Box A: A Neural Network Approach to Forecasting Inflation

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NIESR forecasts of inflation over the next few months are based on Dixon (2021), which outlined a simple method for predicting inflation in the short run, using the simple arithmetic of annual inflation. The level of "headline" annual inflation π_t^A equals the sum of the most recent 12-months month-on-month (mom) inflation π_{t-i}:

$$\pi_t^A = \Sigma \pi_{t-i}$$

This is an approximation which ignores the compounding of inflation but is accurate given that mom inflation is small (the average over 1993-2024 is 0.17 per cent per month). The change in inflation each month is then simply:

$$E_t \Delta \pi_{t+i}^A = E_t \pi_{t+i} - \pi_{t+i-12} : i = 1 \ldots 12$$

New inflation $E_t \pi_{t+i}$ "drops in" and the old inflation π_{t+i-12} "drops out". Thus, for the 12 months t_{t+i} for $t=1 \ldots 12$, we know exactly what will be dropping "out" of the headline figure, because it has already happened (which is why we did not put the expectation on this term). Hence, we know half the story of inflation for the next year because it has already happened. The task for predicting headline inflation over the next 12 months thus reduces to predicting the "other half", the new mom inflation over those months. The current approach used by NIESR involves constructing a series of "scenarios", based on what are reference levels of mom inflation and also expected changes in VAT and the Ofgem price cap. This box discusses replacing the "scenario" approach with a forecast, using machine learning in the form of a Multi-Recurrent Neural Network (MRN), to predict mom inflation over a period of 12 months and longer. This forecast can then be added to the already known dropouts to construct a forecast of annual inflation for the next 12 months.

The MRN, originally introduced by Ulbricht (1994), is a recurrent neural network that combines several types of weighted feedback links from each neuron to other neurons within the same or preceding layers. It is a powerful tool and has been used in a variety of circumstances in a macroeconomic setting (Binner et al., 2010a,b, Orojo et al., 2019, 2023). A detailed description of MRN may be found in Binner et al. (2010a,b) and Tepper et al. (2016) and more recently, Kelly et al. (2024) in the case of Swiss CPI forecasting.

The method is to choose data to let the MRN "learn the structure" as a basis for the forecast. We did this in two stages. We first chose a large set of monthly variables over the period 1999-2019. The large list included a range of "Phillips curve" and cost variables: unemployment, hours worked, GDP, Producer prices (PPI), average earnings, CPI core inflation, CPI inflation (levels and lagged mom inflation). We also included monetary variables: the MPC Bank Rate, 10-year gilt yields and the Divisia index for money and interest rates. Given the large seasonality of the data, we constructed a separate MRN model for each monthly forecast horizon (i.e., each trained to directly predict mom inflation at either $t+1, t+2, \ldots, t+11$ *or* $t+12$). We restricted the MRN's memory to storing the previous

120 months for each variable before making a prediction. The MRN is good at capturing non-linearities and discovering underlying structural relationships which require such a long memory.

We construct the following two types of MRN models of inflation:

a. a simple MRN consisting of two input variables: the mom percentage change in inflation (auto-regressive term) and the natural log of the price level;

b. a complex MRN that includes the following additional five exogenous variables: *real GDP, PPI index for industrial output, UK gilts 10 year yield, sterling effective exchange rate (index level)* and adjusted Divisia price dual. (See Binner et al. (2023) for details of the construction of the Divisia price dual).

