002 - Introduction

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1 Introduction

Forecasting the real economy has been a widely researched topic as it is crucial for effective policy making - nevertheless, there are many options in doing so, be it equity, fixed income, or commodity markets.

Stock & Watson (2003) reviewed over 93 working papers & articles and documented numerous variables (interest rates, term spreads, returns, exchange rates, etc.) that have been used for forecasting macroeconomy. Nevertheless, there is no strong agreement which can do so consistently, as per the conclusion made: ”Some asset prices have been useful predictors of inflation and/or output growth in some countries in some time periods” (Stock & Watson, 2003, p. 822). Furthermore, even less variables are there that can predict macroeconomic real activity through longer time periods (i.e. time periods of over a year).

However, in a work by Cremers et al. (2017), they tackle the topic of predicting the macroeconomic real activity through the treasury implied volatility (YIV) that is derived from options on treasury bond futures of different maturity periods. Furthermore, they focus on predicting the periods of 12-36 months ahead and find that the YIV is able to predict the GDP growth successfully during these periods. Furthermore, they show that YIV is able to predict also consistently industrial production, consumption, and employment.

Thus, the first part of our research aims to replicate the research by Cremers et al. (2017) - predicting GDP growth using YIV.

In the second part of the research we build upon the research of Cremers et al. (2017) in two ways.

Firstly, to account for the state-dependency of forecast models, as shown to be relevant by Chauvet & Potter (2013) and Siliverstovs & Wochner (2020), we conduct separate regression analysis for both recessionary periods and expansionary periods (classification of the US business cycles obtain from NBER).

Secondly, we propose using machine learning models to account for the shortcomings of the simple OLS-based models. More specifically, the inability of simple OLS-based models to account for collinearity, dimensionality, predictor relevance and non-linearity (Bolhuis & Rayner, 2020). To elaborate, we apply the framework of a random forest (RF) model tailored specifically for macroeconomic forecasting (MRF) as it is able to tackle the aforementioned problems - the MRF model is shown to significantly decrease the root mean square forecasting errors (RMSFE) while also being interpretable.

Thus, our research question consists of three sub-questions:

1. **Can options on Treasury bond futures effectively predict the USA's macroeconomic and financial activity?**
2. **If so, is this conclusion robust even after taking into account different business cycles.**
3. **Do Machine Learning methods such as Macroeconomics Random Forest (MRF) improve the forecast accuracy?**

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