Nowcasting with high frequency data, Google trends and machine learning

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Abstract

Observing the current economic trends is one of the constituent parts of conducting a correct and timely economic policy. Generally, data for economic indicators, including gross domestic product (GDP), are published with a delay of several weeks or months by the national statistics services. To fill this information vacuum, the paper offers using nowcasting with traditional and modern nowcasting methods, with high frequency data including Google Trend search category indexes. According to the results of the research, the machine learning methods are relatively more accurate than the traditional methods. Machine learning algorithms such as Lasso, Ridge, SVR, Linear SVM, Neural Network provide on average 17-21 percent better results than the traditional dynamic factor model. Both the dynamic factor model and machine learning methods in most cases correctly estimate the trajectory of economic activity. In addition, these models are good at identifying turning points, especially in cases where there is a sudden drop or spike in economic activity, which was characteristic of the COVID-19 period.

JEL codes: C13, C32, C38, C45, C51, C52, C53, C61

Key words: Nowcasting, Google Data, Google Trends, High Frequency indicators, Machine learning

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Contents

Graphs

Tables

Non-Technical summary

In this paper, various methods of nowcasting (which means forecasting the present) and the possibilities of using them in practice are discussed and checked. The most frequently discussed method for nowcasting in the literature is the type of models in which many so-called quick indicators. From the set of those indicators several factors with common characteristics are singled out, which can explain the most of the set. After that, the current economic activity (gross domestic product growth) is estimated by those estimated factors. Along with this approach, the use of machine learning methods for nowcasting is becoming increasingly popular. This trend is largely attributed to the widespread usage of such methods in the realm of forecasting.

Along with traditional and modern methods, the paper makes use of modern data sources, such as Google Trend search indexes. Using Google data allows for the addition of high frequency and high quality data into modelling.

According to the results for Georgia, modern machine learning methods can produce better results than traditional methods. Furthermore, the models evaluated in the paper estimate the direction of the economic situation with high accuracy; on average, the direction estimated by the mashin lerning models are correctly identified in 70-77 percent of cases. The models are also good at identifying turning points, especially during periods of high economic volatility like the COVID-19 period. For this time period, the models did a good job of capturing both an immediate economic downturn and a spike in economic growth in March 2021.

The outcomes produced by machine learning models exhibit a noticeable improvement of approximately 17-21% when compared to conventional methods. These results align with prior research and investigations conducted with data from different countries.

1. Introduction

Keeping track of current economic trends is an essential aspect of developing accurate and timely economic policy, particularly during crisis periods like the COVID-19 pandemic, which necessitated prompt decision-making. In numerous countries, worldwide, statistical services typically publish primary economic indicators, such as GDP data, with a delay of several weeks or months. Consequently, policymakers are frequently unable to respond promptly to sudden economic changes. Nowcasting, which is the forecasting of current economic growth, helps us to solve this issue. It enables us to estimate current economic growth using the fast economic variables available at the time. Different types of models and methods are utilized for these purposes, with the number of nowcasting methods increasing due to the surge in data sources and new forecasting methods. This study explores diverse approaches to nowcasting, evaluates relevant literature and methods, and presents empirical analysis using Georgia as an example. Furthermore, the goal of this work is to compare modern forecasting methods, such as machine learning algorithms, to traditional models to see how well they can predict and how much better or worse they are compared to traditional methods. These methods are novel because they employ non-traditional data and methods for nowcasting GDP.

2. Literature Review

The application of high frequency data for the analysis of economic processes, particularly to promptly identify the inflection points of the business cycle, has a long history. Traditional nowcasting methods were used precisely for these purposes, which included usage of many high frequency data to estimate those unobserved factors, which determine the current state of economic processes. This idea was initially proposed in by (Sargent & Sims, 1977), where they try to explain business cycle fluctuations with a small number of factors. Subsequently, (Stock & Watson, 1989) showed that it is feasible to observe the collective behavior of numerous macroeconomic variables through a condensed set of "latent" variables, which can be artificially constructed. This method enables the tracking of economic activity over time. This approach, which was later called the Dynamic Factor Model (DFM), can be considered a traditional method for estimating economic activity. In essence, the DFM model functions as a mean of representing N observable variables with a fewer number of unobservable (Latent) variables and uncorrelated residual terms. DFM is a subset of a larger set called state-space and "Hidden Markov" (Hidden Markov) models, where observable variables are estimated by unobservable latent variables, that themselves evolve in time by an autoregressive (AR) or vector autoregressive (VAR) process. The dependence of the observable variable on the factors can be expressed in two ways:

- When dependence is dynamic, meaning that X variables observed in time *t,* can be dependent on factors being in *t, t-n* and *t+n* period. This method is called dynamic form of DFM.
- Second form is static (also referred as stacked) form of DFM, when both observable and unobservable factors are represented in time *t*.

Estimating factors in DFM model has undergone three stages of development. **The First-generation** estimation of factor relied on small dimension (when number of variables N is small) parametric models, which were solved using Gaussian maximum likelihood method and Kalman filter (Watson & Engle, 1983), (Stock & Watson, 1989) , (Sargent, 1989) and (Quah & Sargent, 1993)). **The second-generation** estimation method entails non-parametric techniques, such as cross-sectional mean and Principal Component Analysis (PCA) for estimation. In those methods, large number of variables (there is a high dimensionality) are used. The main result of this method lies into the fact, that when times series together with number of variables are large enough, the accuracy of estimated factors are very high, and thus it is possible to use them as regressors in model. **The third-generation** estimation method combines first and second-generation methods, and these methods are often referred as two stage DFM. During the first stage, factors are estimated via non-parametric method, specifically through the use of PCA. The resulting factor loadings obtained from this estimation are subsequently employed as initial values in a Kalman filter. Next, new factors are estimated from the Kalman filter, and these new estimates are once again utilized to update the factor estimation. This iterative process continues until convergence is achieved. The aforementioned methodology was originally proposed by (Giannone et al., 2009) and (Doz et al., 2006). These researchers applied this approach to perform nowcasting for quarterly GDP and inflation in the United States. Their analysis incorporated approximately 200 variables. (Matheson, 2011) employed the Dynamic Factor Model (DFM) methodology to perform nowcasting for GDP in 32 developed and developing countries. The results indicated that, in the majority of cases, DFM outperformed benchmark estimates. Additionally, the paper highlights that combining or pooling different nowcasting results can enhance accuracy. Since DFM method uses Kalman filter, it is possible to construct current high frequency indexes. The Dynamic Factor Model (DFM) approach, which utilizes the Kalman filter, has been shown to be effective in constructing high frequency indexes for economic activity. (Bańbura et al., 2013) demonstrated the efficacy of this approach by constructing monthly and daily GDP indexes using DFM, which were able to explain a significant portion of the variance in quarterly GDP. This approach has also become popular for nowcasting quarterly GDP, as it enables the state of the current quarter to be updated on a monthly basis.

To improve upon the DFM methodology, (Bräuning & Koopman, 2014) introduced a modified approach known as the Collapsed Dynamic Factor Model (CDFM), which leverages the ability to estimate unobserved monthly GDP. Unlike PCA, which is an unsupervised estimation method where the dependent variable does not participate in parameter estimation, CDFM utilizes Partial Least Squared (PLS) in the final step of estimation. The primary difference between PCA and PLS lies in their reliance on the dependent variable. PLS assigns more weight to variables that that display a stronger correlation with the dependent variable, resulting in more accurate factor estimation. After estimating the monthly GDP index using CDFM, this index can be used as the dependent variable in the PLS estimation to nowcast quarterly GDP. (Ginker & Suhoy, 2021) applied this method to the case of Israel and found that it improves the accuracy of nowcasting.

