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Utilizing Forecasted Values of Annual Neonatal Mortality Rate Calculated By the ARIMA Model to Inform Neonatal Health Policies and Interventions in Portugal

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***Abstract* - This study uses annual time series data on neonatal mortality rate (NMR) for Portugal 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 (2) variable. The optimal model based on AIC is the ARIMA (3,2,5) model. The study findings showed that neonatal mortality is expected to slightly increase but will remain below 5 deaths per 1000 live births throughout the forecast period. We, therefore encourage the Portuguese government to identify and address current significant predictors of neonatal mortality across the country.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Portugal is a Western European country with a population density of 114 inhabitants per square kilometer with the majority of people living in big cities in the coastal regions (Portugal, 2012; Portugal, 2011). Neonatal mortality is still a public health problem in this country. The main causes of neonatal deaths are congenital anomalies, prematurity, asphyxia and neonatal infection (Miranda *et al.* 2020). Portugal has witnessed a significant decrease in infant and neonatal mortality in recent years (Bandeira *et al*. 2016).According to the World Bank, IMRfellfrom84.7in1960to2.8in2019. Eurostat shows that these figures compare favorably with the EUaverageof3.5in2018. Substantial reduction of infant and neonatal mortality was achieved through the government's commitment to universal health coverage. Several strategies were implemented such as the national vaccination program, improved nutrition, reorganization of hospital care, implementation of a network of health care facilities and training of medical staff (Bandeira *et al.* 2016; Matos, 2015; Tomé *et al*. 2009). Additional factors that contributed significantly to this decline included environmental and sanitation infrastructure with improvements in basic sanitation and hygiene; educational policy measures to increase the literacy rate; social policies emphasizing maternal and child healthcare and family planning, and improvements in housing, diet, and overall quality of life, with a significant decrease in poverty rates (Santana & Almendra, 2018; Neto, 2006). The objective of this study is to model and project future trends of neonatal mortality rate (NMR) for Portugal using the Box-Jenkins ARIMA technique. The model is ideal for modelling linear data (Nyoni, 2018; Box & Jenkins, 1970). The findings of this study are envisioned to detect future trends of neonatal mortality and trigger an early response to the problem so as to keep NMR at least around 12 per 1000 live births.

II. LITERATURE REVIEW

Regression analysis was employed by Jawad *et al*. (2021) to assess the association between conflict and maternal and child health globally. Data for 181 countries (2000–2019) from the Uppsala Conflict Data Program and World Bank were analyzed using panel regression models. The study findings showed that armed conflict is associated with substantial and persistent excess maternal and child deaths globally. Weiland *et al.* (2021), in Portugal, examined the effects of the 2006 National Program of Maternal and Neonatal Health policy on spatial inequalities in access to care and consequently avoidable infant mortality. A thematic analysis of qualitative data including interviews and surveys and a quantitative spatial analysis using Geographic Information Systems was applied. Spatial inequalities were found which may lead to avoidable infant mortality. Inequalities exist in freedom of choice and autonomy in care, within a medicalized system. Bandeira *et al*. (2016) described Portugal's achievements in the maternal and child health program. The study highlighted thatthe 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. Another study descriptive

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study in Portugal was done by Guimarães (2015) who outlined the contribution of Portuguese reform of perinatal healthcare in the reduction of perinatal mortality. The author highlighted that the organization in primary, secondary and tertiary healthcare resulted in the improvement of perinatal care centered on both mother and child needs.

III. METHODOLOGY

The Autoregressive (AR) Model

A process P_t (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:

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

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

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

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

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

$$P_t = \emptyset P_{t-1} + Z_t \ldots\ldots\ldots\ldots [3]$$

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

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 P_t sequence and recover Z_t from present and past values of P_t by a convergent sum.

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:

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

Thus:

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

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.

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

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:

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

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

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

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 human health. 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 Portugal 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.

Evaluation of ARIMA Models

Criteria Table

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Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: D(P, 2)
Date: 01/29/22 Time: 11:06
Sample: 1960 2019
Included observations: 58

