Forecasting Georgian Inflation Using Machine Learning and Econometric Models - Research Proposal

Introduction

Inflation is one of the most important statistical metrics in whole economics. Having an accurate forecast of inflation beforehand is very important for central bank officials and policymakers, as well as for economic agents to form their expectations. Since monetary policy transmission is associated with significant lags, central banks aiming to achieve price stability need to be forward-looking in their decisions as well – which underscores the importance of inflation forecasting (Garcia, 2018). Yet inflation dynamics have considerably evolved during the past decades and the search for a reliable model to forecast the metric is still an ongoing research question. As a part of my bachelor's thesis, I want to forecast inflation in Georgia in all, short, medium, and long-term time horizons using predominantly deep learning-based models. I also want to make a comparative analysis between classical econometric and machine learning/deep learning time series forecasting models.

Literature Overview

The traditional literature on inflation forecasting mainly refers to Phillips curve-based models, where inflation is explained by some explanatory variables and autoregressive processes. This approach might be well established but the forecasts based on such models tend to show varying performance over time and can quickly be outperformed by univariate models such as the unobserved components with stochastic volatility (UC-SV) model (Stock & Watson, 2007), or the random walk (Atkeson & Ohanian, 2001). There is a hand full of research papers conducted on forecasting inflation using multi and univariate econometric and machine learning approaches. The studies have been conducted around the world, but rarely in Georgia, especially in multivariable setup. My project aims to contribute in particular to Georgian data-based inflation forecasting literature by studying the ability of neural networks to consistently estimate inflation rates.

During the last decade, increasing growth in R&D and usage of ML models has not left the field of economics without its trace. Studies conducted on inflation forecasting using machine learning models have shown great promise in delivering consistent and accurate predictions for future inflation. These studies usually involve models that describe the nonlinear mappings between explanatory and dependent variables. Such models include support vector regressions (Siermpinis et al., 2014) and random forests (Medeiros et al., 2019). There also is a growing amount of research projects addressing the ability of neural networks to forecast inflation, but they mostly use the basic feed-forward neural network algorithms. Examples of such approaches are discussed in the works of Nakamura (2005) and Chakraborty & Joseph (2017). I want to enrich these studies by focusing on the LSTM model which belongs to a different class of neural networks and is relatively new in the field of inflation forecasting.

I understand that Georgia is not the best country in terms of data collection and the issues might arise because of the small sample data, but that would be another test to see how the models perform with limited data points.

Methodology

As a part of this study, I want to, first of all, compare ML and econometric models to each other in terms of the accuracy of their predictions and then forecast inflation for Georgia. I also want to compare the selected models against the benchmarks that are used by the researchers in classical economics, the autoregressive model of order 1 is one of such classical models. The main machine learning model that I am planning to use to predict inflation is a specific recurrent neural network known as LSTM (long-short term memory) model. There is a list of pros that support choosing this model for these types of time series forecasting tasks.

The main reason behind choosing LSTM relates to the general architecture of the model (Hochreiter, Schmidhuber, 1991). The name suggests that the model should be specialized in handling different types of memory. It is a great model for processing past information. While the traditional feed-forward neural network processes all input lags forwards and simultaneously in the network, recurrent models process each time period sequentially, where the input of a given time step is the output of the previous one (Paranhos, 2021). The recursion generally continues until a certain predefined lag is reached. In real-world examples, this translates into the model that can explicitly determine the dependence between consecutive time periods along the series. Considering the reasons stated above, LSTM models have found great success in the fields such as text translation, speech recognition, music composition, to name a few (Paranhos, 2021).

The second reason why LSTM models are appealing is the characteristic that is referred to as "long-term memory". This exact characteristic differentiates LSTM models from the plain, simple recurrent neural networks, and shows the ability of the model to use information from far in the past as long as it aids in improving the accuracy of the forecast. In practice, this is made possible by adding a number of filters to the recurrent neural network model. The filters control the flow of information across time. The long-memory feature is especially important and significant when predicting long-term trends of the series. As intuition and literature suggest, these types of models should outperform relatively simple models over a longer period of time. This study will also try to test that assumption.

From the more classical, econometrical methodology I want to use univariate Autoregressive integrated moving average (ARIMA) modeling. This technique is one of the go-to strategies when dealing with short-term univariate time series forecasting in the econometric niche. They have often outperformed much more sophisticated and robust models while making short-term forecasts (Stockton & Glassman (1987), Litterman (1986)).

The exact variables used for forecasting are yet to be determined. Following the proven approaches in the field (McCracken and Ng, 2016), a combination of factors such as past inflation rates, employment rate, the balance of payments, the prices of main import/export goods, etc. will be chosen as the explanatory variables. The data will reflect the business activity, industrial production, price levels, import-export balance in the country, etc. Georgia started collecting inflation data in 1996 and the sample will contain monthly measures from 1996 to 2022. The data on inflation is going to be collected from the database of the National Bank of Georgia, any additional data will be gathered from the National Statistics Office of Georgia. To validate and test the performance of the models, I am planning to use two approaches of cross-validation.

The first is a very common and standard testing framework (Brownlee, 2020). Divide the data into three parts: training, validation, and test datasets, each of the three parts will contain 80%, 10% and 10% of the data accordingly. The training will commence on the first 80% of the data, the models will be validated on before unseen validation dataset, and will finally be tested on the testing dataset. The metrics that will determine the accuracy of the models will be RMSE (root mean squared error) and MAE (mean absolute error).

The second one would be also a fairly common approach for testing. Dividing the data into only training and test datasets and commencing cross-validation in multiple rounds, using different partitions of the datasets, and combining the validation results over the rounds to reduce the variability of the results.

The research is planned to commence according to the following schedule: The research proposal will be prepared and submitted by March 31. From April 1 to May 13 the first draft of the project will be worked on. This stage consists of selecting and reviewing relevant literature in a broader way; Fundamentally forming the modeling framework, deciding on all of the necessary variables; Collecting relevant data, and analyzing it using the statistical models and tools stated above; Finding the best models according to the error statistics and discussing the results, giving the final recommendations.

After submitting the first draft on May 13, the paper will be reworked by implementing the suggestions and recommendations from the supervisor and the final draft of the project will be submitted on June 27.

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