DFM method was actively used during Covid-19 for nowcasting purposes. (Sampi Bravo & Jooste, 2020) utilized Google Mobility indicators in a DFM model to estimate the effect of the pandemic on industrial output in the Latin America and Caribbean regions. Similarly(Lewis et al., 2022) created weekly economic activity index using the DFM approach. Also, other research on this topic include (Baumeister & Guérin, 2020), (Chapman & Desai, 2021) and (Antolin-Diaz et al., 2021))

In addition, traditional nowcasting methods include models that connect high-frequency data with low-frequency data. The simplest such method is the "Bridge" model, which gained popularity through its simplicity and low technical requirements. This method uses one-equation regressions on quarterly GDP and a small amount of high-frequency data, which is aggregated to quarterly frequency by various methods - arithmetic mean, sum or some other transformation (see (Baffigi et al., 2004)). However, issue arises when making nowcasts during the quarter or in periods where explanatory variables have not yet been published (Also called the "ragged" or "jagged" edge problem). To address this, explanatory variables are typically predicted using autoregressive (ARMA) models, which in many cases requires a large number of lags, which in turn increases the number of parameters to be estimated and, accordingly, reduces the degree of freedom of the model and the reliability of the results The mixed data sampling (MIDAS) method provides a solution to this issue by replacing the lag structure with a non-linear function (see (Clements & Galvao, 2009), (Kuzin et al., 2011). This group of methods also includes mixed frequency vector autoregressions (Mixed frequency VARs), which offer an alternative to single-equation models (see (Giannone et al., 2009) and (Kuzin et al., 2011)). The effectiveness of these aforementioned methods has been evaluated in the work of (Camacho et al., 2013).

Although those methods mentioned above are main methods used for nowcasting in different institutions, in recent period machine learning algorithms are gaining more and more popularity for performing the given task. In addition to the fact that different machine learning algorithms estimate parameters in different ways, it also allows finding complex non-linear relationships between data and making more data driven predictions, which has the potential to reduce the deviation between the estimated value and the actual data (Nowcast/Forecast error).

Furthermore, machine learning methods have a wide range of applications in economics beyond nowcasting. For instance, they can be employed for variable selection to determine the most significant predictors (Kohlscheen, 2021), policy analysis ((Mariam Dundua & Otar Gorgodze, 2022),(Chakraborty & Joseph, 2017), predicting recession probabilities (Basuchoudhary et al., 2020), forecasting (Ter-Martirosyan et al., 2018) and etc. Although machine learning methods have been primarily developed and utilized for forecasting, their relevance for nowcasting is also increasing. In a recent study, (Richardson et al., 2021) employ approximately 600 local and international variables to forecast New Zealand's GDP, demonstrating that machine learning algorithms, particularly Boosted Trees, Support Vector Machines, and Neural Networks, outperform simple autoregressive models and DFM. Using various machine learning methods on quarterly macroeconomic and financial data (Muchisha et al., 2021) comes to a similar conclusion that machine learning methods provide better results than the autoregressive benchmark model.

As in the case of DFM, machine learning methods can also be used to derive an economic activity index. (Woloszko, 2020) using Google trends, specific word searches and a Neural Network algorithm created weekly economic activity index for OECD countries. The results of this study revealed that the model relying solely on Google trends and specific words yielded a 17 percent improvement over the results obtained using the AR (1) process.

In the work of (Dauphin et al., 2022), the effectiveness of DFM and machine learning methods for nowcasting is evaluated in crises and "normal" periods for European countries. Their findings indicate that the DFM method demonstrates high accuracy during non-crisis periods. Whereas, machine learning methods have better performance in detecting turning points, i.e., identifying the transition from boom to recession or vice versa.

In their study (Barhoumi et al., 2022) explore the use of machine learning techniques as a viable solution to address the issue of data scarcity in sub-Saharan African countries. Their findings suggest that machine learning methods can provide more accurate results when compared to conventional methods.

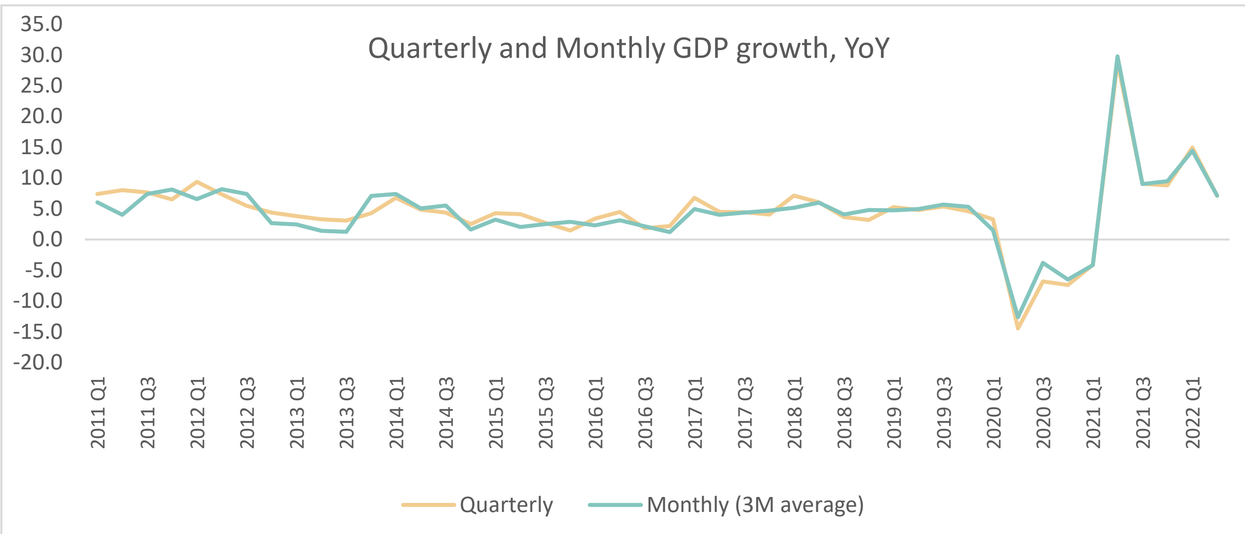
In their work (Bolhuis & Rayner, 2020) on the example of Turkey demonstrate the potential for combining machine learning methods with a model ensemble approach to achieve more accurate forecasts and nowcasts. Specifically, their findings suggest that the combination of machine learning methods and model ensemble can reduce forecasting and nowcasting errors by an average of 30 percent, compared to traditional approaches. Similarly, previous studies, such as the one conducted by (Tiffin, 2016) on the nowcasting of Lebanon's GDP, have also shown the potential of machine learning methods, including Elastic Net Regression (ENR) and Random Forest (RF) algorithms, for achieving better results than traditional methods. Tiffin's study found that ENR outperformed RF, and that a model ensemble approach further improved the accuracy of the nowcasting results.

3. Data

3.1 Peculiarities of Data for Georgia

The literature reviewed above predominantly focuses on the task of nowcasting quarterly GDP by utilizing higher frequency data through various methods. However, the situation differs when it comes to the task of nowcasting Georgia's GDP. This is because the National Statistics Service of Georgia (GeoStat), along with other countries such as Great Britain, Kazakhstan, Armenia, Azerbaijan and others, releases monthly estimates of the previous month's GDP (graph 1)

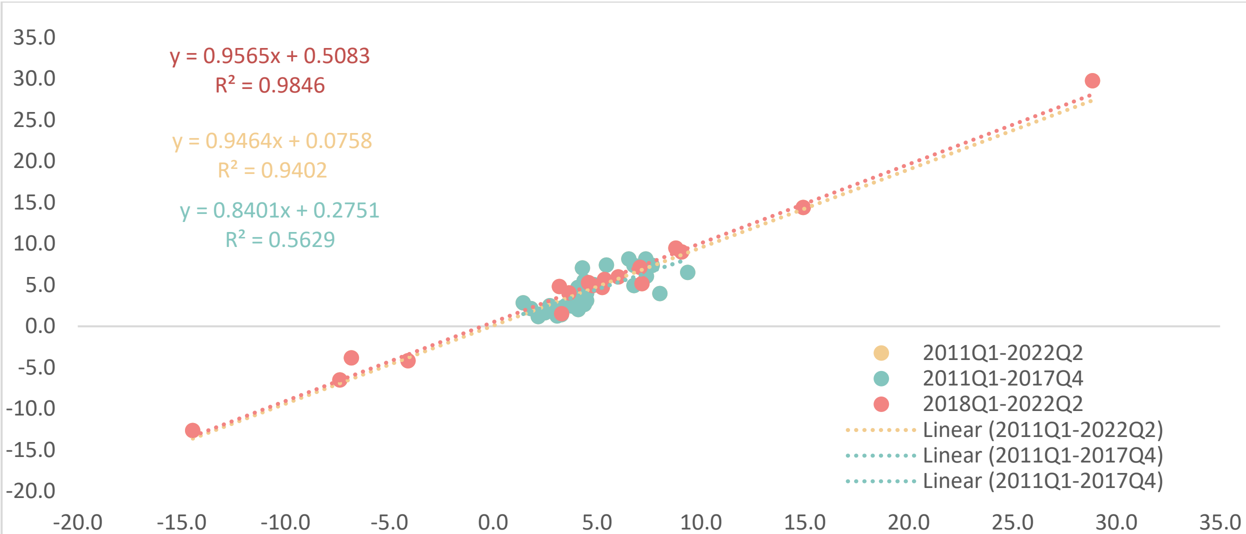
Graph 1. Quarterly and Monthly GDP growth rates, YoY



