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Relying on Forecasted Values of Annual Neonatal Mortality Rates Generated By the ARIMA Model to Address Major Causes of Neonatal Deaths in the United Kingdom

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***Abstract* - The UK government has made tremendous progress in controlling neonatal mortality, however more needs to be done to end all avoidable deaths by the end of 2030. Application of time series forecasting techniques will highlight likely future trends of neonatal mortality to inform public health decisions and resource allocation to neonatal healthcare interventions. This study uses annual time series data on neonatal mortality rate (NMR) for the United Kingdom from 1960 to 2019 to predict future trends of NMR over the period 2020 to 2030. Unit root tests have shown that the series under consideration is an I (1) variable. The optimal model based on AIC is the ARIMA (3,1,2) model. The ARIMA model predictions indicate that neonatal mortality will remain under control throughout the out of sample period. Therefore, we encourage the UK government to address existing socio-economic inequalities amongst other measures in order to keep neonatal and infant deaths under control.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

The United Kingdom has made significant progress in controlling maternal and child mortality over the past decades as evidenced by the substantial reduction in maternal mortality ratio and neonatal mortality rate (NMR) (Pryce *et al.* 2012). This was as a result of improvements in sanitation, nutrition, family planning, and advancement in healthcare (Harpur *et al.* 2021). In recent years early neonatal deaths have been noted to be the contributing factor to the rise in infant mortality in England (Harpur *et al.* 2021). Socioeconomic inequalities are of major concern in the UK as infants in England who are deprived have 90% risk of dying when compared to least deprived areas (Nath *et al.* 2020; Robinson *et al.* 2019). The objective of this study is to model and project future trends of NMR for the UK using the popular Box-Jenkins ARIMA model. This econometric and statistical technique is appropriate for modelling linear data (Nyoni, 2018; Box & Jenkins, 1970). We expect forecast results to detect abnormal trends of NMR and guide neonatal policy in order to keep neonatal deaths under control.

II. LITERATURE REVIEW

Harpur *et al.* (2021) investigated trends in infant mortality rates (IMR) and stillbirth rates by socio-economic position (SEP) in Scotland, between 2000 and 2018, inclusive. Data for live births, infant deaths, and stillbirths between 2000 and 2018 were obtained from National Records of Scotland. Annual IMR and stillbirth rates were calculated and visualized for all of Scotland and when stratified by SEP. Negative binomial regression models were used to estimate the association between SEP and infant mortality and stillbirth events, and to assess for break points in trends over time. The study revealed that IMR fell from 5.7 to 3.2 deaths per 1000 live births between 2000 and 2018, with no change in trend identified. Stillbirth rates were relatively static between 2000 and 2008 but experienced accelerated reduction from 2009 onwards. When stratified by SEP, inequalities in IMR and stillbirth rates persisted throughout the study and were greatest amongst the sub-group of post-neonates. Nath *et al.* (2020) examined the effect of extreme prematurity and early neonatal deaths on infant mortality rates in England. Authors used aggregate data on all live births, stillbirths and linked infant deaths in England in 2006–2016 from the Office for National Statistic. Infant mortality decreased from 4.78 deaths/1000 live births in 2006 to 3.54/1000 in 2014 (annual decrease of 0.15/1000) and increased to 3.67/1000 in 2016 (annual increase of 0.07/1000). This rise was driven by increases in deaths at 0–6 days of life. A descriptive study was carried out by McNamara *et al.* (2018) to reveal intrapartum fetal deaths and unexpected neonatal deaths in Ireland from 2011 to 2014. Anonymised data pertaining to all intrapartum fetal deaths and unexpected neonatal deaths for the study time period were obtained from the national perinatal epidemiology centre. The findings of the study indicated that the corrected intrapartum fetal death rate was 0.16 per 1000 births and the overall unexpected neonatal death rate was 0.17 per 1000 live

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births.Bandeira *et al*. (2016) described Portugal's achievements in the maternal and child health program. The study highlighted that the joint venture of pediatricians and obstetricians with adequate top-down government commissions for maternal and child health for the decision making by health administrators and a well-defined schedule of preventive and managerial measures in the community and in hospitals, registry of special diseases and training of medical personnel are the most likely explanations for this success. Chow *et al*. (2015) carried a selected review to examine the etiology of neonatal mortality rates in different countries by utilizing electronic databases. The findings indicated that mortality rates in neonatal ICU units vary in different countries but are still high in both developing and developed countries.