Model	LogL	AIC*	BIC	HQ
(3,5)(0,0)	-1.727554	0.404398	0.759647	0.542775
(4,5)(0,0)	-1.719143	0.438591	0.829365	0.590805
(1,5)(0,0)	-5.876947	0.478515	0.762714	0.589217
(2,5)(0,0)	-5.235748	0.490888	0.810612	0.615427
(5,2)(0,0)	-5.260743	0.491750	0.811474	0.616289
(5,3)(0,0)	-4.446423	0.498153	0.853401	0.636529
(5,0)(0,0)	-7.763925	0.509101	0.757775	0.605964
(3,3)(0,0)	-7.095003	0.520517	0.804716	0.631219
(2,3)(0,0)	-8.238845	0.525477	0.774152	0.622341
(5,4)(0,0)	-4.446003	0.532621	0.923394	0.684835
(5,1)(0,0)	-7.683574	0.540813	0.825012	0.651514
(4,3)(0,0)	-6.724406	0.542221	0.861945	0.666760
(0,5)(0,0)	-8.781104	0.544176	0.792850	0.641040
(3,4)(0,0)	-7.046279	0.553320	0.873044	0.677859
(3,2)(0,0)	-9.207421	0.558877	0.807551	0.655740
(2,4)(0,0)	-8.238592	0.559951	0.844150	0.670653
(0,4)(0,0)	-10.777080	0.578520	0.791669	0.661546
(4,4)(0,0)	-6.832694	0.580438	0.935687	0.718814
(0,3)(0,0)	-12.142283	0.591113	0.768738	0.660301
(4,1)(0,0)	-10.710888	0.610720	0.859394	0.707584
(1,4)(0,0)	-10.755566	0.612261	0.860935	0.709124
(1,3)(0,0)	-12.036597	0.621952	0.835101	0.704978
(5,5)(0,0)	-6.190232	0.627249	1.053548	0.793301
(3,1)(0,0)	-14.036869	0.690927	0.904076	0.773952
(4,2)(0,0)	-12.349288	0.701700	0.985899	0.812401
(4,0)(0,0)	-14.404155	0.703592	0.916741	0.786618
(2,0)(0,0)	-16.986118	0.723659	0.865759	0.779010
(0,2)(0,0)	-17.536758	0.742647	0.884746	0.797997
(3,0)(0,0)	-16.926404	0.756083	0.933707	0.825271
(2,1)(0,0)	-16.954850	0.757064	0.934688	0.826252
(2,2)(0,0)	-16.481608	0.775228	0.988377	0.858254
(1,2)(0,0)	-20.983520	0.895983	1.073608	0.965172
(0,1)(0,0)	-25.725263	0.990526	1.097101	1.032039
(1,1)(0,0)	-25.379968	1.013102	1.155202	1.068453
(1,0)(0,0)	-28.893053	1.099760	1.206335	1.141273
(0,0)(0,0)	-31.031116	1.139004	1.210054	1.166679

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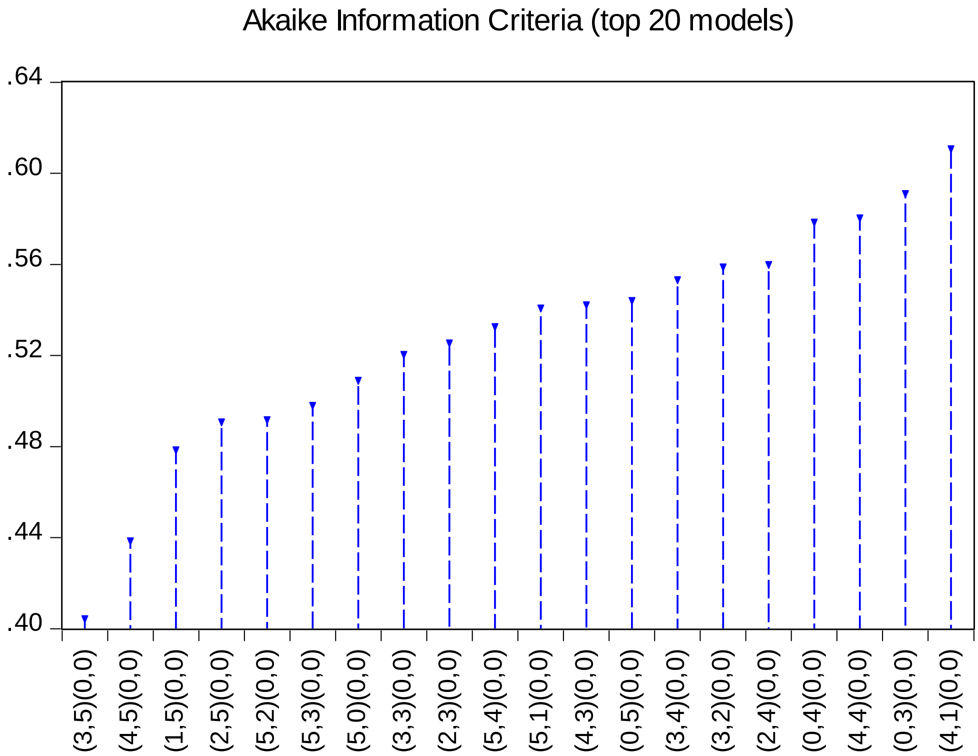
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