Source: GeoStat, Author Calculations

This allows information on quarterly GDP growth to be received with a delay of only one month. Economic growth data, assessed monthly by GeoStat allows to estimate the quarterly growth rate with high accuracy, as can be seen in graph 2. Especially in recent years, economic growth is estimated with high accuracy. Therefore, unlike traditional methods, whose main goal is to nowcast quarterly economic growth in the present with the data available at that time, in the case of Georgia it is also important to nowcast monthly GDP in the current period with fast economic indicators. **The purpose of this paper is to nowcast monthly economic activity using monthly indicators.**

Graph 2. Correlation of Quarterly and Monthly GDP growth rates



Source: GeoStat, Author Calculations

Since the monthly indicators available at the beginning of the month are obtained in small quantities, it is necessary to use other non-traditional sources and variables. For this purpose, paper uses Google Trends[3] data.

3.2 Description and Processing of Data

Data used for this research4 is obtained from different sources, which includes Ministry of Finance of Georgia (MOF), Georgian Revenue Service (GRS), National Bank of Georgia (NBG), Statistics office of Georgia (GeoStat) and Google. Data from those sources can be divided into three types

- Type one represents the data, which is published within one week after the end of the month.
- Type two data is available after two weeks from the end of the month and
- Type three data is available between third and fourth weeks after the end of the month.

Type three data encompasses a variety of economic indicators on monetary and financial sector (loans, deposits, monetary aggregates and others), detailed trade data, industrial/import/export prices, bankcard transactions, and real effective exchange rate**.** Alongside official statistics, several research organizations also publish data on a monthly basis, including the PMCG Labor Market Survey [5](Employment Tracker), which analyzes the number of vacancies posted on online employment platforms during the past month. In addition, and the Consumer Confidence Index [6] published by ISET-PI. The aforementioned data sources

[3] Also good quality high frequency data can be obtained from Google Mobility report, but from October 2022 Google stopped publishing it and it is no longer open source. Because of this, Google Mobility data is not used in models.
[4] For more detailed description of Data's source and publication date see Appendix 8.1.
[5] https://pmcresearch.org/periodic/11
[6] https://iset-pi.ge/en/indexes/5-consumer-confidence

provide valuable insights into the current state of the economy in terms of their content and quality. However, their publication is delayed by 3-4 weeks, rendering them unsuitable for nowcasting purposes. This is because GeoStat publishes a preliminary assessment of economic growth on the last working day of the month, making the use of delayed data of little value for nowcasting. **Type two** data includes data on remittances, income from tourism, detailed data on foreign trade in goods and turnover of enterprises paying value added tax, which are available for the 15th-16th days of the following month. **Type one** data includes exchange rates, real-time gross settlement (RTGS) operations, GEL money market indicators, Tbilisi interbank interest rates, consumer price inflation, tax revenues, government expenditures, foreign trade in goods from declarations across the border and cash turnover are available within first week after the end of the month.

The availability of type one data, which can be obtained within the first week after the end of the month, is limited in quantity. This issue is not unique to Georgia and underscores the growing need for new approaches to obtain data with accurate content and quality. To address this challenge, there has been increasing interest in utilizing data provided by Google, such as Google Trends and Google Mobility. While the latter is a highly valuable indicator for measuring economic activity, it has unfortunately been discontinued and is no longer publicly available as of October 2022. Google Trends data, on the other hand, provides a many types of information. Existing literature has mainly utilized two forms of Google Trends data, the first is the information about the search frequency of specific words (key words) (see. (Woloszko, 2020), (Narita & Yin, 2018)). And second when data is received about a topic/category (see. (Barhoumi et al., 2022), (Robin, 2018), (Austin et al., 2021),(Carrière-Swallow & Labbé, 2010)). The selected method for utilizing Google Trends indexes in Georgia is the category-based approach. This approach is more suitable for predicting economic events in non-Latin script developing countries where predicting a recession or similar phenomenon through specific keywords may be challenging. The monthly category indexes provided by Google Trends are available within 72 hours after the end of the month, providing a valuable source of type one data for analysis.

In addition to the available information Feature engineering is a powerful technique that can help in creating new variables from the existing ones to improve the predictive power of a model. It can involve transforming, scaling, or combining existing features to create new ones.

In the case of nowcasting Georgia's GDP, feature engineering can be used to create new variables that capture the relationships between the available data. For example, new dummy variables can be created to capture the effect of specific events or policies on the economy. Transforming existing variables such as taking the logarithm or square root can help in capturing non-linear relationships. Multiplying or dividing variables can help in creating interaction terms that capture the joint effect of different variables on the outcome variable. Although often there is no theoretical basis behind the creation of new variables, and this process serves purely forecasting purposes. Also, it is important to note that feature engineering should be done carefully and with a clear understanding of the underlying data and the problem at hand. Over-engineering can lead to overfitting, where the model becomes too complex and performs poorly on new data. Therefore, the selection of relevant features and their engineering should be guided by a sound understanding of the underlying data and the problem being addressed. In this case, it is possible to engineer the data so that both theoretical and practical parts are satisfied.

New data can be created so that it has theoretical grounds and then tested to see how useful it is in modeling. For example, by taking subtracting inflation and the Tbilisi interbank interest rate, it is possible to create a new variable, which will be the real interest rate. Also, by multiplying the exchange rate with trade/tourism/money transfers, we get the given variables in GEL, then it is possible to deflate them with the price growth rate to get variables in real terms. Also, other variables which are denominated in GEL can be transformed into their real values by dividing with price level. Finally, the data in the paper is engineered only if it carries economic intuition, if the correlation of the newly created variable is higher than the original one then it replaces this variable in the database and vice versa. Also, for non-linearity of linear models, the data is transformed by taking it to the appropriate degree, where the logic is the same: if its correlation with GDP exceeds the original one, it replaces it, otherwise it is not used. A double filter is used for the selection of variables, the correlation of the variable with GDP should exceed 0.4, and its standard deviation should not exceed the average standard deviation of the total data by more than 10%.

After performing data engineering and initial filtering, the number of variables for the first type was reduced to 12 (from the initial 41 variables), and for the first and second type, it was reduced to 17 (from the initial 47 variables). The data was then transformed using annual growth rates, and standardized to have a mean of zero and a standard deviation of one. Standardization is an important step for methods such as principal component analysis (PCA), partial least squares (PLS), dynamic factor models (DFM), and machine learning algorithms, as it helps to avoid giving undue weight to variables with high absolute variance that may not be better explanatory variables.

The data covers the period from 01.2012 to 09.2022. The research initially uses only those variables that are available in the first week of the month, and then it is evaluated how much the addition of the second type data increases the ability of nowcasting.

4. Models and Methodology

The research uses both traditional methods such as DFM as well as machine learning methods to nowcast monthly economic activity.