III. METHODOLOGY

The Autoregressive (AR) Model

A process U_t (annual NMR at time t) is an autoregressive process of order p, that is, AR (p) if it is a weighted sum of the past p values plus a random shock (Z_t) such that:

$$U_t = \emptyset_1 U_{t-1} + \emptyset_2 U_{t-2} + \emptyset_3 U_{t-3} + \cdots + \emptyset_p U_{t-p} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

Using the backward shift operator, B, such that $BU_t = U_{t-1}$, the AR (p) model can be expressed as in equation [2] below:

$$Z_t = \emptyset(B) U_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

where $\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \emptyset_3 B^3 - \cdots - \emptyset_p B^p$

The 1[st] order AR (p) process, AR (1) may be expressed as shown below:

$$U_t = \emptyset U_{t-1} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

Given $\emptyset = 1$, then equation [3] becomes a random walk model. When $|\emptyset| > 1$, then the series is reffered to as explosive, and thus non-stationary. Generally, most time series are explosive. In the case where $|\emptyset| < 1$, the series is said to be stationary and therefore its ACF (autocorrelation function) decreases exponentially.

The Moving Average (MA) Model

A process is reffered to as a moving average process of order q, MA (q) if it is a weighted sum of the last random shocks, that is:

$$U_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \cdots + \theta_q Z_{t-q} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [4]$$

Using the backward shift operator, B, equation [4] can be expressed as follows:

$$U_t = \theta(B) Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [5]$$

where $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$

Equation [4] can also be expressed as follows:

$$U_t - \sum_{j \le 1} \pi_j U_{t-j} = Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [6]$$

for some constant π_j such that:

$$\sum_{j \le 1} |\pi_j| < \infty$$

This implies that it is possible to invert the function taking the Z_t sequence to the U_t sequence and recover Z_t from present and past values of U_t by a convergent sum.

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The Autoregressive Moving Average (ARMA) Model

While the above models are good, a more parsimonious model is the ARMA model. The AR, MA and ARMA models are applied on stationary time series only. The ARMA model is just a mixture of AR (p) and MA (q) terms, hence the name ARMA (p, q). This can be expressed as follows:

$$\emptyset(B)U_t = \theta(B)Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [7]$$

Thus:

$$U_t\left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) = Z_t\left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right) \ldots\ldots\ldots [8]$$

where $\emptyset(B)$ and $\theta(B)$ are polynomials in B of finite order p, q respectively.

The Autoregressive Integrated Moving Average (ARIMA) Model

The AR, MA and ARMA processes are usually not applied empirically because in most cases many time series data are not stationary; hence the need for differencing until stationarity is achieved.

$$\left.\begin{array}{c} The\ first\ difference\ is\ given\ by: \\ U_t - U_{t-1} = U_t - BU_t \\ The\ second\ difference\ is\ given\ by: \\ U_t(1-B) - U_{t-1}(1-B) = U_t(1-B) - BU_t(1-B) = U_t(1-B)(1-B) = U_t(1-B)^2 \\ The\ third\ difference\ is\ given\ by: \\ U_t(1-B)^2 - U_{t-1}(1-B)^2 = U_t(1-B)^2 - BU_t(1-B)^2 = U_t(1-B)^2(1-B) = U_t(1-B)^3 \\ The\ d^{th}\ difference\ is\ given\ by: \\ U_t(1-B)^d \end{array}\right\} \ldots [9]$$

Given the basic algebraic manipulations above, it can be inferred that when the actual data series is differenced "d" times before fitting an ARMA (p, q) process, then the model for the actual undifferenced series is called an ARIMA (p, d, q) model. Thus equation [7] is now generalized as follows:

$$\emptyset(B)(1-B)^d U_t = \theta(B)Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [10]$$

Therefore, in the case of modeling and forecasting NMR, equation [10] can be written as follows:

$$\emptyset(B)(1-B)^d U_t = \theta(B)Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [11]$$

The Box – Jenkins Approach

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018). The Box – Jenkins technique was proposed by Box & Jenkins (1970) and is widely used in many forecasting contexts, including medicine. In this paper, hinged on this technique; the researcher will use automatic ARIMA modeling for estimating equation [10].

Data Issues

This study is based on annual NMR in the United Kingdom for the period 1960 to 2019. The out-of-sample forecast covers the period 2020 to 2030. All the data employed in this research paper was gathered from the World Bank online database.

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Evaluation of ARIMA Models

Criteria Table

Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: DLOG(U)
Date: 01/29/22 Time: 12:18
Sample: 1960 2019
Included observations: 59

