*Title:* Multi-period forecasting of inflation at risk using parsimonious neural networks

*Abstract:* We propose to forecast the quantiles of the conditional distribution of macroeconomic variables at multiple horizons for multiple countries using flexible dynamic encoder-decoder models. By parameter-sharing between encoders of different countries we provide a parsimonious model that is applicable in typical sample sizes of macroeconomic data sets. The encoder part of the model, which is identical for each of the countries, captures nonlinearities in the data and allows for the extraction of shared dynamics, while the decoder is country-specific and aims to explain the country-individual effects. Our estimation routine combines the temporal convolutional neural network (TCN) as an encoder with an output layer that enforces non-crossing quantile estimates by penalization. The TCN provides a parameter-efficient model architecture for extracting complex temporal dependencies between variables. The multi-quantile, multi-horizon loss function is minimized using a stochastic gradient descent algorithm. In the simulation study, we open the black box of the neural network by comparing isolated model variants and establishing the hyperparameter importance. We study the finite sample properties by considering a range of linear and nonlinear data generating processes. The simulation study demonstrates that our neural network design outperforms the linear quantile regression, even in small sample sizes. We further find that the encoder-decoder structure and parameter-sharing lead to a more efficient modeling approach for (non)linear dependencies between predictors and quantiles. In an empirical illustration, we analyze the out-of-sample performance of the model on inflation data. We find that the method outperforms linear quantile regression in predicting the economic vulnerability of 21 EU countries for 6, 9, and 12-month-ahead forecasting during the out-of-sample period 2014-2023.