4.1 DFM Methodology

The DFM model employed in this study is a third-generation model with a static representation, expressed in the following form:

$$X_t = \Lambda f_t + e_t$$

$$f_t = \psi(L) f_{t-n} + \eta_t$$

Where X_t = $(X_{1t,} X_{2t}, \ldots., X_{nt})$ is (n x 1) stationary process, n is number of variables and t number of observations. Λ is (n x r) matrix which includes f_t factor parameters (Factor loadings). e_t is idiosyncratic shock, which does not correlate with factors, and its expectations is zero. Interrelationship of f_t factors are modeled as VAR process of order p. Estimation of those equations are done in two steps, in first step to obtain factor loadings PCA analysis is done. On second stage given those factor loadings Kalman filter is used on those equations to estimate new factors, and this process of second stage continues until convergence. In the first stage, PCA analysis is used for the preliminary estimation of the parameters, CFDM-model is not used with the PLS methodology for the following reason. Since the dependent variable (in this case, the GDP growth rate) is needed to evaluate the factors through PLS, it is impossible to obtain the components with the PLS model in the current period t. Which is needed later in DFM, for PLS to be estimable in period t, before GDP growth rate is known, it is necessary to create a lower frequency GDP index, which goes beyond the goals of the mentioned paper. Visual diagnostics of scree plots are used to determine the number of static factors. At the first stage, two approaches can be used for PCA analysis - "Naïve" PCA and structural PCA. According to the first approach, components are obtained from the group of variables and the number of components is determined so that 60-80% of the total variation is explained by the obtained components. While according to the second method, the initial sectors are identified (for example, variables related to financial, real or other common characteristics) and then from those identified sectors one component from each of them is extracted. First method of PCA is used in this paper. The number of lags in the VAR model of the factors is determined based on the Akaike information criterion (AIC) outside the model. After receiving the factors, the monthly GDP is calculated using the static least squares method.

$$Y_t = \alpha + \beta_1 F_t^1 + \beta_2 F_t^2 + .. + \beta_n F_t^n$$

4.2 Machine Learning Methods and Models

For research following machine learning algorithms are used - Regularized regression (Ridge, Lasso, Elastic Net) , Support Vector Machine – SVM, Decision Trees, Random Forest, Gradient Boosting (Ada, XGboost, LGBM), Neural Networks (NN) and Model Ensemble (Stacked generalization).

Table 1. Brief Description of Machine Learning Models[7]

Method	Description
Regularized regression - Lasso, Ridge, Elastic Net	LASSO (least absolute shrinkage and selection operator), Ridge regression and Elastic Net are modified variants of linear regression where different types of regularization are introduced to improve the predictive ability of the model. Compared to traditional regression models, these models cope well with the inclusion of a large number of variables in the model, multicollinearity and overfitting of the model. However, despite these advancements, they remain unable to handle non-linearity as they still adhere to linear modeling principles.
Kernel methods - Support Vector Machine (SVM)	The SVM model creates hyperplanes to partition the combinations of explanatory variables and then makes point predictions for each partition as in kernel regularized regressions. SVM copes well with problems related to non-linearity, multicollinearity, inclusion of a large number of variables in the model and overfitting, but its estimation ability depends on the correct selection of kernel function and regularization parameters.
Decision Trees (DT)	Decision trees are diagram-like structures designed to predict a specific outcome. Each level of the tree represents a question with a binary yes or no answer, such as "Is the turnover growth of VAT-paying enterprises higher than 20%?" followed by other levels with binary answers. Following the diagram and answering the questions one by one eventually solves the initial problem. Decision trees work well for problems where nonlinear interactions are important. However, a potential disadvantage is that the method is very flexible and therefore prone to overfitting - With enough questions, a large tree can categorize each observation into its own individual bin, perfectly fitting each observation of the explanatory variable.
Random Forest - RF	Random forest represents combinations of predictions obtained from individual regression trees. As a non-parametric algorithm, RF copes well with linear regression problems associated with nonlinearity, multicollinearity, and large number of variables in the model. Despite its flexibility, RF's ability to predict outliers is limited.

[7] For detailed description of Machine Learning models see appendix 8.2

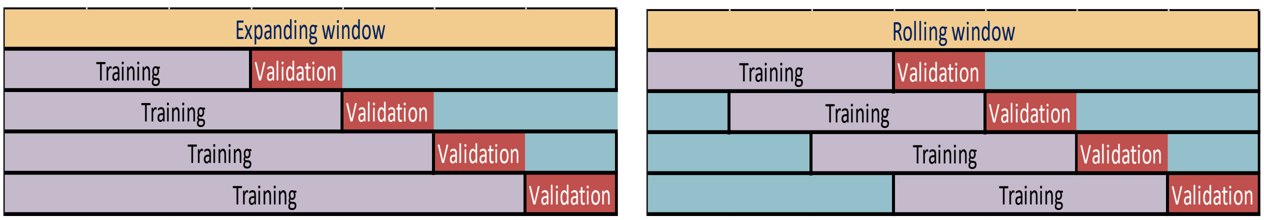
Gradient Boosting- (XGboost, Catboost) Adaptive boosting - AdaBoost	**The gradient boosting** algorithm is similar to the RF algorithm in that it involves combining a large number of decision trees. Instead of averaging all the models, this method does it sequentially, where each decision tree is built one at a time, with each tree trying to correct the "mistakes" of the previous tree. Based on the predictions of the first tree, the second tree tries to estimate the errors of the first tree, and then the third tree repeats the same for the second tree, and so on. The final prediction is the sum of all individual tree predictions. **Adaptive boosting** takes a slightly different approach. Instead of predicting the errors of the previous model, each iteration tries to generate predictions based on a reweighted database, where the weights are determined by the previous model. More weight is given to cases that the previous model handled poorly, and less weight to cases that the previous model handled well. The final prediction is the weighted sum of all models, with weights determined by the accuracy of each model
Neural Networks (NN)	NN is a multi-layer nonlinear method that relates a set of data to an explanatory variable. A network consists of layers that represent artificial neurons (also often referred to as nodes). Each neuron receives data from the previous layer, then uses a transformation function to transform the received data into an output, and then sends this result to the next layer. NN is very flexible, since it is possible to use different transformation functions in each node, and it is possible to identify each layer with different structures. NN as a sophisticated and flexible algorithm is considered a powerful tool for prediction, which solves the shortcomings of traditional regression methods.
Stacked generalization	Stacked generalization is a feedforward neural network that uses the method of model ensemble by (Wolpert, 1992). Unlike Neural Networks which uses sigmoid or any other transformation function, stacked generalization uses any machine learning algorithms.

4.3 Choosing the Model and Measurement of Nowcasting Accuracy

Machine learning models are evaluated in several stages, where several elements need to be considered. For machine learning models, it is necessary to provide some parameters (Hyperparameters) from outside, so that the subsequent algorithm can cope with the task well. Determining the correct hyperparameters is an important step in machine learning and the final result largely depends on it. Therefore, at the initial stage of model evaluation, it is necessary to determine the optimal (or suboptimal, given the often-impossibility of determining a genuinely optimal pair of hyperparameters) hyperparameters, which will be used later in the evaluation of the entire model. For this, it is necessary to divide the initial data into 2 parts - Training sample and test samples. To accomplish this task, the original data must be divided into two separate samples: a training sample and a testing sample. Typically, the test data represents around 10-15% of the total dataset. Within the training sample, the process of determining the hyperparameters of the model takes place. Within the training sample, the process of determining the model's hyperparameters takes place, involving a technique known as cross-validation, in the process of which pseudo out-of-sample predictions are made on splits, which is carried out in several stages (k-fold cross-validation).

There are two cross-validation methods for time series - Rolling window and Expanding window (see Figure 3). The selection of an appropriate evaluation method depends on the practical requirements of the task at hand. If historical data is frequently updated or becomes outdated quickly, the rolling window method may be preferred. On the other hand, if new observations are continuously added to the dataset and the model needs to be re-estimated each time, the expanding window method may be more suitable. In the case of nowcasting for Georgia, where the goal is to make real-time predictions, the expanding window method was deemed more appropriate for cross-validation purposes, as it provides an accurate reflection of the current state of the data.

Graph 3. Cross Validation for Time series.



