Intelligent forecasting of economic growth for African economies: Artificial neural networks versus time series and structural econometric models

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Forecasting Issues in Developing Economies (IMF, IJF, GWU)

Plan of Talk

Motivation

- Forecasting economic time series for developing economies is a challenging task, especially because of the peculiar idiosyncrasies they face.

1. There is a bigger element of uncertainty.
2. Other factors not captured in mainstream economic theories play a significant role.
3. There is a large shadow (informal) economy that is not officially captured in statistics.
4. Data problems: often only low frequency is available, it is delayed, it is discontinuous and incomplete etc.

Motivation . . .

- These idiosyncrasies imply that economic relationships in these environments are likely to be more unstable with sudden stops, reversals, turning points, and big jumps—in short, nonlinearities.
- Typical forecasting models—Box-Jenkins, linear and nonlinear structural econometric models—used in the field are not best suited for these environments.
- However, models based on computational intelligence systems offer an advantage through their functional flexibility and inherent learning ability.
- Nevertheless, they have hardly been applied to forecasting economic time series in these kinds of environment.

What we do

- Following the relative successful applications of ANN models to forecast economic events in US (see Qi, 2001) and Europe (see Heravi et al., 2004)

- Our aim is twofold:

  1. To determine whether forecasting by artificial neural networks provide superior forecasting performance when compared to traditional techniques—ARIMA, SMs.

  2. To identify the relevant (most influential) inputs in a neural network that help to forecast GDP growth for African economies.

How we do

- We achieve these objectives by:

1. Performing in- and out-of-sample forecasts using estimates from ANN, ARIMA and SEMs on quarterly data for Kenya, Nigeria, and South Africa—these three account for 54% of the weight distribution used at AfDB for growth forecasts in Africa.

2. Examining forecast performance using absolute and relative forecast evaluation criteria: MSPE & MAPE

Preview of main results

- Results show that ANN performs somewhat better than SEM and ARIMA models in forecasting GDP growth in developing economies
- This result holds especially when the relevant primary commodity prices, trade, inflation, and interest rates are used as the input variables in ANN.
- One explanation for this is because ANN is better able to capture the non-linear and chaotic behaviour of the important input variables for growth forecasting in Africa.
- There are, however, some country-specific exceptions—to be shown later.

Some practical implications

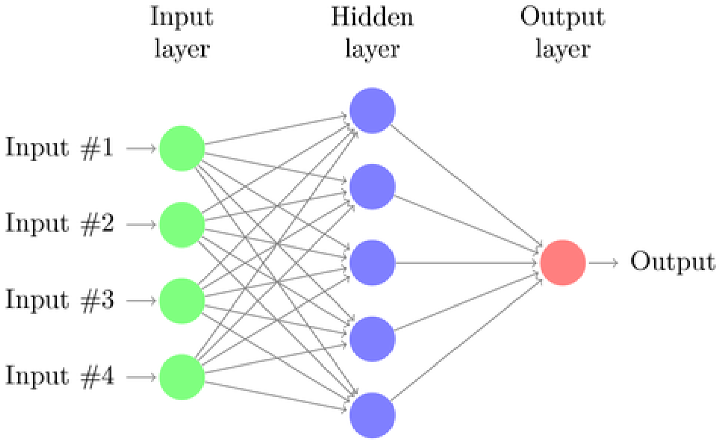
- Because improvements are only marginal and could be misleading atimes, it is important that practitioners hedge against wide errors by using a combination of ANN and SEM for practical applications.
- It is recommended that forecasts from ANN should always be revalidated with forecasts from SEM.
- Finally, ARIMA models should only be considered as a last resort in these kinds of environment, as they almost always perform worse than others.

Forecasting models

Artificial neural networks

- ANNs are models designed to mimic the biological neural system—especially the brain and are composed of processing elements called neurons.
- Each neuron in the network receives signals from external stimuli or other nodes and processes this information locally through an activation function; after which it produces a transformed output (forecast)
- The model is formed intelligently from the characteristics of the data, and hence, does not require any prior model specification.
- We adopt a single hidden layer feed-forward network, characterized by a network of three layers of simple processing units.

