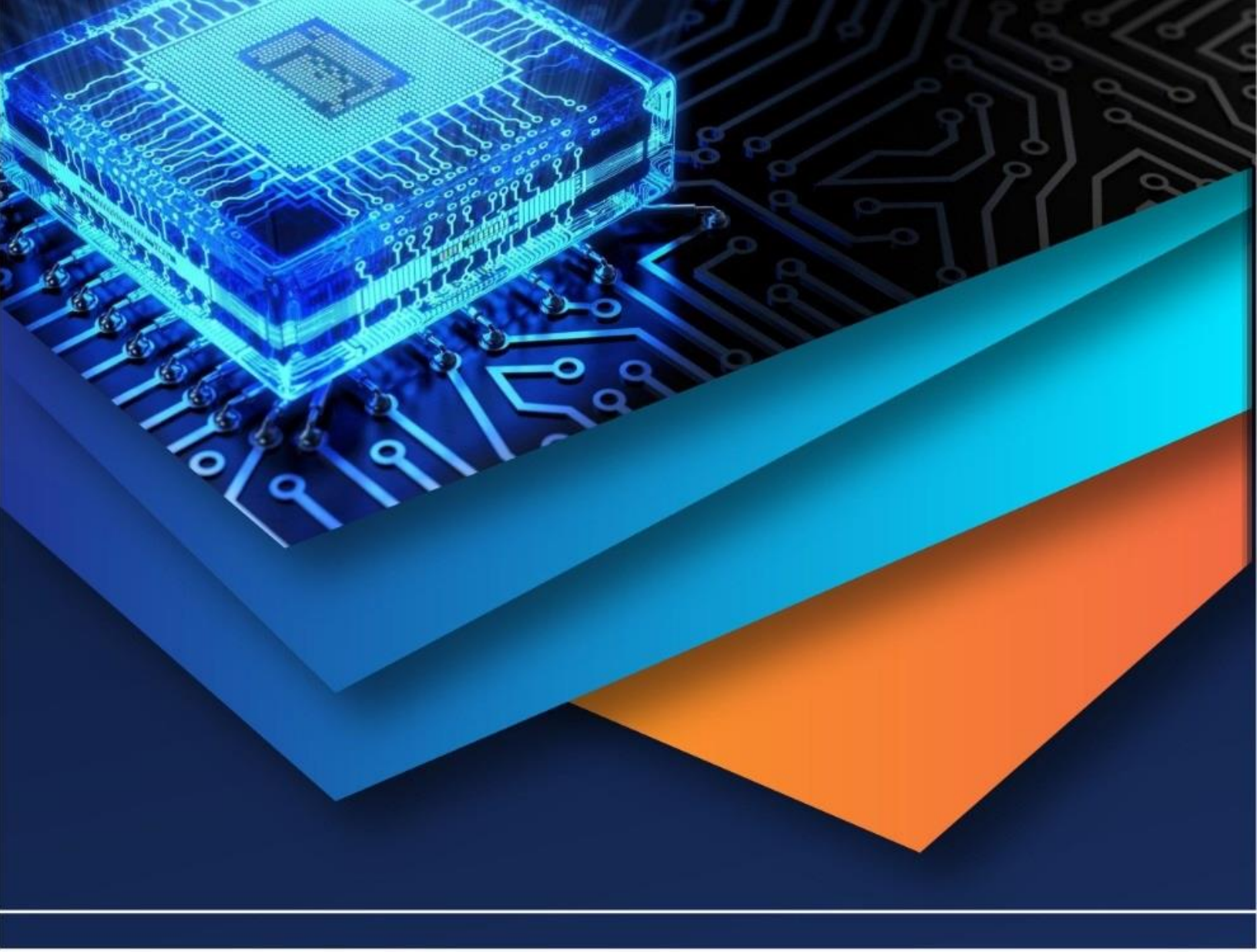

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