Upon determining the optimal hyperparameters through cross-validation, the models are estimated on the entire training sample, and their accuracy is tested on the test sample. While this approach is commonly used in forecasting competitions such as Kaggle[8], in practice it shows some shortcomings, because it is possible to improve the models under the influence of the test sample, because the models are modified until it shows better results on the test sample, this phenomenon is called test sample leakage. Therefore, in the research, along with this method, another method is used, which is known by the name of back testing. It allows pseudo out-of-sample predictions to be made. For example, starting from January 2015, the model will be estimated with the data available for January 2015, and then the nowcast will be made. After that, the data of the next month will be added and model will be re-estimated and new nowcast will be made so on till it covers all the data. In the end, whichever model has the smallest error in during the back testing will be the best model. The accuracy of the model is evaluated using two indicators, namely, the Root Mean Squared Error (RMSE) indicator.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}{N}}$$

[8] www.kaggle.com

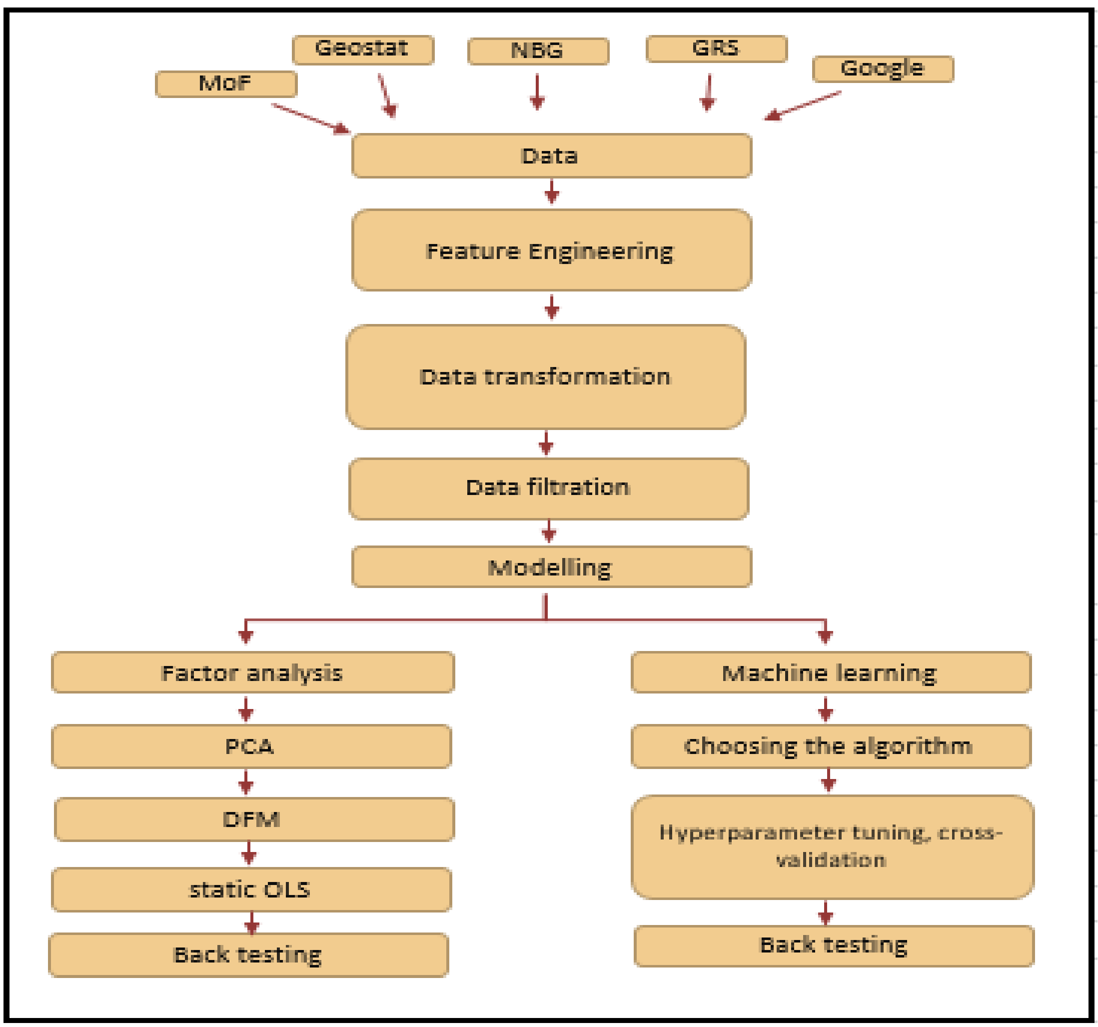
Which estimates the magnitude of the average error between the $\hat{y}_t$and realized y_t values. When evaluating only with this indicator, we may come to wrong conclusions, because along with the accuracy of the forecast, it is important that it also show us the right direction, which means an increase/decrease compared to the previous month's data. Mean Directional Accuracy (MDA) indicator is used for these purposes.

$$MDA = \frac{1}{N}\sum 1[sgn(y_t - y_{t-1}) = sgn(\hat{y}_t - y_{t-1})]$$

$$Where \quad 1_A = \begin{cases} 1 \; if \; x \in A \\ 0 \; if \; other \end{cases} and \quad sgn(x) = \begin{cases} -1 \; \text{თუ} \; x < 0, \\ \;0 \; \text{თუ} \; x = 0, \\ \;1 \; \text{თუ} \; x > 0 \end{cases}$$

The modeling process used in the paper is as follows (Graph 4):

Graph 4. Modelling Process



In the pursuit of identifying the optimal model, diverse automatic machine learning and artificial intelligence packages were employed to facilitate model selection and optimization. This involved the evaluation of a significant number of models and their corresponding parameters, with the aim of selecting the best model from each machine learning class.

5. Results

The results (Table 2) are mixed. First, it should be noted that the majority of the models employed demonstrate a high level of accuracy in predicting the trajectory of GDP growth, with accuracy rates surpassing 70% in most cases. Moreover, the results indicate that incorporating the second type of data leads to a substantial improvement in accuracy, with an average reduction in models forecast error of 20% after its inclusion.

Table 2. Model results

Models	Type on Data		Type two data	
	RMSE	MDA	RMSE	MDA
AR(1)	5.71	66.2%	5.71	66.2%
DFM	4.45	70.1%	3.40	71.6%
LASSO	3.26	70.6%	2.58	76.5%
Ridge	3.25	69.1%	2.55	76.5%
Elastic Net	5.04	63.2%	3.33	67.6%
XGboost	6.04	64.7%	5.28	70.6%
Catboost	5.38	66.2%	4.56	73.5%
SVR	3.21	69.1%	2.48	73.5%
Linear SVR	3.42	69.1%	2.51	70.6%
Random Forest	5.94	63.2%	5.23	70.6%
Adaboost	6.31	63.2%	5.68	64.7%
Neural Network	3.74	61.8%	2.58	66.2%
Stack Generalization	4.98	69.1%	3.34	75.0%
Simple average	4.00	69.1%	3.00	57.4%

Source: Author Calculations

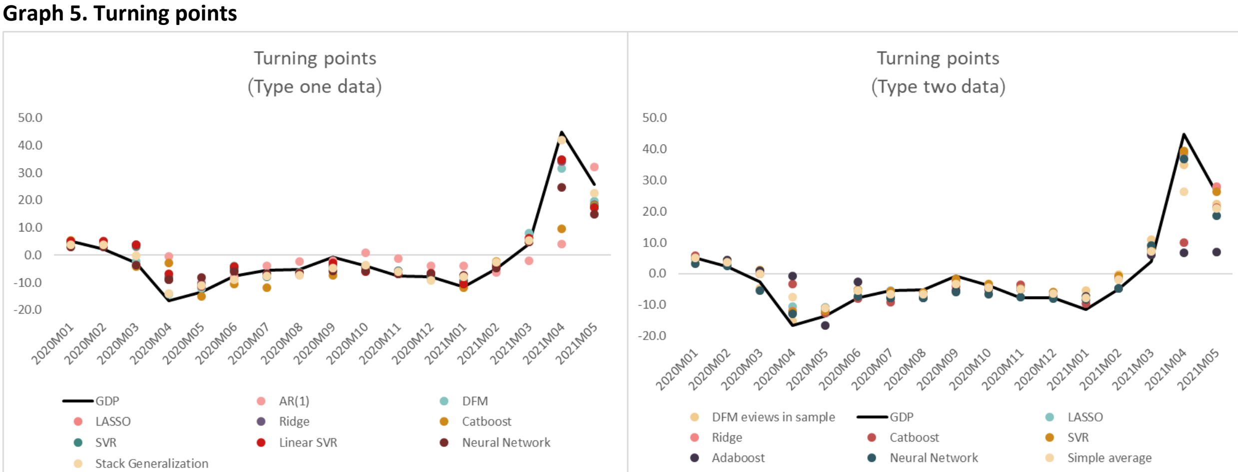
Upon analysis, it has been observed that the majority of models exhibit higher accuracy rates compared to the benchmark AR(1) model when using the first type of data. However, some tree-based models, such as Random Forest, Adaboost, Catboost, and XGboost, perform worse than the AR(1) model. This result was expected, given that the analysis incorporated high and low volatility periods, and non-parametric models tend to perform poorly in situations involving extreme events that were not evident in the past training sample. Therefore, the use of similar types of models is more appropriate for low volatility periods. The same observation holds true for type two data as well.

