A comparison of multivariate and univariate time series approaches to modelling and forecasting Emergency Department demand in Western Australia

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ABSTRACT

Objective: To develop multivariate vector-ARMA (VARMA) forecast models for predicting emergency department (ED) demand in Western Australia (WA) and compare them to the benchmark univariate autoregressive moving average (ARMA) and Winters' models.

Methods: Seven-year monthly WA state-wide public hospital ED presentation data from 2006/07 to 2012/13 were modelled. Graphical and VARMA modelling methods were used for descriptive analysis and model fitting. The VARMA models were compared to the benchmark univariate ARMA and Winters' models to determine their accuracy to predict ED demand. The best models were evaluated by using error correction methods for accuracy.

Results: Descriptive analysis of all the dependent variables showed an increasing pattern of ED use with seasonal trends over time. The VARMA models provided a more precise and accurate forecast with smaller confidence intervals and better measures of accuracy in predicting ED demand in WA than the ARMA and Winters' method.

Conclusion: VARMA models are a reliable forecasting method to predict ED demand for strategic planning and resource allocation. While the ARMA models are a closely competing alternative, they under-estimated future ED demand.

Key words: *ARMA models, emergency department demand, time series analysis, VARMA models, Winters' method, modelling and forecasting medical services*

1 Introduction

Time series analysis (TSA) and forecasting are used extensively in business for tactical, strategic or operational planning and management.[1] However, use of TSA in health care has been limited. Wargon et al [2] identified nine studies on ED forecasting in their systematic review: only five used TSA and the remainder used generalised linear regression models. Four of the five that used TSA were single centre studies. The other study applied the univariate autoregressive integrated moving average (ARMA) model on multicentre region-wide ED presentations.[3] This study suggested that ARMA was a useful tool for predicting ED demand. However, the models and forecasts need to be updated when more data become available.

There are significant challenges of ever-increasing demand and costs of health care systems in developed countries.[4] The systems struggle to adequately cope with demand, which manifests as Emergency department (ED) overcrowding.[5] Hence, access to and quality of health care is diminished and this is a threat to patient safety and public health.[6, 7] The knowledge gained from an accurate prediction of the amount of future ED demand would provide valuable information for strategic planning and possibly ameliorate ED overcrowding. A complex system involves multiple inter-related factors. In order to understand the relationship between factors such as age, place of treatment, Australasian Triage Scale (ATS) and disposition, accurate predictions of future demand can provide detailed information for policymakers.

Our aim is to develop multivariate vector autoregressive moving average (VARMA) forecast models [8] for predicting emergency department (ED) demand in Western Australia (WA) and also, to compare the performance of the VARMA models with univariate ARMA models [9] and Winters' method [10].

2 Methods

2.1 Study setting, design and data source

Western Australia (WA) is the largest state of Australia, and occupies one-third of the continent with a total area of over 976,790 square miles. Its population was 2.57 million in 2014 and 80% of the population reside in Perth, the capital city. Health services are concentrated in metropolitan WA which has a population of more than 2 million served by public EDs. There are four large central metropolitan hospitals (one exclusively paediatric), three smaller outer metropolitan hospitals, and two privately administered public hospitals. There is also one private hospital ED. In non-metropolitan WA, the population is served by 73 small public EDs, with six being regional centres (larger hospitals). The health system in WA is typical of Australia.

This study was a population-based time-series analysis using monthly ED presentations from all state-wide public hospitals, for the seven-year period 2006/07 to 2012/13. Data were extracted from the WA Emergency Department Data Collection (EDDC) database, a core dataset routinely collected and managed by the WA Department of Health for statutory purposes. All WA EDs except one metropolitan private hospital ED contributed data to this database.

2.2 Variables and Measures

The dependent variables in the study were the numbers of ED presentations stratified by age group (<15 years, 15-44, 45-64 and ≥ 65), place of treatment (metropolitan WA, non-metropolitan WA), triage category (1-5)[11] and disposition (admitted, transferred, non-admitted). Each variable category is a time series of ED presentations observed over time. The addition of all the series in each variable category gives the total number of ED presentations to WA state-wide public hospitals. Triage is a rating tool for prioritising ED patients for treatment based on clinical urgency to allow patients with more urgent conditions to have earlier treatment. The Australasian Triage Scale (ATS) has five triage categories[11]: ATS 1 – Critical/Resuscitation Condition (requires immediate treatment), ATS 2 – Emergency/Very Urgent Condition (requires treatment within 10 minutes), ATS 3 – Urgent Condition (requires treatment within 30 minutes), ATS 4 – Semi–Urgent Condition (requires treatment within 60 minutes) and ATS 5 – Non–Urgent Condition (requires treatment within 120 minutes). The independent variable was time (monthly).

2.3 Descriptive Analysis

We used SAS Econometric Time Series (SAS/ETS) Software for modelling and forecasting (version 9.3, SAS Institute, Cary, NC, USA). All graphs and plots were generated using TSA package in R project.

Before the modelling process, the data were split into two sets: one used to develop the models (test data) and the other to validate the models. The first five-years of monthly ED presentations were modelled and the last two-year monthly ED presentations were held for model validation. The test data were examined for trends and variability using visual analysis of the time plots, autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of ED presentations for each variable and subgroup. The ACF and PACF plots provided a graphical representation of the autocorrelation and partial autocorrelation structures of ED presentations. The ACF and PACF plots can be used to determine to what extent and magnitude the past values of ED presentations are related to future values. These plots provided an insight into how reliable past ED presentations would be for forecasting future ED demand [12].

2.4 Modelling Techniques

2.4.1 VARMA Models

This allowed us to study the dynamic relationships between age groups, place of treatment, triage category and disposition, as well as improving the accuracy of predictions. The VARMA method was used to develop multivariate time series models to forecast state-wide WA public hospital ED demand. The VARMA modelling technique allowed several dependent time series to be modelled together and accounted for both cross- and within-correlations of the series.

Suppose z_t is a k-dimensional stationary ED presentation series, then the class of VARMA (p, q) models employed to forecast ED demand for each category can be expressed as:

$$\Phi(B)z_t = \phi_0 + \Theta(B)a_t$$

Where t is time, ϕ_0 is a constant vector, $\Phi(B) = I_k - \sum_{i=1}^{p} \Phi_i B^i$ and $\Theta(B) = I_k - \sum_{i=1}^{q} \theta_i B^i$ are two matrix polynomials of orders $p > 0$ and $q > 0$ respectively, ; B is a back-shift operator defined by $Bx_t = x_t - x_{t-1}$ and a_t is a sequence of independent and identical distributed random vectors with mean zero and positive-definite covariance matrix $\sum_a$.

For any two time series z_{1t} and z_{2t}, VARMA (1, 1) can be expressed as

$$\begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} - \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} z_{1t-1} \\ z_{2t-1} \end{bmatrix} = \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix} - \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} \begin{bmatrix} a_{1t-1} \\ a_{2t-1} \end{bmatrix}$$

The mathematical theory, and the applications of forecast processes associated with multivariate time series analysis of VARMA forecast models is complex and has been discussed in detail in a textbook by Tsay[8].