Model	LogL	AIC*	BIC	HQ
(3,2)(0,0)	168.179929	-5.463726	-5.217239	-5.367508
(1,2)(0,0)	166.018873	-5.458267	-5.282204	-5.389539
(1,3)(0,0)	166.999074	-5.457596	-5.246321	-5.375123
(2,2)(0,0)	166.661141	-5.446140	-5.234865	-5.363667
(4,2)(0,0)	168.572128	-5.443123	-5.161423	-5.333159
(3,3)(0,0)	168.486274	-5.440213	-5.158513	-5.330248
(2,4)(0,0)	168.099497	-5.427102	-5.145402	-5.317137
(1,4)(0,0)	167.097230	-5.427025	-5.180537	-5.330806
(2,3)(0,0)	167.052389	-5.425505	-5.179017	-5.329286
(1,5)(0,0)	168.018044	-5.424340	-5.142640	-5.314376
(2,0)(0,0)	163.881111	-5.419699	-5.278849	-5.364717
(3,0)(0,0)	164.839053	-5.418273	-5.242211	-5.349545
(0,5)(0,0)	166.708740	-5.413856	-5.167368	-5.317637
(5,2)(0,0)	168.690804	-5.413248	-5.096335	-5.289538
(4,3)(0,0)	168.659923	-5.412201	-5.095288	-5.288491
(3,4)(0,0)	168.653420	-5.411980	-5.095068	-5.288271
(2,1)(0,0)	164.402809	-5.403485	-5.227423	-5.334757
(2,5)(0,0)	168.385715	-5.402906	-5.085993	-5.279196
(4,0)(0,0)	165.284783	-5.399484	-5.188209	-5.317011
(4,4)(0,0)	169.218579	-5.397240	-5.045115	-5.259785
(0,4)(0,0)	165.158240	-5.395195	-5.183920	-5.312721
(3,1)(0,0)	165.016522	-5.390391	-5.179116	-5.307917
(5,0)(0,0)	165.928314	-5.387400	-5.140913	-5.291182
(0,3)(0,0)	163.896402	-5.386319	-5.210256	-5.317591
(5,4)(0,0)	169.728061	-5.380612	-4.993275	-5.229411
(3,5)(0,0)	168.497431	-5.372794	-5.020669	-5.235339
(4,1)(0,0)	165.491118	-5.372580	-5.126093	-5.276362
(0,2)(0,0)	162.347283	-5.367704	-5.226855	-5.312722
(5,3)(0,0)	168.150704	-5.361041	-5.008916	-5.223585
(5,1)(0,0)	165.935068	-5.353731	-5.072031	-5.243767
(5,5)(0,0)	169.719568	-5.346426	-4.923876	-5.181480
(4,5)(0,0)	168.592180	-5.342108	-4.954770	-5.190907
(1,1)(0,0)	161.461340	-5.337673	-5.196823	-5.282690
(1,0)(0,0)	158.087522	-5.257204	-5.151567	-5.215968
(0,1)(0,0)	147.096232	-4.884618	-4.778981	-4.843381
(0,0)(0,0)	137.983581	-4.609613	-4.539188	-4.582122

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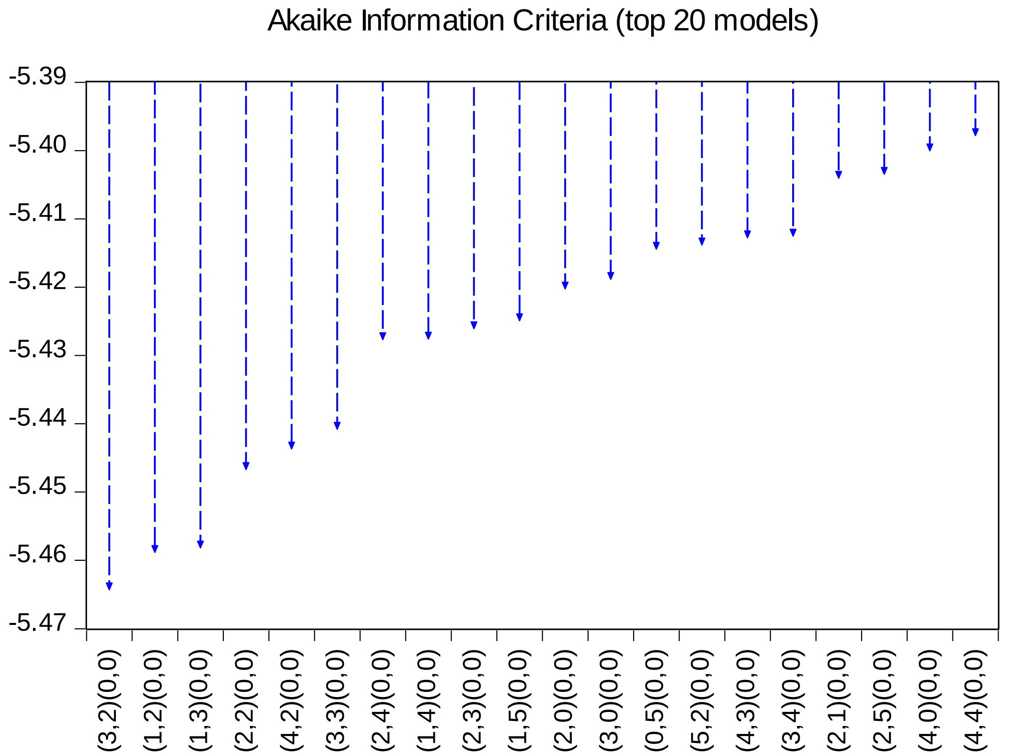
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