For the first type of data, machine learning methods - Lasso, Ridge, SVR, Linear SVM, Neural Network - provide better results than the DFM method. Linear SVM showed the best result, which outperforms DFM by 27.8 percent. On average, for the first type of data, machine learning methods (except for decision tree-type models) give 17.9 percent better results than DFM. The results align with published literature, which suggests that regularized models tend to perform better than more complex models in many cases.

Regarding the second type of data, the results are comparable to those of the first type, except for one notable exception where the Elastic Net methodology exhibited a considerable improvement after the incorporation of the second type of data. It is noteworthy that the NN model displayed a low error rate, considering that models of this type typically demonstrate high accuracy when trained on large amounts of data. Regularized linear models, kernel-type models, and neural network-type models were found to produce superior results when compared to traditional methods, irrespective of the data type. Consistent with the findings for the first type of data, Linear SVM yielded the best performance for the second type, with results 26.2 percent higher than those of DFM. On average, machine learning techniques (excluding decision tree-type models) were found to produce 21.4 percent better results.

Through the application of Stacked Generalization, the results obtained under both types of data do not reveal a better level of accuracy in comparison to the simple average. For the first type of data, a better result is achieved with the DFM model than with the combination of forecasts, and for the second type of data, a slight improvement is observed compared to the DFM. In this analysis, the results of the models are combined through linear regression, because combined results under linear regression showed best results compared to other algorithms.

Graph 5. Turning points



Source: Authors Calculations

It is worth noting that turning points are "captured" well by most of the models, thereby highlighting both the importance of accurate identification and estimation of models, as well as the quality of high-frequency data employed (see Annex 8.1). As shown in the data analysis, the data in the models effectively reflects the current economic situation, as evidenced by the sharp decline in GDP and most high-frequency data in March 2020. Similarly, in the recovery period in March 2021, the selected data exhibited a significant annual increase, partly attributable to the low base effect and the resurgence of economic activity.

In this study, the same database was utilized for all models after a filtering process was carried out as described in the data description subsection. This approach may not be equally beneficial for all models, and primarily for non-linear models, as the selection of variables was based mainly on the correlation coefficient, implying a linear relationship. Additionally, as a result of filtering, the number of variables was sharply reduced. On the one hand, the quality of the DFM model increased with this approach, because the factors included less variables that were characterized by high volatility, but had a low correlation with GDP. On the other hand, it is possible to "aggressively engineer" the data to improve DFM results by adding highly correlated variables (which would not have any economic interpretation). Nevertheless, this issue is beyond the scope of this paper and is the subject of a separate study. Since the main goal of this paper is to compare modeling methods in equal conditions, the results of each model can be improved by fitting the data to each model individually.

6. Conclusion

The purpose of this research was to explore the possibility and efficacy of modern modelling and data sources for the purposes of nowcasting GDP.

The results show that, it is possible to observe current economic activity with high accuracy and little delay. In the process of analysis machine learning algorithms and especially regularized linear models, kernel models and Neural Networks showed higher accuracy than those of DFM and benchmark models. These models estimate with high accuracy both the scale and direction of economic activity. Almost all models were able to predict an instantaneous economic downturn in 2020, which also indicates the quality of the fast data, both from traditional data sources and from Google trend search indexes. In the process of analysis, it appeared that it is possible to find such high-frequency variables with the help of Google Trend, which well and instantly reflect the current economic situation. But in fact, many of these data are unsuitable in modeling.