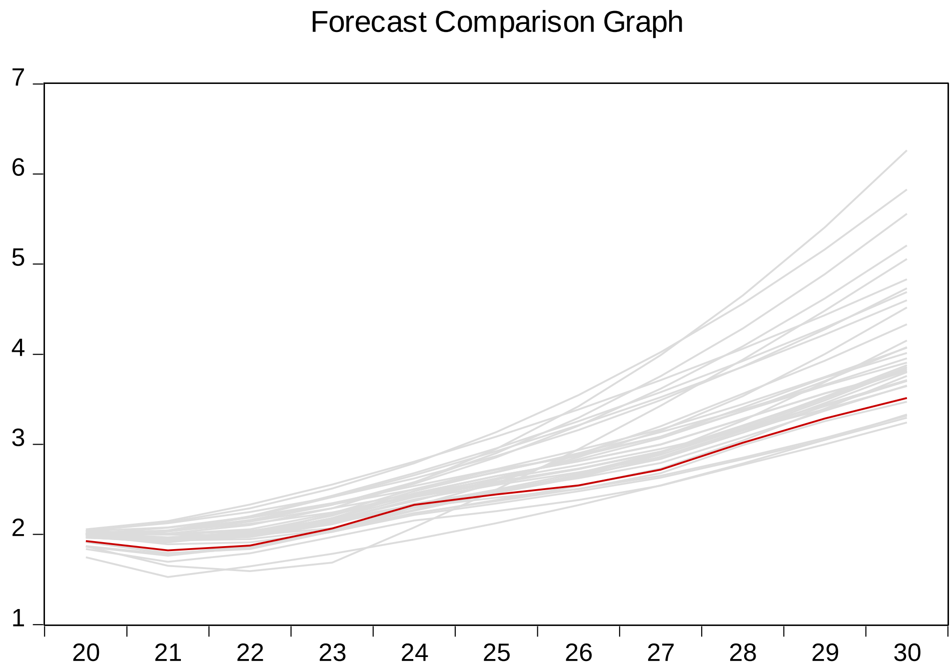


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (3,2,5) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (3,2,5) model.

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: D(P, 2)
Date: 01/29/22 Time: 11:06
Sample: 1960 2019
Included observations: 58
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (3,5)(0,0)
AIC value: 0.404398422017

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: D(P,2)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/29/22 Time: 11:06
Sample: 1962 2019
Included observations: 58
Convergence achieved after 307 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019309	0.009335	2.068600	0.0440
AR(1)	-0.449410	0.126820	-3.543696	0.0009
AR(2)	-0.442526	0.137751	-3.212506	0.0024
AR(3)	-0.690970	0.088867	-7.775322	0.0000
MA(1)	1.242734	367.2876	0.003384	0.9973
MA(2)	0.345203	240.3223	0.001436	0.9989
MA(3)	-0.712837	254.2679	-0.002803	0.9978
MA(4)	-1.078913	566.8491	-0.001903	0.9985
MA(5)	-0.796188	639.0309	-0.001246	0.9990
SIGMASQ	0.049669	10.30865	0.004818	0.9962

R-squared	0.709032	Mean dependent var	0.041379
Adjusted R-squared	0.654476	S.D. dependent var	0.416769
S.E. of regression	0.244982	Akaike info criterion	0.404398
Sum squared resid	2.880780	Schwarz criterion	0.759647
Log likelihood	-1.727554	Hannan-Quinn criter.	0.542775
F-statistic	12.99631	Durbin-Watson stat	2.050639
Prob(F-statistic)	0.000000		

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Inverted AR Roots	.21+.87i	.21-.87i	-.86	
Inverted MA Roots	1.00	-.22+.86i	-.22-.86i	-.90-.43i
	-.90+.43i			

ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	1.92621663465665
2021	1.824287895651948
2022	1.875808905870056
2023	2.066103416334868
2024	2.32983513772289
2025	2.442997750901527
2026	2.54531566410765
2027	2.718269348223691
2028	3.018190778505931
2029	3.287161228553954
2030	3.514921962453469

Table 2 clearly indicates that neonatal mortality is expected to slightly increase but will remain below 5 deaths per 1000 live births throughout the forecast period.

V. POLICY IMPLICATION & CONCLUSION

Portugal has done very well in addressing the problem of neonatal mortality through local strategies that were designed to ensure universal health coverage. The authorities managed to identify health system weaknesses and efficiently addressed them. In this piece of work we applied the Box-Jenkins ARIMA technique to predict future trends of neonatal mortality rate and the results indicate that neonatal mortality is expected to slightly increase but will remain below 5 deaths per 1000 live births throughout the forecast period. We, therefore encourage the government to identify and address current significant predictors of neonatal mortality across the country.

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