2.4.2 ARMA Models

The ARMA models are developed from univariate time series modelling methods with a modelling process that is similar to the VARMA method. However, unlike the VARMA models, where several time series are modelled together, the ARMA method allows only one time series to be modelled at a time. This method was developed by Box and Jenkins [13]. The model was developed to provide a general framework for forecasting non-stationary observed time series data. Suppose x_t is a stationary observed ED presentation series, then the class of generalised ARMA models for forecasting ED demand is of the form:

$$\phi(B)x_t = \mu + \theta(B)a_t$$

where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ is the autoregressive operator of the model; $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ is the moving-average operator of the model; B is a back-shift operator defined by $Bx_t = x_t - x_{t-1}$; and the variable $a_t \sim N(0, \sigma^2)$ is a random error or white noise. This modelling approach is an iterative process to identify a best forecast model through three steps.

1. *Model identification*: First, historical data were used to identify a tentative model, where seasonal and/or non-seasonal trends and variability in the data were examined and removed by differencing and appropriate transformation, in the case of variability. Once stationarity was achieved, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the stationary ED presentation data were examined by comparing them to theoretical ACF and PACF to tentatively identify the orders for autoregressive (AR) and moving average (MA).
2. *Model estimation*: The parameters of the tentatively identified model were estimated using maximum likelihood estimation and the resultant residuals were checked for white noise.
3. *Diagnostic check*: Various statistical techniques were used including Akaike Information Criterion, Schwarz Information Criterion or Schwarz Bayesian Criterion and residual analysis of ACF and PACF to judge the goodness- of-fit of the model. If necessary, an alternative model was considered and the process was repeated until the best model was obtained.

   The detailed mathematical theory associated with Box-Jenkins forecast modelling has been discussed in a textbook by Box, Jenkins & Reinsel [9].

2.4.3 Winters' Method

This method of forecasting was an exponential smoothing model that employed three smoothing steps or equations to forecast time series data - one for the level, one for the trend and one for seasonality, also known as triple exponential smoothing. A detailed description of this is provided by Chatfield [10]. There are two forecast methods (equations) for Winters' method (additive and multiplicative); in our case we used the additive forecast method since the fluctuation of the data appeared relatively constant. The forecast model of Winters' additive model was given by

$$\hat{y}_{t+h/t} = l_t + hb_t + s_{t-m+h_m^+}$$

Where h is forecast horizon and

1. Level: $l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1})$
2. Trend: $b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}$
3. Seasonality: $s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$

and α, β^* and γ are parameters defined as $0 \leq \alpha \leq 1, 0 \leq \beta^* \leq 1$ and $0 \leq \gamma \leq 1-\alpha$, m is the period of seasonality and y_t is the ED presentation series.

2.5 Model validation and forecast comparison

Our main aim was to assess the accuracy and validity of multivariate VARMA models to provide accurate forecasts of ED demand in WA hospitals. This was evaluated by calculating the various measures of accuracy for each sub-group of the variables used (age, place of treatment, triage category and disposition). The measures of accuracy used were mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE). Using the test data, we generated two-years-ahead forecast data. The two-years-ahead forecast was subtracted from the two-years-holding data to obtain forecast residuals. The resultant residuals were used to compute the values for MAE, RMSE and MAPE. The ARMA models and Winters' forecasting method were used as the benchmarks for comparison. ARMA models are reliable forecasting techniques that have been used to provide forecast, for ED demand [14]. Winters' method was one of the univariate time series forecasting methods widely used for predicting seasonal data[10].

3 Results

3.1 Descriptive results

The time series plots for age groups, place of treatment, triage category and disposition are presented in Figures 1 to 4. The time plots of all the groupings of the variables depicted a long-term increasing trend with little or no visible variability except ATS 5 which shows a decreasing trend.

The ACF plots of ED presentations and the first order difference are presented in Figure 2. These plots confirmed the increasing trends in all variable categories and the decreasing trend of ATS 5. The ACFs decayed over time with a persistent autocorrelation structure significant at lags of up to about one year. The ACF plots of the first order difference exhibited significant autocorrelation at lags 12 and 24, suggesting that ED presentations followed a 12-month seasonal trend. The increasing trend and seasonality of the data showed by the ED presentation series in all the variable categories indicated the non-stationarity nature of the data and both seasonal and non-seasonal differencing were performed.

3.2 Modelling and forecasting results

Our results from the post-sample forecast and hold-up sample for model validation of the three forecasting methods for each variable by categories are presented in Table 1. We presented forecast errors (MAE, RMSE and MAPE) for the 12-months-ahead forecast for age group, place of treatment, triage and disposition categories. The lower the value of the three measures of accuracy the better the performance of the forecast method. Since MAE and RMSE depended on the mean value of the variable, which hinders comparisons of models for predicting variables that had different mean values[2], MAPE would be easier and understandable for examining forecast accuracy or model comparison. Moreover, all the three measures of accuracy gave similar results and we thus concentrated on the values of MAPE for the model comparisons.

The graphical representation of the observed and forecast data for each category of age group, place of treatment, triage category and disposition are presented in Figures 9 to 12. The plots provided comparisons of the predicted ED demand with the observed ED presentations (hold up data) for 24 months (2 years). The forecast from all the three modelling methods appeared consistent in terms of directions. The VARMA plots provided predictions that deviated the least from observed data compared to ARMA plots, while the Winters' plots provided the mean forecast of the observed data. The VARMA models provided smaller values of the accuracy measures for almost all the variable categories. The ARMA models were also competing models to VARMA which performed creditably well especially for ATS 2, 4 and 5. The VARMA and ARMA models were used to produce a forecast of ED demand in Western Australia. The average forecast per month for each category over a five-year forecast horizon and the corresponding average annual growth rate (AAGR) are presented in Table 2. The results demonstrated that ED demand would increase over the next five years in all age groups, place of treatment, triage (except ATS 5) and disposition categories with the greatest contributions to this growth coming from age 65 years and over, metropolitan WA, patients classified as ATS 2 and 3, and admitted patients. Our findings indicate that ARMA models underestimate ED growth forecasts (Compare AAGR in Table 2).

4 Discussion

In this paper, we developed both multivariate and univariate time series methods to forecast WA state-wide public hospital ED demand by age group, place of treatment, triage category and disposition category. Three different methods were used. Two of the methods, VARMA and

ARMA models, are based on stationarity of the data whilst the Winters' method is not. All three methods are widely used for forecasting data with a seasonal component. We examined the performance of each method by comparing two years ahead forecast with two years holding period of the data. All three forecasting methods were able to forecast the direction and magnitude of ED demand with reasonable monthly forecast errors. The best forecast method was the VARMA models, while ARMA models were a closely competing method. However, ARMA models under-predicted ED demand. The forecasts produced by the Winters' method were not accurate enough, and even produced a poor forecast for some variables. Both VARMA and ARMA plots indicated that the models were able to capture the seasonal variation of the data, but the Winters' model could not, making VARMA and ARMA models suitable for modelling ED demand. Our finding that multivariate models provided more accurate forecasts for ED demand than univariate models is consistent with the findings of Jones and colleagues [12].

Our findings revealed prominent seasonal patterns in all the series except the ATS 1 category. Apart from ATS 1 where significant autocorrelation was observed in lag 12, all other categories of ATS showed significant autocorrelation at lag 12 and 24 depicting a seasonal trend with a period of 12 months. Our forecasts show an increase in ED demand in all age groups, place of treatment, triage category and disposition category except ATS 5 which declined over the forecast period. These findings are also consistent with our previous study [15] and the findings of others [16-18]. The general outcome from the models is that state-wide ED demand in WA will increase in the next five years with the highest growth coming from age 65 years and over, metropolitan WA, ATS 2 and 3 and admitted patients. The main drivers of these increases may be the growing and ageing population, increasing disease complexity, patient expectations and other social factors such as drug and alcohol abuse [16, 19, 20].