7. Literature

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8. Appendix

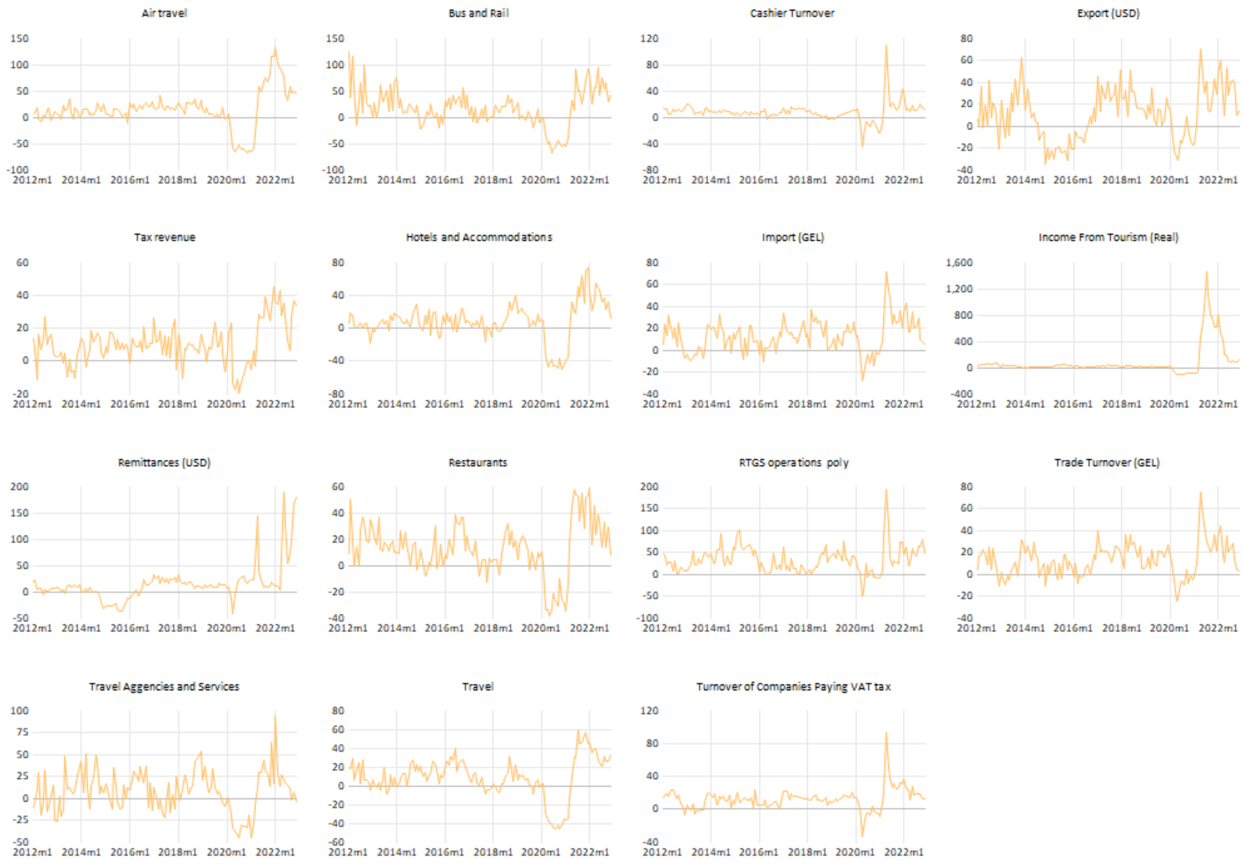
8. 1. Used Data

Table 3 . Used Data in paper

Source	Variable	Type	Update date	Correlation with GDP
MOF	Cash Turnover	I	First day of next month	0.68
	Tax revenues	I	First day of next month	0.55
	Government Expenditure	I	First day of next month	0.06
	Trade in Goods (Imports)	I	First day of next month	0.63
	Trade in Goods (Exports)	I	First day of next month	0.43
	Trade in Goods (Turnover)	I	First day of next month	0.65
	Turnover of companies paying VAT taxes	II	15th day of next month	0.93
NBG	Currency (USD/GEL)	I	First day of next month	-0.29
	Currency (NEER)	I	First day of next month	0.27
	TIBR	I	2nd day of next month	-0.09
	M2 (Prelimenary)	I	3rd day of next month	0.22
	RTGS operation	I	5th day of next month	0.62
	Income from tourism	II	15th day of next month	0.56
	Remittances	II	15th day of next month	0.41
GeoStat	CPI inflation	I	3rd day of next month	0.28
	Trade in Goods (Imports)	II	15th day of next month	0.62
	Trade in Goods (Exports)	II	15th day of next month	0.75
	Trade in Goods (Turnover)	II	15th day of next month	0.76
Google	Travel index	I	3rd day of next month	0.58
	Air travel	I	3rd day of next month	0.63
	Bus and rail	I	3rd day of next month	0.57
	Car rental and taxi service	I	3rd day of next month	0.25
	Cruises and charters	I	3rd day of next month	0.27
	Hotels and Accommodations	I	3rd day of next month	0.60
	Tourist destinations	I	3rd day of next month	0.32
	Travel aggencies and services	I	3rd day of next month	0.50
	Travel guides and travelogues	I	3rd day of next month	0.34
	Auto index	I	3rd day of next month	0.23
	Vehicle licensing and registration	I	3rd day of next month	0.21
	Vehicle parts and accessories	I	3rd day of next month	0.35
	Advertising and marketing	I	3rd day of next month	-0.23
	Business news	I	3rd day of next month	-0.21
	Construction and maintenance	I	3rd day of next month	0.19
	Energy and utilities	I	3rd day of next month	0.28
	Metals and minming	I	3rd day of next month	0.14
	small busniess	I	3rd day of next month	-0.38
	transportation and logistics	I	3rd day of next month	0.21
	Financial planing	I	3rd day of next month	0.27
	Investing	I	3rd day of next month	-0.18
	non-alcoholic beverages	I	3rd day of next month	0.28
	Restaurants	I	3rd day of next month	0.67
	Apparel	I	3rd day of next month	0.28
	Consumer resources	I	3rd day of next month	0.22
	Weddings	I	3rd day of next month	0.24
	luxury goods	I	3rd day of next month	0.17
	tobacco products	I	3rd day of next month	0.33
	clubs and nightlife	I	3rd day of next month	0.34
	Events and listings	I	3rd day of next month	0.33
	concerts and music festivals	I	3rd day of next month	0.32

Source: Ministry of Finance, Revenue Service, GeoStat, National Bank, Google Trends

Graph 6. Data used in Models.



Source: Ministry of Finance, Revenue Service, GeoStat, National Bank, Google Trends

8. 2 Machine Learning Models

8.2.a Regularized Linear Regressions (LASSO, Ridge, Elastic Net)

Regularization is a widely-used technique in machine learning that aims to reduce the overfitting of models by shrinking the coefficients of the variables in regression towards zero. It can be applied to various machine learning models, but is particularly prevalent in linear regressions, where it reduces beta coefficients to zero. The most popular linear regularization models are Ridge, least absolute shrinkage and selector operator (LASSO) and Elastic Net regressions Similar to the traditional least squares method, regularized regression minimizes the loss function, albeit with slight modifications. If the linear model has the following form:

$$y_t = x_t'\beta + \varepsilon_t$$

Where y_t represents the dependent variable, and x_t' represents a vector of *n × 1* explanatory variables, and ε_t is the residual term. When estimating the parameters of the equation, the traditional method of least squares minimizes the corresponding loss function:

$$\hat{\beta} = \min \left[\sum_{1}^{t} (y_t - x_t'\beta)^2 \right]$$

Which means reducing the sum of squared of residuals. The regularization method, in order to avoid overfitting, modifies the loss function by adding a "penalty" to the function.

LASSO - the absolute value of the coefficient is added as a "penalty" to the loss function of the least squares method, which is also called L1 regularization. The modified function has the following form:

$$\hat{\beta} = \min \left[\sum_{1}^{t} (y_t - x_t'\beta)^2 + \lambda_1 |\beta| \right]$$

Ridge - the square of the absolute value of the coefficient is added to the loss function of the least squares method as a "penalty", which is also called L2 regularization. The modified function has the following form:

$$\hat{\beta} = \min \left[\sum_{1}^{t} (y_t - x_t'\beta)^2 + \lambda_2 |\beta|^2 \right]$$

Elastic Net is a combination of L1 and L2 regularizations, and the loss function takes the following form:

$$\hat{\beta} = \min\ [\sum_1^t (y_t - \ x_t'\beta)^2 + \lambda_1|\beta| + \lambda_2|\beta|^2]$$

λ_1 and λ_2 are hyperparameters. Their adjustment to the model (Tuning) is done by various quantitative methods, such as Grid and Random search methods. In the paper, cross-validation is used to adjust hyperparameters. Parameters, which, during cross-validation, have a better result, are chosen for final model.

8.2.b Kernel methods (Support Vector Machine (SVM))

Kernel methods, including Support Vector Regression (SVR), model complex, nonlinear relationships by initially transforming the data into a higher dimension and then estimating the coefficients through a hyperplane. There are several ways how the hyperplane can be estimated. SVR uses the sum of the absolute values of the residual term, if it exceeds a predetermined limit, rather than the sum of the squared residuals (the loss function of the least squares method). Which means that when estimating the coefficients, their magnitude is reduced to ensure that the residual terms remain within a specified range.

Like linear regression, the dependent variable is modeled as follows:

$$f(x_t) = \ x_t'\beta + \ \varepsilon_t$$

The goal of the SVM algorithm is to find the function $f(x_t)$ so that it is as flat as possible and at the same time, the residual terms are within a predetermined range. SVM minimizes the loss function by combining beta and observation specific constants ζ_t and ζ_t^*

$$\frac{1}{2}\beta'\beta + C\sum_{t=1}^{T}(\zeta_t + \zeta_t^*)$$

Subject to the following restrictions, $y_t - f(x_t) \ \leq \ \varepsilon + \zeta_t$

$$And\ f(x_t) - \ y_t \ \leq \ \varepsilon + \zeta_t^*$$

Accordingly, at each observation point, the residual term is limited to$[-\varepsilon, \varepsilon]$, and it is possible to disturb this range by the magnitude of ζ_t and ζ_t^*. The constant C is a hyperparameter that controls how much the residual term should be reduced, or in other terms how much model should over/under fit the data. If C=0, then a fitted plane of the simplest form will be constructed, where all observation points are within the acceptable range. As C increases, so does the complexity of the fitted line, and the value of the residual terms approaches zero, posing a danger of overfitting. In SVM analysis, it is possible to change the kernel function and it can be - linear, polynomial of various degrees, sigmoid function, etc. The most popular method is the Gaussian Radial Basis Function (RBF) kernel.

$$k(x_i, x_j) = \exp\left(\left|x_i + x_j\right|^2\right)$$

8.2.c Ensemble methods (Decision trees, Random Forests, Gradient boosting, Adaptive boosting)

Decision trees are non-parametric models, where instead of estimating the coefficients, it partitions the sample data into subgroups based on binary responses to a series of questions. Therefore, we can think of decision trees as diagram-like structures designed to predict a specific outcome. Take for example a chart where each level is a question with a binary yes or no answer (for example, "VAT turnover growth higher than 20% ?") followed by other levels with binary answers. Following the diagram and answering the questions one by one eventually solves the initial problem In the case of regression analysis, decision trees generate predictions by splitting the data into subsets with homogeneous response values. Specifically, a binary split partitions the data into two subsets with response values that are the arithmetic means of the response values of the data points in each subset. For example if sample is split sample into two parts according to the VAT turnovers, resulting in two leaves. The first leaf meets the question whether VAT turnover exceeding 20%, and the value of the leaf is defined as the arithmetic mean of GDP growth (the dependent variable we are trying to predict) while VAT turnover growth was greater than 20%. The value of the second leaf is carried out in the same way, but with the difference that the average of the GDP is taken in when VAT turnover growth was less than 20%. As the number of leaves (We add more questions) increases, so does the complexity of the model and the risk of overfitting arises. The latter will deteriorate the ability of the model to accurately extrapolate the relationship between the variables in the future. For example, if we take a model with one explanatory variable (VAT Turnover growth rate) and divide the sample as many times as there are observation points for VAT Turnover growth rate (Creating as many leaves (Questions) as are observation points of VAT turnover growth rate), then we will get one value of GDP for each VAT turnover indicator. This is certainly wrong and the model cannot work on new data. Which is a classic example of overfitting. The formal representation of a regression decision tree is as follows:

$$\hat{f}(x) = \sum_{m=1}^{M} \hat{c}_m \, I(x \in R_m)$$

Where $I(\cdot)$ is indication function,$\hat{c}_m = avg(y_i|(x \in R_m)$, and R_m represents the groups (leaves) that are obtained as a result of division. The goal of the algorithm is to find optimal R_m and $\hat{c}_m$, during which the sum of the squared residuals will be minimized.