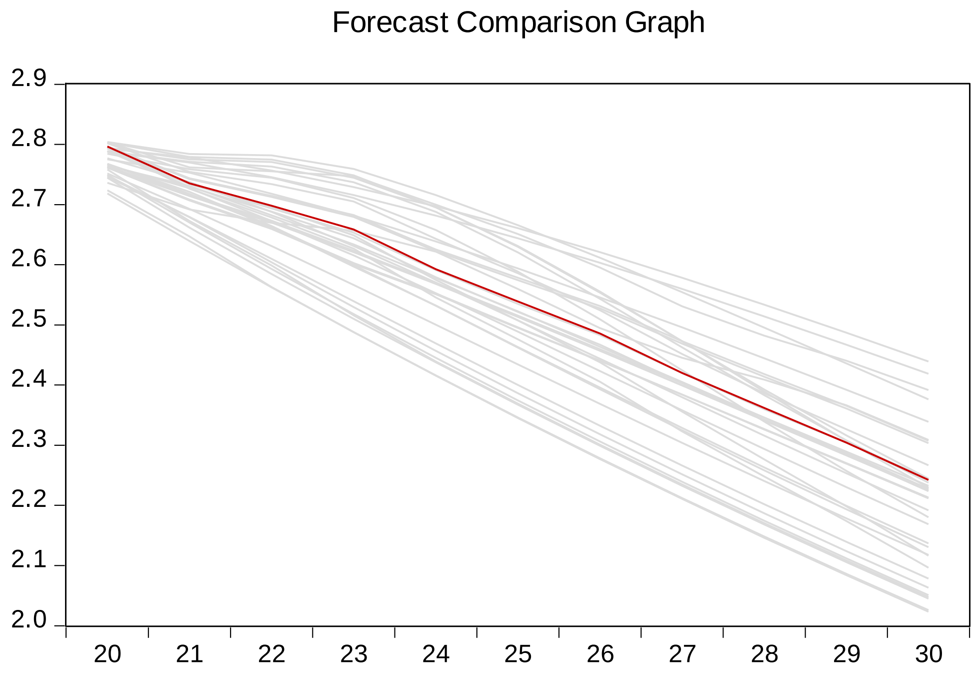


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (3,1,2) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (3,1,2) model.

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(U)
Date: 01/29/22 Time: 12:18
Sample: 1960 2019
Included observations: 59
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (3,2)(0,0)
AIC value: -5.46372640411

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: DLOG(U)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/29/22 Time: 12:18
Sample: 1961 2019
Included observations: 59
Failure to improve objective (non-zero gradients) after 60 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.027882	0.011066	-2.519529	0.0149
AR(1)	-0.025942	0.142458	-0.182102	0.8562
AR(2)	-0.000606	0.125981	-0.004808	0.9962
AR(3)	0.510953	0.182262	2.803399	0.0071
MA(1)	0.600076	65.58440	0.009150	0.9927
MA(2)	0.999997	218.5391	0.004576	0.9964
SIGMASQ	0.000176	0.019154	0.009178	0.9927

R-squared	0.677265	Mean dependent var	-0.029542
Adjusted R-squared	0.640026	S.D. dependent var	0.023539
S.E. of regression	0.014123	Akaike info criterion	-5.463726
Sum squared resid	0.010372	Schwarz criterion	-5.217239
Log likelihood	168.1799	Hannan-Quinn criter.	-5.367508
F-statistic	18.18715	Durbin-Watson stat	2.089797
Prob(F-statistic)	0.000000		

Inverted AR Roots	.79	-.41-.69i	-.41+.69i
Inverted MA Roots	-.30-.95i	-.30+.95i	

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	2.796299499597994
2021	2.735438157528734
2022	2.697937436593957
2023	2.658620970683848
2024	2.592382525900162
2025	2.539105394706014
2026	2.485538345381701
2027	2.420049093316497
2028	2.361997107377728
2029	2.304544417104686
2030	2.242334728229877

Table 5 clearly indicates that neonatal mortality will be remain under control throughout the out of sample period.

V. POLICY IMPLICATION & CONCLUSION

The UK has made significant milestones in addressing the problem of neonatal mortality in the country; however socioeconomic inequality is currently the issue that requires government attention. In this study we applied the ARIMA model to predict future trends of NMR for the UK and the model projections suggest that neonatal mortality will remain under control throughout the out of sample period. We, therefore encourage the UK government to address existing socio-economic inequalities amongst other measures in order to keep neonatal and infant deaths under control.

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