5 Strengths and limitations

The use of the VARMA modelling process allowed us to account for the inter-relationship between all the variables. The influence of each series on the other was fully addressed by the VARMA modelling approach thereby improving forecast accuracy. This makes the forecast produced by VARMA models more reliable for decision making. Disaggregating the data into age groups, place of treatment, triage category and disposition provides an insight into which categories of patients and areas are major contributors to the growth of ED demand in WA that require immediate attention. Judging from the accuracy of the forecast provided by VARMA models and their ability to provide insight into the dynamics of ED demand by various categories, VARMA modelling is a useful technique that can help to improve planning, resource management and decision making for ED services.

The VARMA modelling techniques provide an insight to the dynamic relationships of the series involved, but practically are very complex. Very large time series data points are required for implementation when many series are involved. Due to this limitation, we were unable to include disease categories because we have only seven years of data for this analysis. However, the VARMA model was found to be the best forecasting method. When larger datasets become available, they can be used to provide accurate forecasts..

The VARMA model was generated under the 'business as usual' condition (status quo modelling). We did not perform 'what-if' scenarios (scenario modelling) to take into account potential changes in population projections and in health policy and clinical practice, as well as potential bed, workforce and budget constraints that may affect ED use.

This study did not attempt to identify the drivers of ED presentations or seasonal fluctuations since it aimed only to identify the best modelling method for ED presentations in WA. Further study is underway to identify the factors/drivers that contribute to the increasing trend of ED presentation..

The outputs of demand modelling and forecasting (status quo and scenario) underpin the development of health services strategic planning that is used by health services planners, and guide workforce modelling, infrastructure and financial modelling.

6 Conclusion

VARMA models are a reliable forecasting method to predict ED demand by patient subgroups, and provide a more accurate forecast for ED demand than the normal or standard univariate ARMA and Winters' methods. We observed that the prediction deviations (residuals) were smaller in the VARMA models, resulting in smaller confidence intervals, making VARMA models an attractive method to forecast ED demand for strategic planning. The ARMA models are a closely related competing model for forecasting ED demand. However, they under-estimated ED future demand compared with the VARMA models.

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Contributors

PAS: conception and design of the study, formulation of analysis plan, analysis and interpretation of data, writing the first draft of the manuscript.

QM: conception and design of the study, acquisition of data, interpretation of data, contributing to the draft of the manuscript, revision of the manuscript for important intellectual content, incorporating all co-authors' feedback.

FMS, LMS, DBP, DMF: reviewed and edited the manuscript critically for important intellectual content.

All authors: final approval of the submission.

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Competing interest None.

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References

1. Arsham, H. *Time-Critical Decision Making for Business Administration*. 1994.
2. Wargon, M., et al., *A systematic review of models for forecasting the number of emergency department visits.* Emerg Med J, 2009. **26**(6): p. 395-9.
3. Milner, P.C., *Ten-year follow-up of ARIMA forecasts of attendances at accident and emergency departments in the Trent region.* Stat Med, 1997. **16**(18): p. 2117-25.
4. Organisation for Economic Co-operation and Development. *OECD Health Data 2013*. 2013 [cited 2013 October 29]; Available from: http://www.oecd.org/health/health-systems/oecdhealthdata2013-frequentlyrequesteddata.htm
5. Graff, L., *Overcrowding in the ED: an international symptom of health care system failure.* Am J Emerg Med, 1999. **17**(2): p. 208-9.
6. Fatovich, D.M., *Emergency medicine.* BMJ, 2002. **324**(7343): p. 958-62.
7. Trzeciak, S. and E.P. Rivers, *Emergency department overcrowding in the United States: an emerging threat to patient safety and public health.* Emerg Med J, 2003. **20**(5): p. 402-5.
8. Tsay, R., *Multivariate time series analysis: with R and financial applications*. First ed. 2014, Hoboken, New Jersey: John Wiley & Sons, Inc. 492.
9. Box, G.E.P., G.M. Jenkins, and G.C. Reinsel, *Time Series Analysis: Forecasting and Control*. 3rd ed. 1994, NJ: Prentice Hall: Englewood Cliffs.
10. Chatfield, C., *The Holt-Winters forecasting procedure.* Applied Statistics, 1978. **27**(3): p. 264-279.
11. Australian College of Emergency Medicine. *Policy on the Australia Triage Scale*. 2013 [cited 2015 January 30]; Available from: https://www.acem.org.au/getattachment/693998d7-94be-4ca7-a0e7-3d74cc9b733f/Policy-on-the-Australasian-Triage-Scale.aspx.
12. Jones, S.S., et al., *A multivariate time series approach to modeling and forecasting demand in the emergency department.* J Biomed Inform, 2009. **42**: p. 123-139.
13. Tiao, G.C. and G.E.P. Box, *Modeling multiple time series with applications.* J Am Statist Assoc, 1981. **76**(376): p. 802-816.
14. Weiss, T.W., C.M. Ashton, and N.P. Wray, *Forecasting areawide hospital utilization: a comparison of five univariate time series techniques.* Health Serv Manage Res, 1993. **6**(3): p. 178-90.
15. Mai, Q., et al., *Predicting the number of ED presentations in Western Australia: A population-based time series analysis.* Emerg Med Australas, 2014(In press).
16. Lowthian, J.A., et al., *Systematic review of trend in emergency department attendances: an Australian perspective.* Emerg Med J, 2011. **28**: p. 373-377.
17. Lowthian, J.A., et al., *Demand at the emergency department front door: 10-years trends in presentation.* Med J Aust, 2012. **196**(2): p. 128-132.
18. Tang, N., et al., *Trends and Characteristics of US Emergency Department Visits, 1997-2007.* J Amer Med Assoc, 2010. **304**(6): p. 664-670.
19. Lowthian, J.A., et al., *Demand at the emergency department front door: 10-year trends in presentations.* Med J Aust, 2012. **196**: p. 128-32.
20. Australian Bureau of Statistics, *3222.0 - Population Projections, Australia, 2012 (base) to 2101*. 2013, Australian Bureau of Statistics,: Canberra.