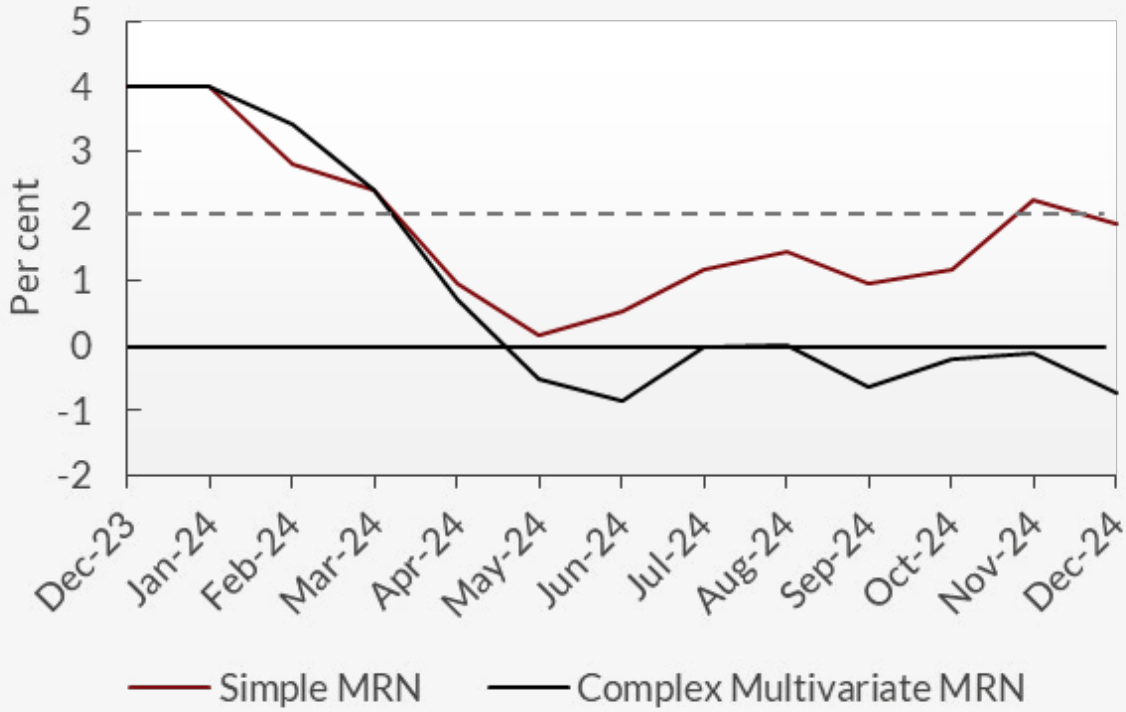
The in-sample period for model fitting and selection was January 1999 until December 2023. The out of sample forecasts were generated by each of the trained MRNs once they were given input data for January 2014 until December 2023. The MRNs trained to predict t+1, were responsible for the January 2024 predictions, the model trained to predict t+6 responsible for June 2024 predictions and so on. It is important to note that an ensemble-based scheme was implemented where each MRN forecast is an average of three independently trained MRNs. The final list of forecasts was obtained by concatenating the respective individual direct predictions made by each of the 12 MRN models (i.e. one for each month/forecast horizon). Table 1 shows the predicted path of monthly inflation "drop ins" and the inferred annual percentage change in the CPI for both the Simple and Complex MRN model classes. The actual outcomes are shown in the table for January and February, which were available at the time of writing. Table 1 presents the predicted path of inflation for the remainder of 2024, based on forecasts made with data up to December 2023, along with the actual outcomes for the first two months which were available at the time of writing.

Table A1: MRN Forecasts for CPI inflation

		Simple MRN		Complex MRN	
Month (2024)	Drop outs (percentage points)	Predicted Drop ins (percentage points)	Predicted annual CPI inflation (per cent)	Predicted Drop ins (percentage points)	*Predicted annual CPI inflation (per cent)*
January	*0.56*	*-0.58*	*3.98*	*-0.58*	*3.98*
February	*-1.14*	*0.59*	*3.41*	*0.59*	*3.41*
March	*-0.77*	*0.36*	*2.4*	*-0.23*	*2.4*
April	*-1.21*	*-0.22*	*1.0*	*-0..45*	*0.7*
May	*-0.67*	*-0.11*	*0.2*	*-0.55*	*-0.5*
June	*-0.13*	*0.47*	*0.5*	*-0.23*	*-0.9*
July	*+0.43*	*0.22*	*1.2*	*0.42*	*0.0*
August	*-0.34*	*0.60*	*1.4*	*0.36*	*0.0*
September	*-0.50*	*0.02*	*1.0*	*-0.17*	*-0.7*
October	*-0.01*	*0.22*	*1.2*	*0.45*	*-0.2*
November	*+0.24*	*0.79*	*2.2*	*-0.16*	*-0.1*
December	*-0.42*	*0.06*	*1.9*	*-0.19*	*-0.7*

Note: This Table was written before the March 2024 inflation figures were published. Actual values are shown for January and February and a -0.6 percentage point adjustment was made in April to account for the Ofgem price cap change; all other values are predicted.

Figure A1: Monthly forecasts of UK Annual CPI inflation using the MRN models



Notes: The simple MRN predicts a return to the 2 per cent target in the fourth quarter of this year. The complex MRN predicts a sharp decline to -0.9 per cent inflation by June 2024 and remains stubbornly around 0 per cent for the remainder of 2024.

As we can see from table A1, and more starkly from figure A1, there are similarities and differences in the forecasts generated by the Simple and Complex MRNs. Both indicate a rapid decline in annual CPI inflation to just below 2 per cent in April with the forecast for annual inflation from the Simple MRN falling to a low of 0.2 per cent in May and then gradually increasing back towards 2 per cent in the fourth quarter of 2024. The Complex MRN forecast, however, suggests that annual CPI inflation continues following a sharp downwards trajectory, to an unexpected rate of -0.9 per cent in June, and remains persistently at or just below 0 per cent for the remainder of the year. The impact of the additional exogeneous variables is surprising, suggesting a much longer latency than expected in the response of consumers to falling inflation after being so used to higher prices and interest rates. It will be interesting to observe the changes in our forecasts as the models are recalibrated using new observed data for the first quarter.

This work is particularly timely as we are widely embracing machine learning and Artificial Intelligence techniques to increase the speed and accuracy of data analysis and decision support. Academic economists and practitioners alike are keen to discover the information hidden in vast amounts of data to help us make smarter decisions and deliver increasingly sophisticated simulations, calibrations, and forecasts of the economy. Advances in data-driven modelling techniques such as machine learning are transforming everyday life. This study, presenting novel findings making use of this important tool, is timely as the Bank of England prepares for its 'once in a generation' overhaul in forecasting.

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