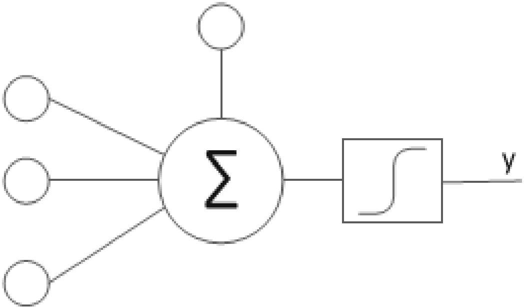
Figure: Topological structure of a feed-forward neural network



ANN . . . Activation function

- Using the Sigmoid activation function

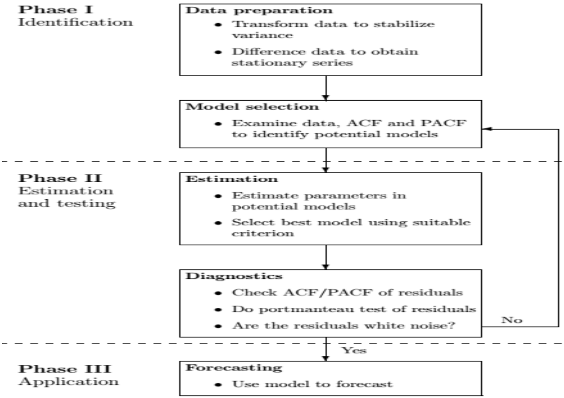
Figure: Structure of a Sigmoid (Logistic) neuron



- We show details of the backpropagation algorithm in paper

The ARIMA time series approach

Figure: Schematic representation of Box-Jenkins methodology



Source: Adapted from Makridakis et al 2008

The structural econometric approach

- In the SEM approach, economic theory is used to develop mathematical statements about how a set of observables (endogenous) variables, y, are related to another set of observables (explanatory) variables, x

- Our structural econometric specification follows the style of the linear specification in Tkacz (2001). Thus

$$y_t = \alpha + \sum_{j=1}^{J} \beta \cdot X_j + \epsilon \tag{1}$$

- In order to obtain the best linear models from a broad search, the explanatory variables are allowed to enter individually at levels and with various lag combinations between 1 and 4