Table 1: Measurements of accuracy parameters from diagnostic analysis of VARMA, ARMA and WINTERS' Models for two-year forecast horizon holding period

Model Variables	**Accuracy parameters for each model**								
	MAE			**RMSE**			**MAPE**		
	VARMA	**ARMA**	**WINTERS'**	**VARMA**	**ARMA**	**WINTERS'**	**VARMA**	**ARMA**	**WINTERS'**
Place of Treatment									
Metropolitan	1206.37	1490.55	2422.02	939.61	1077.69	1870.47	1.94	2.23	3.92
Non-Metropolitan	1202.50	1401.44	1717.53	928.35	1139.98	1358.40	2.74	3.41	3.41
Age group (years)									
0-14	714.37	749.12	1457.47	862.85	1078.49	1858.06	3.42	3.54	7.09
15-44	648.94	780.85	1590.96	776.13	994.75	1953.88	1.93	2.32	4.71
45-64	298.14	372.76	721.91	345.08	434.21	865.73	1.99	2.51	4.82
65+	222.58	281.91	577.06	301.89	387.49	746.87	1.79	2.67	4.74
Australia Triage Scale									
ATS1 (Immediately)	33.66	40.83	47.76	24.39	29.60	34.64	4.50	5.33	6.30
ATS2 (Within 10 minutes)	250.34	253.96	367.37	189.30	217.66	262.32	2.30	2.64	3.23
ATS3 (Within 30 minutes)	805.57	821.31	1200.67	636.75	687.81	970.02	2.59	2.79	4.02
ATS4 (Within 60 minutes)	1549.49	1563.89	2110.52	1240.72	1109.16	1718.11	3.19	2.87	4.49
ATS5 (Within 120 minutes)	441.18	429.66	670.21	370.92	325.98	526.15	3.81	3.43	5.62
Disposition									
Admitted	424.28	553.23	750.50	323.45	380.47	541.33	1.81	2.13	3.05
Transferred	75.17	93.44	139.04	60.64	66.14	108.95	3.08	3.56	5.47
Non-admitted	2242.26	2362.99	3521.44	1453.06	1776.45	2819.24	2.36	2.87	4.60

MAE: Mean absolute error
RMSE: Root mean square error
MAPE: Mean absolute percentage error
ARMA: Autoregressive moving average
VARMA: Vector autoregressive moving average
ATS: Australasian

Table 2: Average forecast of ED demand over a five-year period from the ARMA and VARMA models by age group, place of treatment, triage category and disposition

Model	**Actual (AAGR* (%))**	**VARMA (AAGR (%))**	**ARMA (AAGR (%))**
Total ED demand	868,262 (4.8)	1,143,812 (5.0)	1,076,191 (2.9)
Place of Treatment			
Metropolitan	496,632 (6.0)	695,065 (5.7)	660,511 (3.7)
Non-Metropolitan	371,630 (3.3)	448,747 (4.0)	415,679 (1.4)
Age group (years)			
0-14	225,572 (4.5)	292,608 (4.5)	251, 138 (0.4)
15-44	360,048 (4.4)	468,936 (4.8)	452, 331 (3.4)
45-64	156,966 (5.5)	209,782 (5.0)	202,600 (3.7)
65+	125,676 (5.8)	172,486 (5.1)	170,062 (4.4)
Australia Triage Scale (ATS)			
ATS1 (Critical)	5,804 (5.8)	7,932 (5.5)	7,804 (4.4)
ATS2 (Emergency)	78,240 (10.1)	129,868 (7.9)	130,468 (7.7)
ATS3 (Urgent)	235,376 (9.1)	373,943 (7.4)	366,199 (6.2)
ATS4 (Semi-Urgent)	420,070 (4.4)	534,410 (4.7)	482,522 (1.4)
ATS5 (Non-Urgent)	128,772 (-4.2)	97,659 (-4.6)	89,197 (-7.6)
Disposition			
Admitted	173,380 (8.5)	281,765 (8.6)	255,011 (5.1)
Transferred	20,967 (5.1)	30,400 (5.4)	26,803 (1.4)
Non-admitted	673,915 (3.9)	831,647 (4.0)	794,377 (2.2)

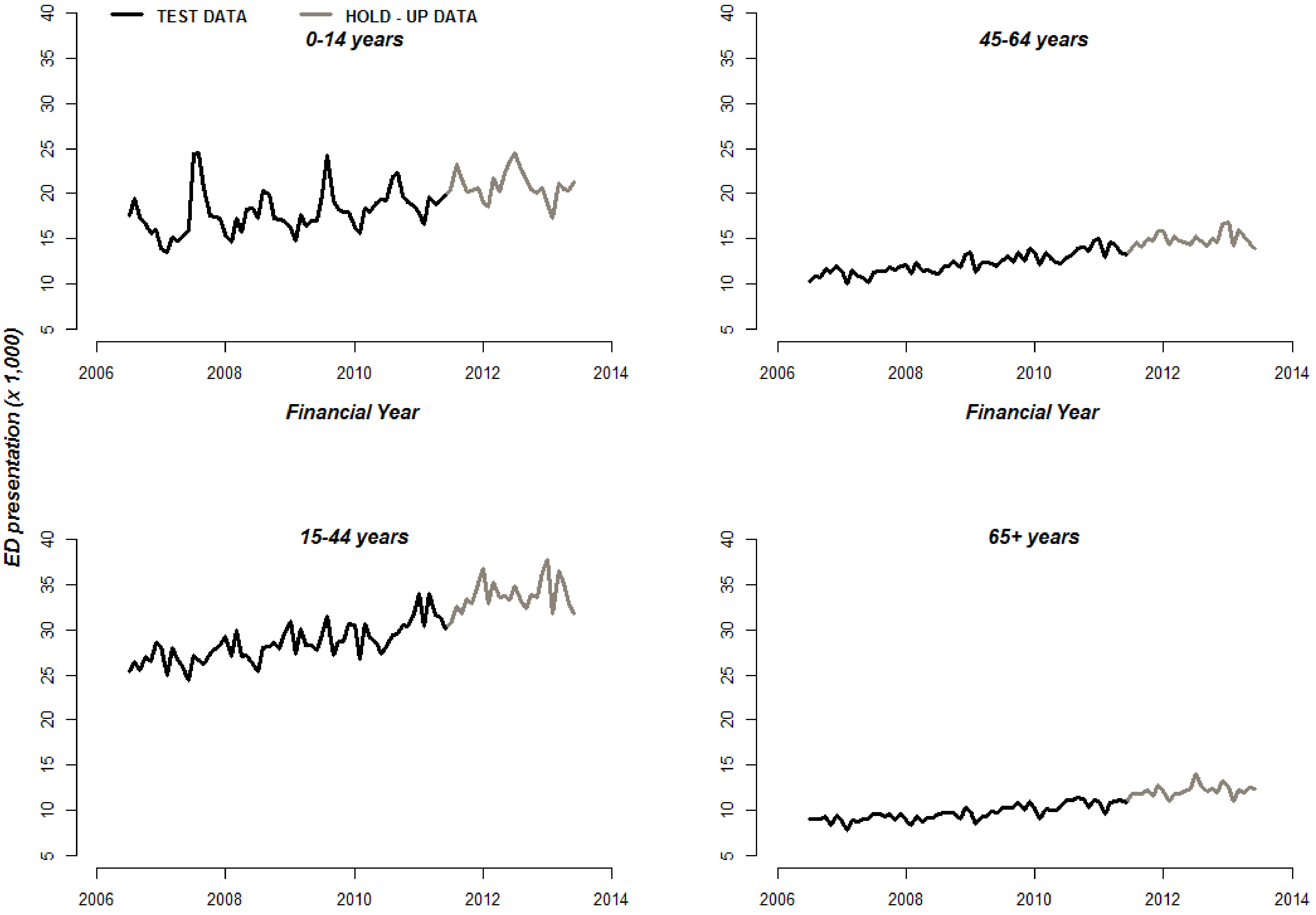
*AAGR: average annual growth rate (in parentheses).
MAE: Mean absolute error
ARMA: Autoregressive moving average
VARMA: Vector autoregressive moving average
ATS: Australasian

Figure legend

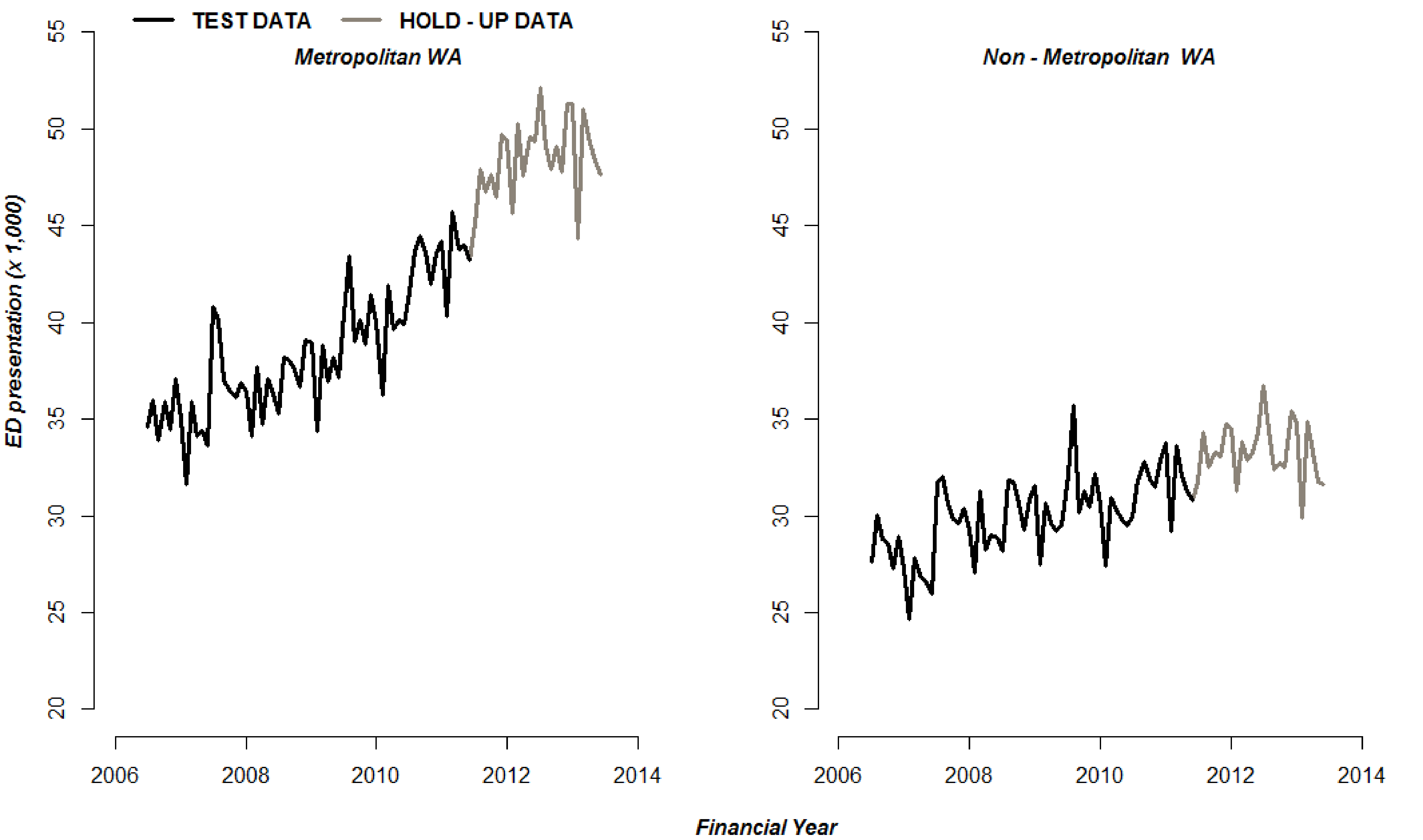
Figure 1: Time series plots of historical ED presentations by age group, place of treatment, triage category and disposition for test data (black) and 24-month validation data (grey)
1a. Age group
1b. Place of treatment
1c. Australasian Triage Scale (ATS) category
1d. Disposition category

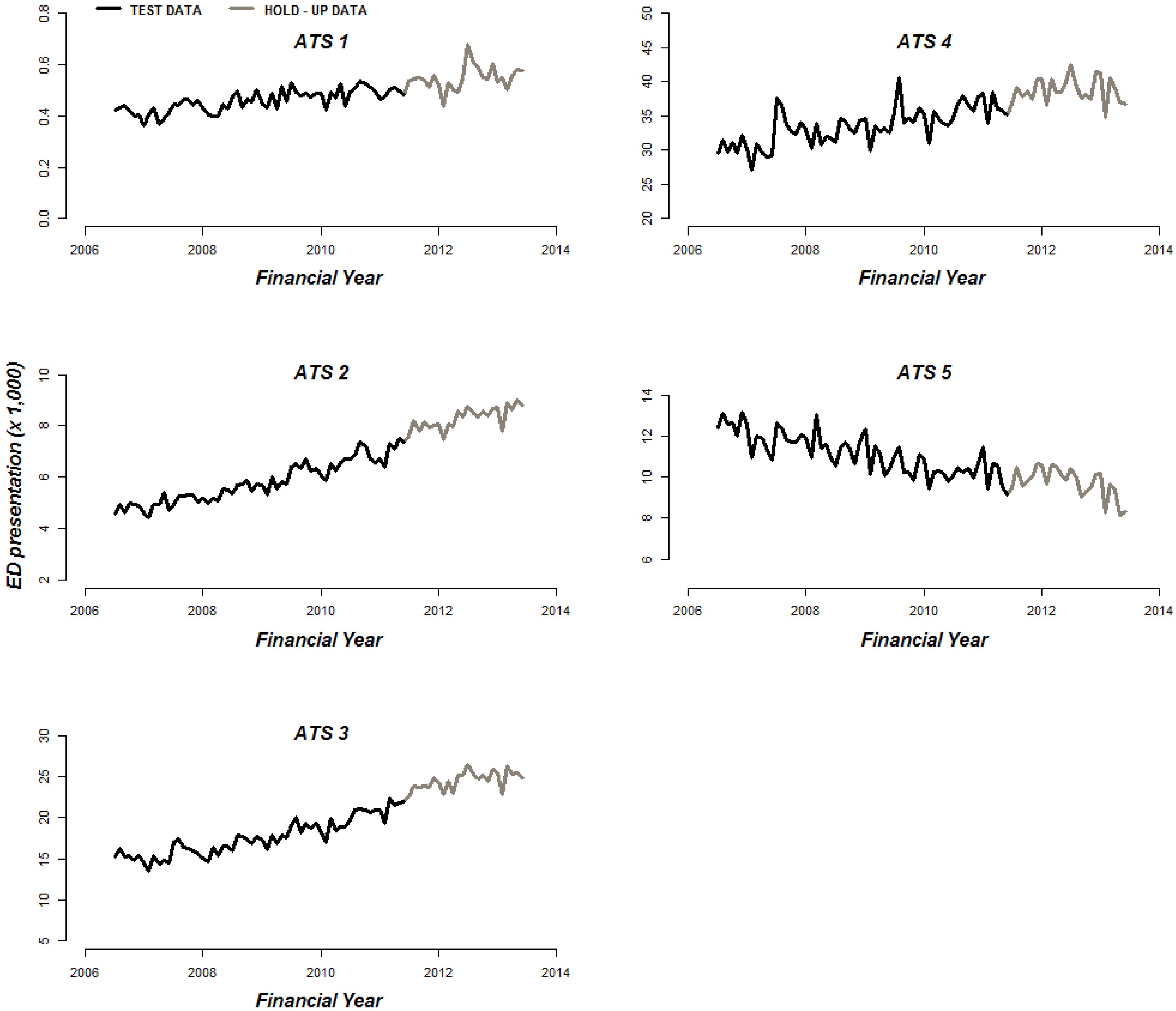
Figure 2: Sample and first order differencing ACF plots by age group, place of treatment, triage category and disposition
2a. Age group
2b. Place of treatment
Australasian2d. Disposition category