Results

Figure: South Africa—trained neural network for GDP growth

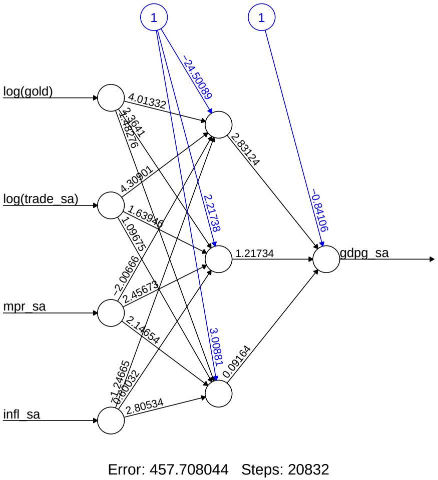


Figure: Nigeria—trained neural network for GDP growth

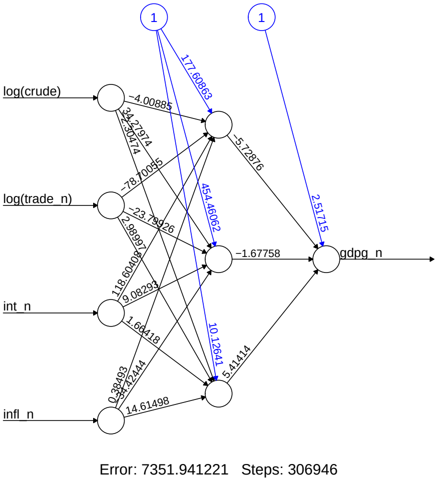


Figure: Kenya—trained neural network for GDP growth

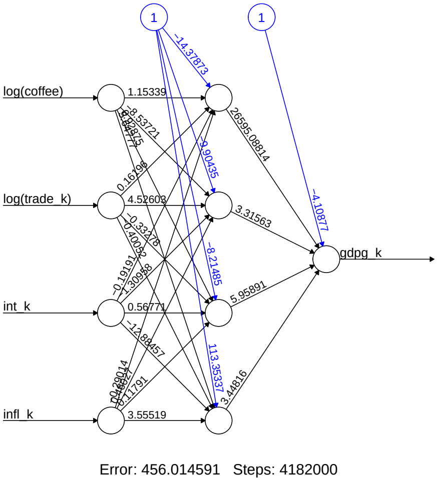


Figure: South Africa—generalized weights for covariates

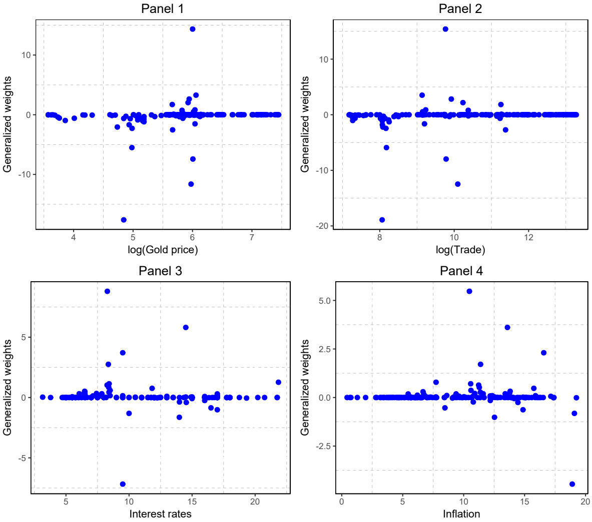


Figure: Nigeria—generalized weights for covariates

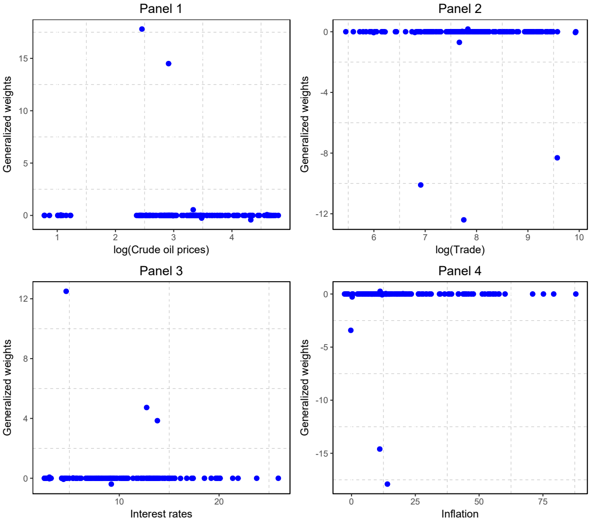


Figure: Kenya—generalized weights for covariates

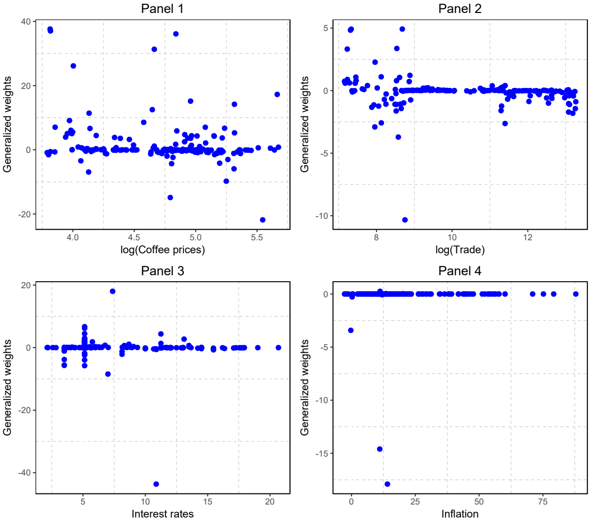


Figure: South Africa—Actual versus model predictions

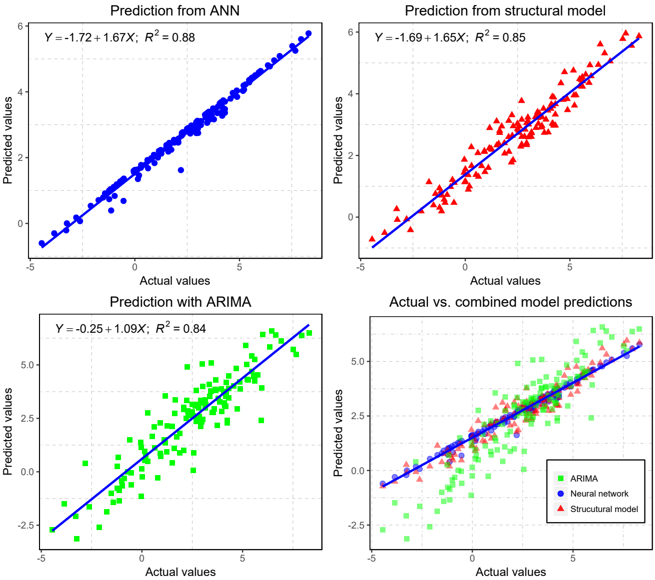


Figure: Nigeria—Actual versus model predictions

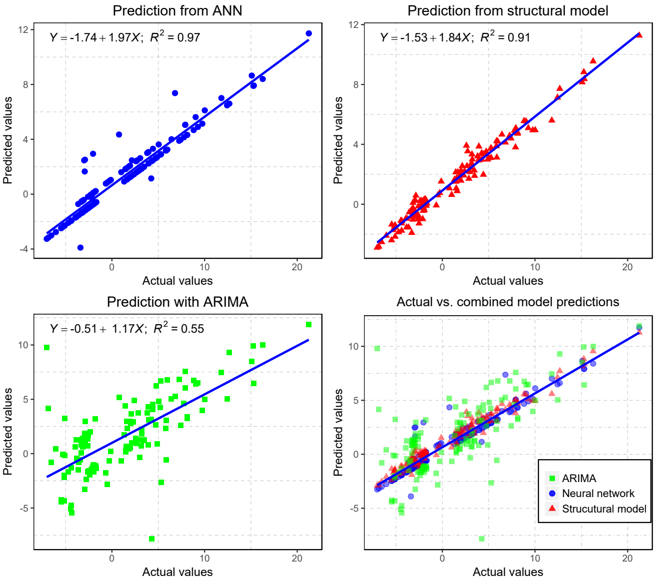
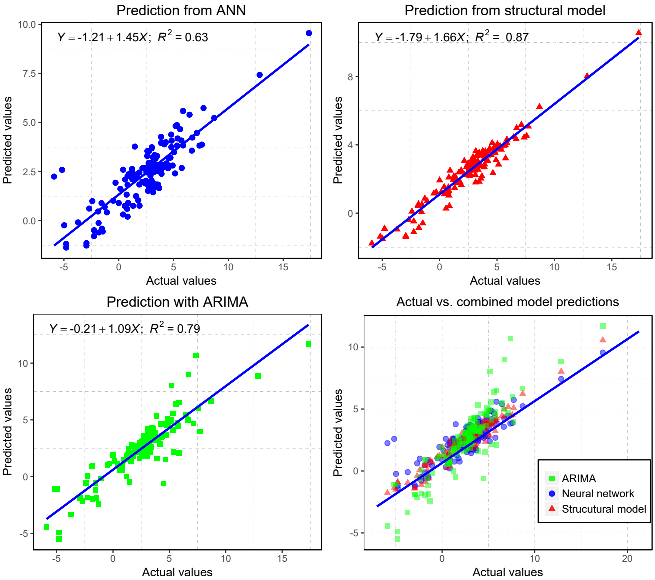


Figure: Kenya—Actual versus model predictions



Forecast performance measures

Table: Forecast performance comparison

	South Africa			Nigeria			Kenya		
	MSE	MAPE	R^2	MSE	MAPE	R^2	MSE	MAPE	R^2
ARIMA	0.971	37.22	0.84	19.784	74.815	0.55	1.849	49.343	0.79
Structural model	0.928	36.01	0.85	3.623	58.538	0.91	1.187	36.731	0.87
Neural network	0.725	34.51	0.88	0.937	56.182	0.97	3.334	61.589	0.63

Recap and Conclusion

Recap and Conclusion

- We set out to determine the relative performance of ANN vs. ARIMA and SEM in forecasting GDP growth in selected African frontier economies.
- ANN models perform somewhat better than SEM and ARIMA when the relevant commodity prices, trade, inflation, and interest rates are used as input variables.
- Because of idiosyncrasies, practitioners should hedge against wide errors by using a combination of ANN and SEM
- Details must be on a case-by-case basis

The End