Figure 3: Observed ED presentations for two-year hold-up period compared with two- year ahead forecast
3a. Age group
3b. Place of treatment
3c. Australasian Triage Scale (ATS) category
3d. Disposition category

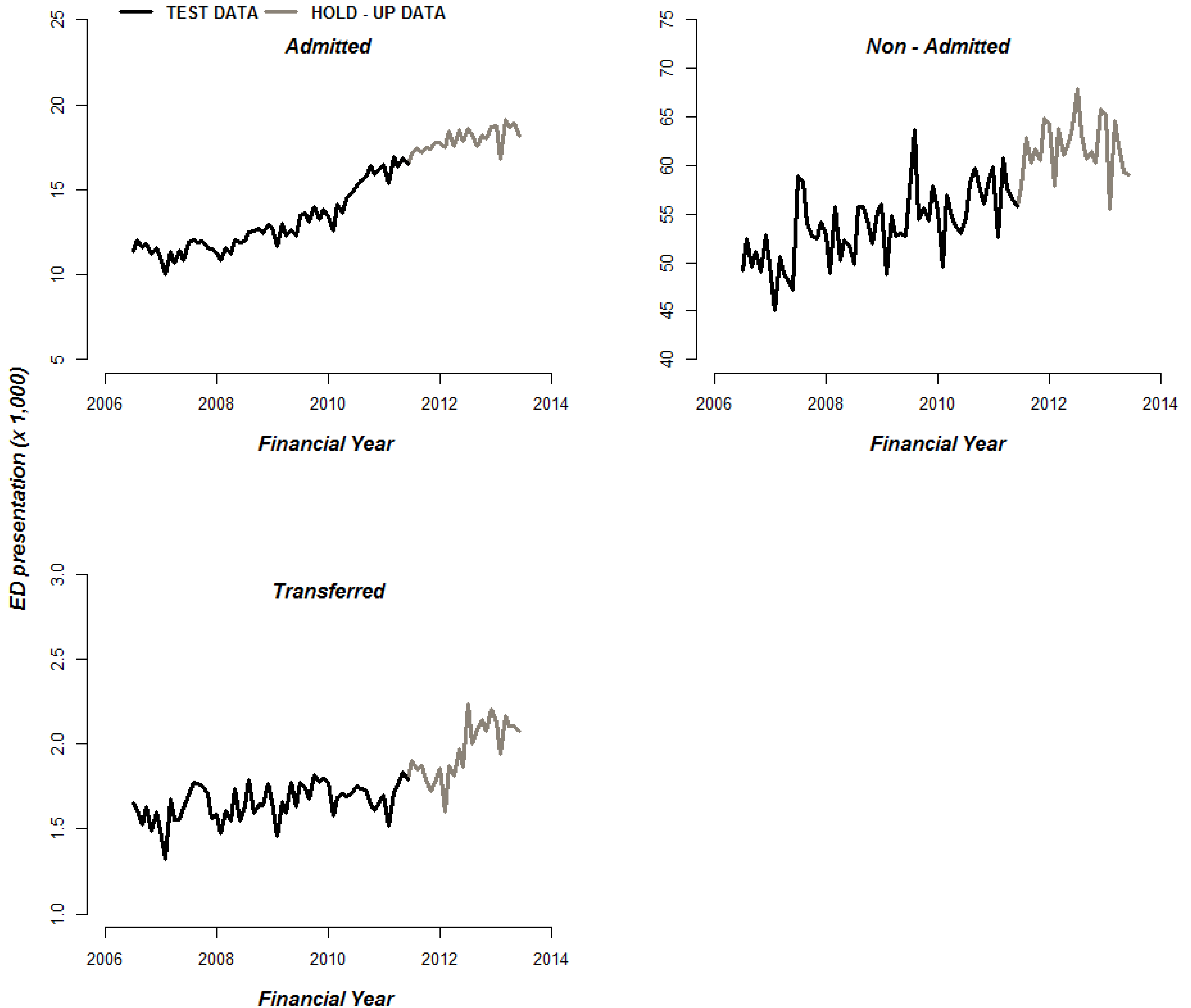


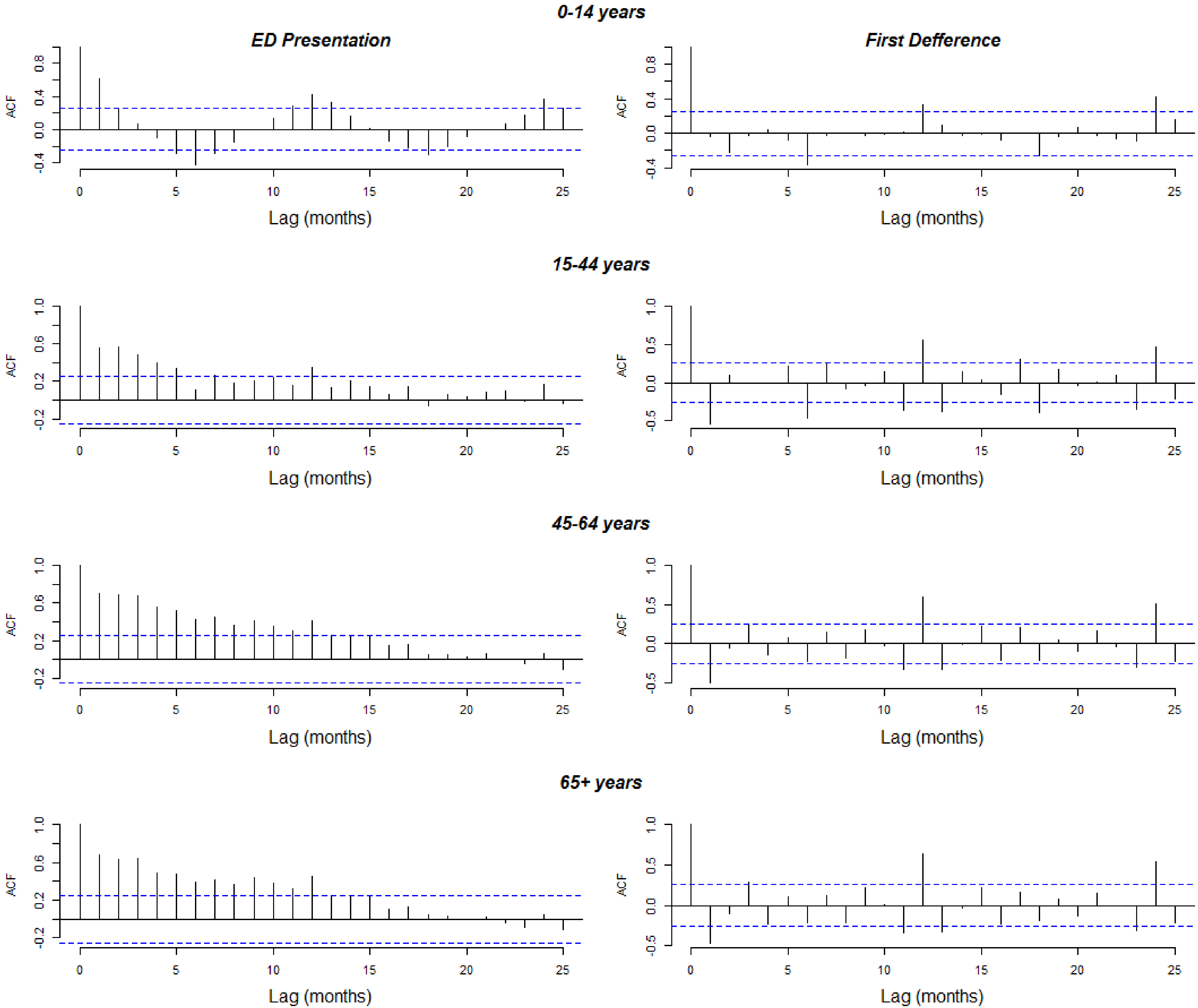
TEST DATA
HOLD - UP DATA
0-14 years
45-64 years
15-44 years
65+ years
ED presentation (x 1,000)
Financial Year
Financial Year
40
35
30
25
20
15
10
5
2006
2008
2010
2012
2014

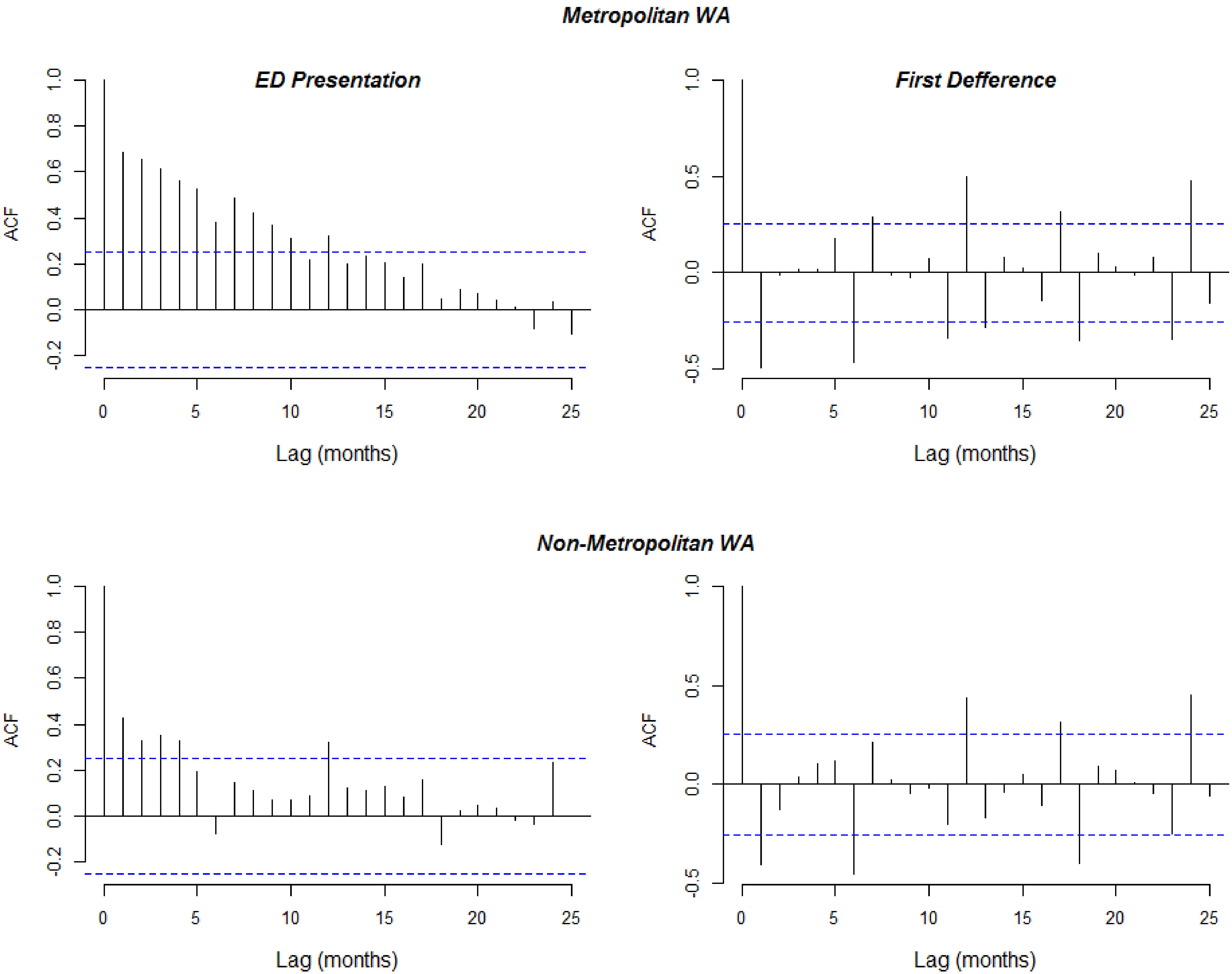

TEST DATA
HOLD - UP DATA
Metropolitan WA
Non - Metropolitan WA
ED presentation (x 1,000)
20
25
30
35
40
45
50
55
2006
2008
2010
2012
2014
Financial Year



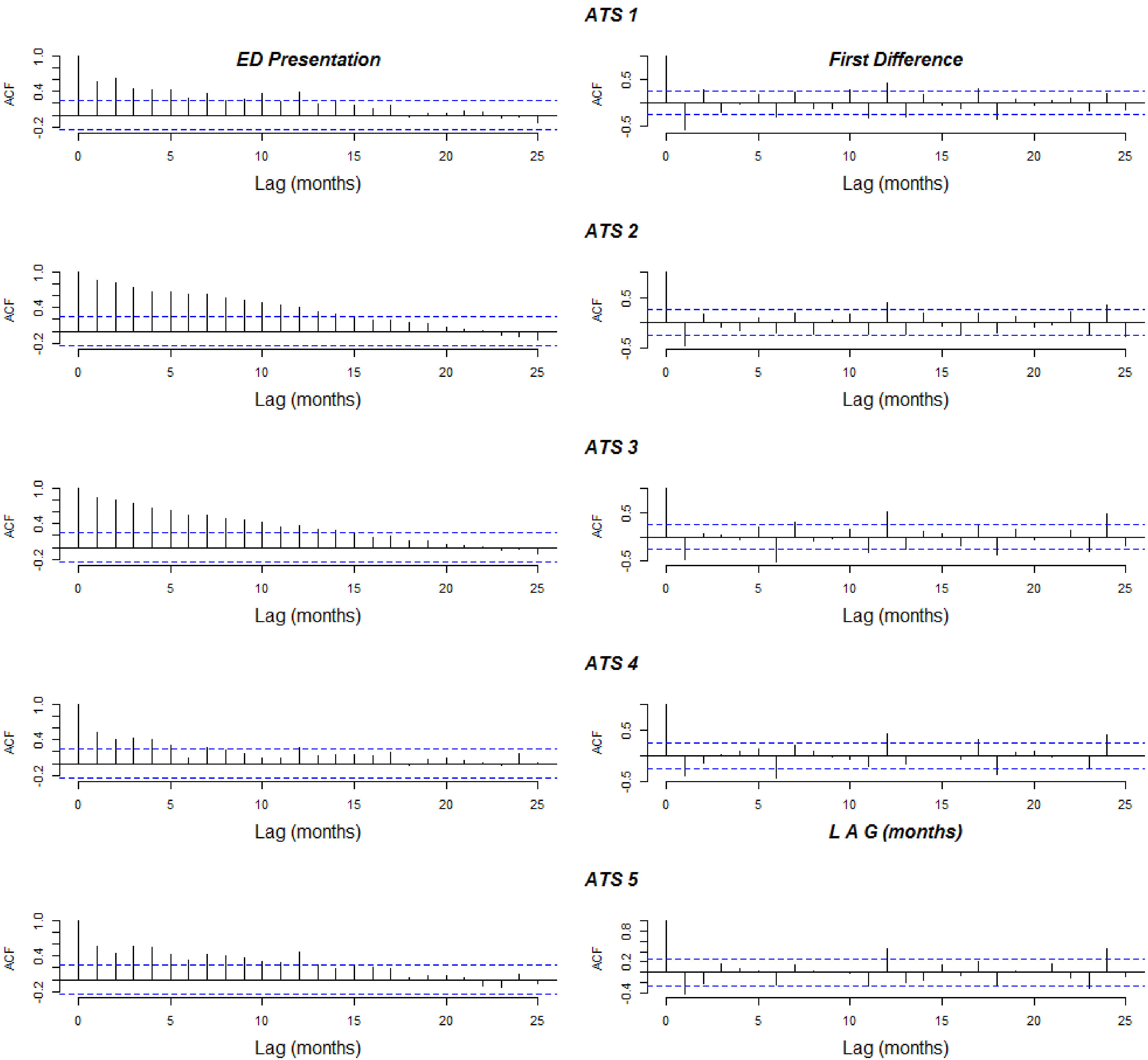
TEST DATA
HOLD - UP DATA
ATS 1
ATS 2
ATS 3
ATS 4
ATS 5
ED presentation (x 1,000)
Financial Year
2006
2008
2010
2012
2014


TEST DATA
HOLD - UP DATA
Admitted
Non - Admitted
Transferred
ED presentation (x 1,000)
Financial Year
Financial Year
Financial Year
25
20
15
10
5
75
70
65
60
55
50
45
40
3.0
2.5
2.0
1.5
1.0
2006
2008
2010
2012
2014

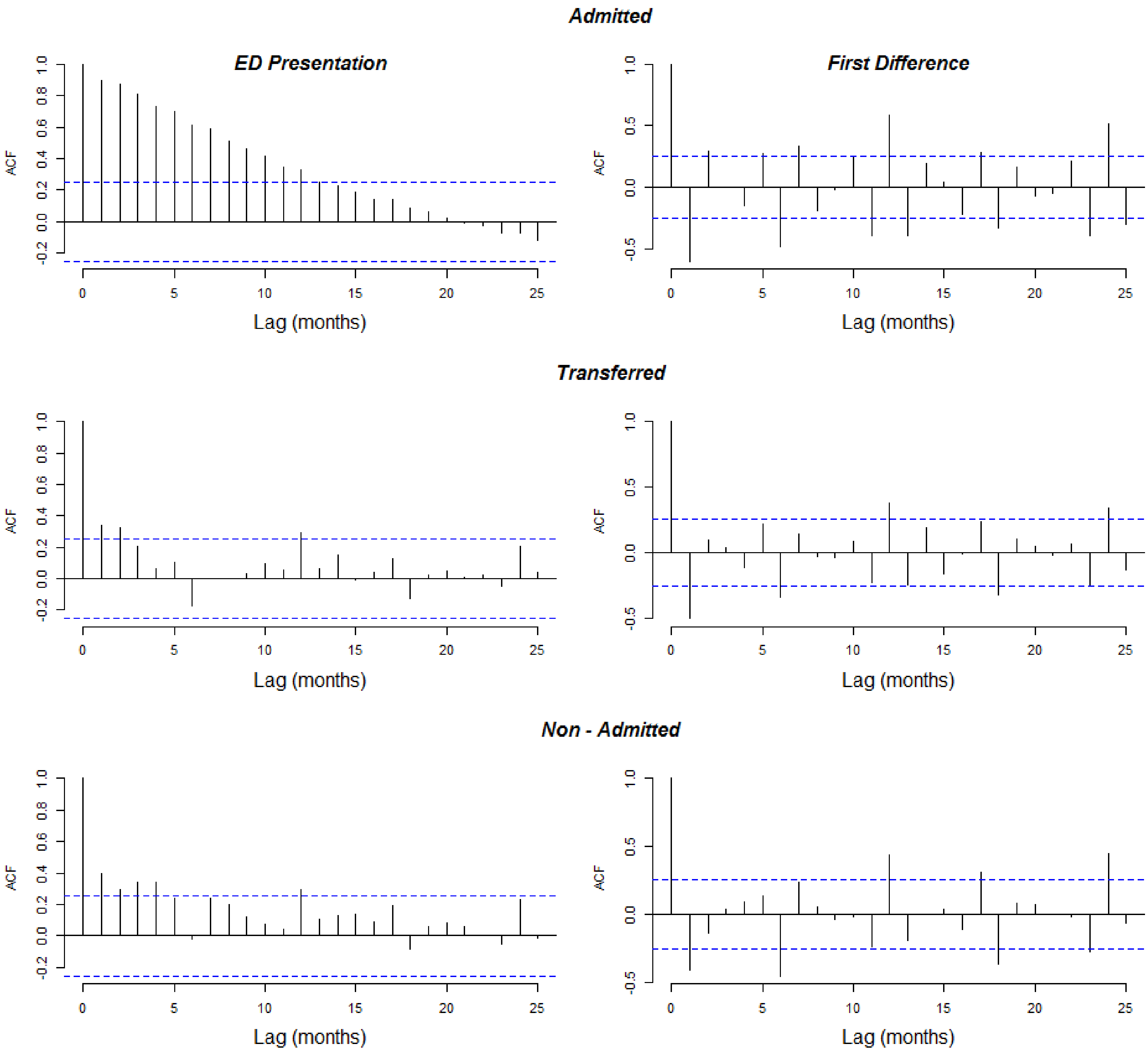

0-14 years
ED Presentation
First Defference
15-44 years
45-64 years
65+ years
ACF
Lag (months)
0
5
10
15
20
25
-0.4
0.0
0.4
0.8
-0.2
0.2
0.6
1.0
-0.5
0.5



Metropolitan WA
ED Presentation
First Defference
ACF
Lag (months)
Non-Metropolitan WA
ACF
Lag (months)



ATS 1
ED Presentation
First Difference
ACF
Lag (months)
ATS 2
ACF
Lag (months)
ATS 3
ACF
Lag (months)
ATS 4
ACF
Lag (months)
L A G (months)
ATS 5
ACF
Lag (months)


Admitted
ED Presentation
First Difference
ACF
Lag (months)
Transferred
Non - Admitted