Random Forest (RF) is an ensemble method that combines the predictions from multiple decision trees. Since a single-tree model is prone to overfit and relies heavily on local optimization rather than global optimization, the RF algorithm is designed to address these challenges. To construct a "forest" of decision trees, RF employs bootstrap[9] aggregation called bagging[10]. Each decision tree in the RF is built on one of these random samples. In regression analysis, the final prediction of the RF is the arithmetic mean of the results generated by all the decision trees in the forest.

Gradient boosting is a popular ensemble method that shares similarities with the Random Forest approach. However, a significant difference lies in the manner in which predictions are aggregated. Unlike the Random Forest approach, Gradient boosting constructs decision trees sequentially, with each subsequent tree relying on the predictions generated by the previous tree to minimize the residual term. The final result is obtained by averaging the results of all the decision trees that contributed to the process. Three Gradient boosting algorithms are common in practice, XGboost (Extreme gradient boosting), LightGBM (light gradient boosting machine) and Catboost (Categorical boosting). The latter two were developed by Microsoft and Yandex While XGboost is known to be relatively slow, LightGBM and Catboost have significantly faster evaluation times, which makes them more practical for use in real-world scenarios.

Adaptive boosting uses a slightly different method, while Gradient boosting tries to "correct" the errors of the previous model, the Adaptive boosting approach gives more weight to decision trees with poor results (weak learners) at each subsequent iteration to transform them from "weak learners" to "strong learners". Ultimately, the results are a weighted average, where the weights are allocated based on the accuracy of each model.

The main problem of all the above-mentioned tree based models can be explained by two circumstances. The first is the tendency to overfit, even if we use methods that are more complex (Gradient boosting, Adaptive boosting). The second circumstance is that the extrapolation of model results is limited. If the data from which the model is estimated does not represent the population well, then the model is limited

[9] Bootstrap is a statistical procedure, when data points are randomly chosen from dataset in order to create new dataset.

[10] Bagging, also known as bootstrap aggregation is the ensemble learning method that is commonly used to reduce variance within a noisy dataset. In bagging, a random sample of data in a training set is selected with replacement meaning that the individual data points can be chosen more than once.

by the sample values used in the estimation, since the final result represents the averages of the dependent variable (and not any combination of parameters and variables, like in parametric models). Accordingly, such models are highly successful for classification where probabilities are the subject of estimation, while in regression analysis they cannot forecast/nowcast outliers if some kind of outlier was not involved in the estimation. Therefore, if the reduction/growth of GDP is jump-like and amounts to a historical maximum, which is much higher than the previous maximum, the results obtained from those models will also be far from the real picture. However, using these types of models in normal periods when the volatility is less is appropriate.

8.2.d Neural Network

Neural Network (NN) is a multi-layer[11] non-linear method connecting explanatory variables. Each layer consists of nodes, also called artificial neurons. Each node receives information from the original data, or from the nodes of the previous layer. The result of each node is a weighted sum of the received data (often a simple linear model is used, which transforms the received data into a single result), which is further transformed (activated) by a non-linear function[12] to form a new result. Commonly used forms of the activation function are

- Rectified linear unit (ReLU)) - $f(z) = \max(0, z)$
- Logistic function - $f(z) = \frac{1}{(1+e^{-z})}$
- Hyperbolic tangent - $f(z) = \frac{e^{z}-e^{-z}}{(e^{z}+e^{-z})}$

Due to the structure of the neural network, it is not possible to obtain a unique way of estimating the parameters (closed form solution). Therefore, the stochastic gradient descent method is used to estimate the parameters of the neural network. In which in the first stage an assumption is made on the values of the parameters, in the second stage the value of the loss function is calculated with respect to these randomly taken values, and in the third stage, the values of these parameters are changed so that the loss

[11] In its simplest form, when the neural network consists of only two layers, which only have the initial data and the final result layers, and no hidden layers participate in the model, and the only activation function that connects the first layer to the final one is a linear function, such a neural network is a simple linear model.

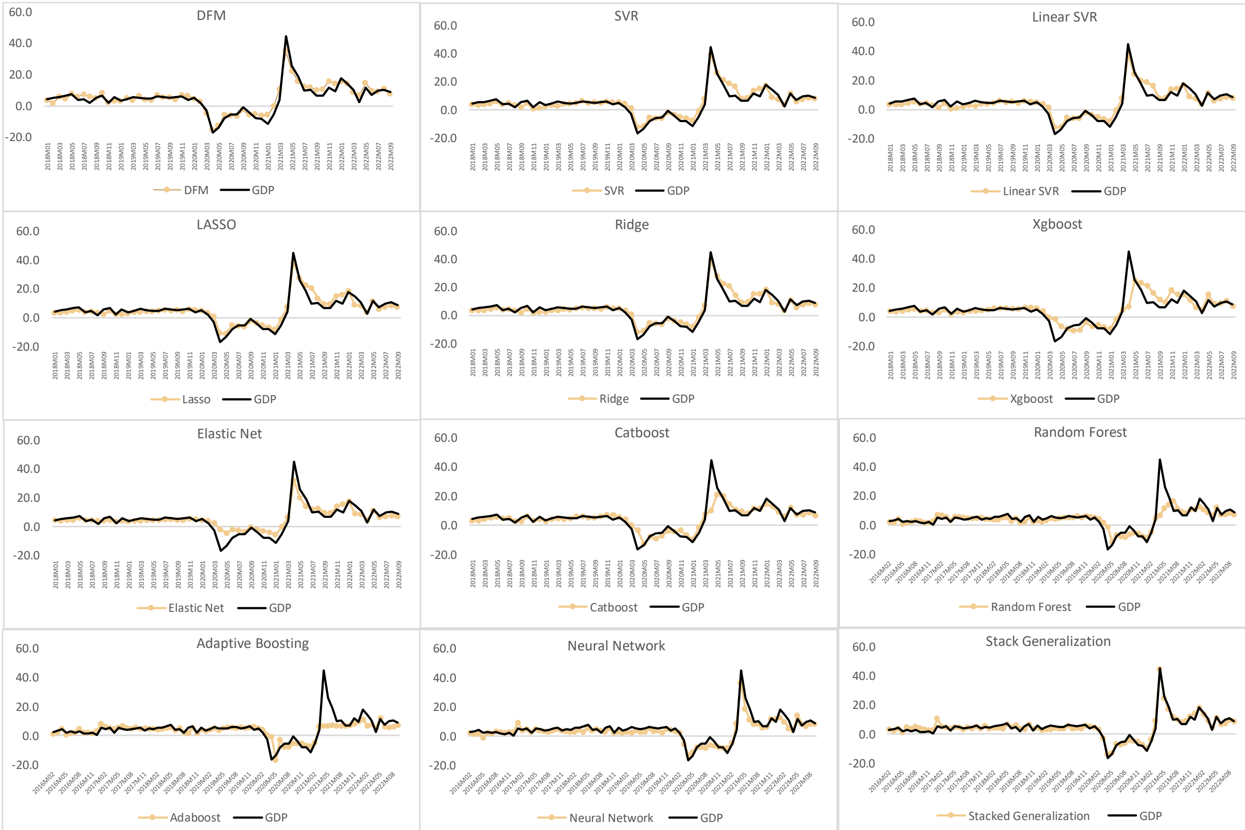
[12] During the regression analysis, it is necessary that the final layer consisting of only one node (the value estimated by the final model of the explanatory variable) is transformed by a linear activation function. Otherwise, if the transformation (activation) function of all layers is linear, then this means that each layer and final result is a linear combination of the first layer, which makes it pointless to add additional layers, as the explanatory power of the model does not increase.

function is reduced. In regression analysis, the loss function is typically defined as the sum of the squared residuals, although other forms of loss function can also be used, although it is possible to define the loss function in another form, but this does not change the principle how the feedforward neural network works. In its standard form, a feedforward neural network is fully connected, implying that every node in each layer is connected to every node in the next layer and the final layer is a one-node layer[13] that produces the final result.

[13] In an analysis where multiple results need to be obtained simultaneously, the last layer can contain as many nodes as there are variables being modeled. Most often, this approach is used in the classification of images, when the obtained result is a distribution of probabilities. in which the activation function is Softmax - $f(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$

8.3 Model Results

Graph 7. Model Results for Type two Data



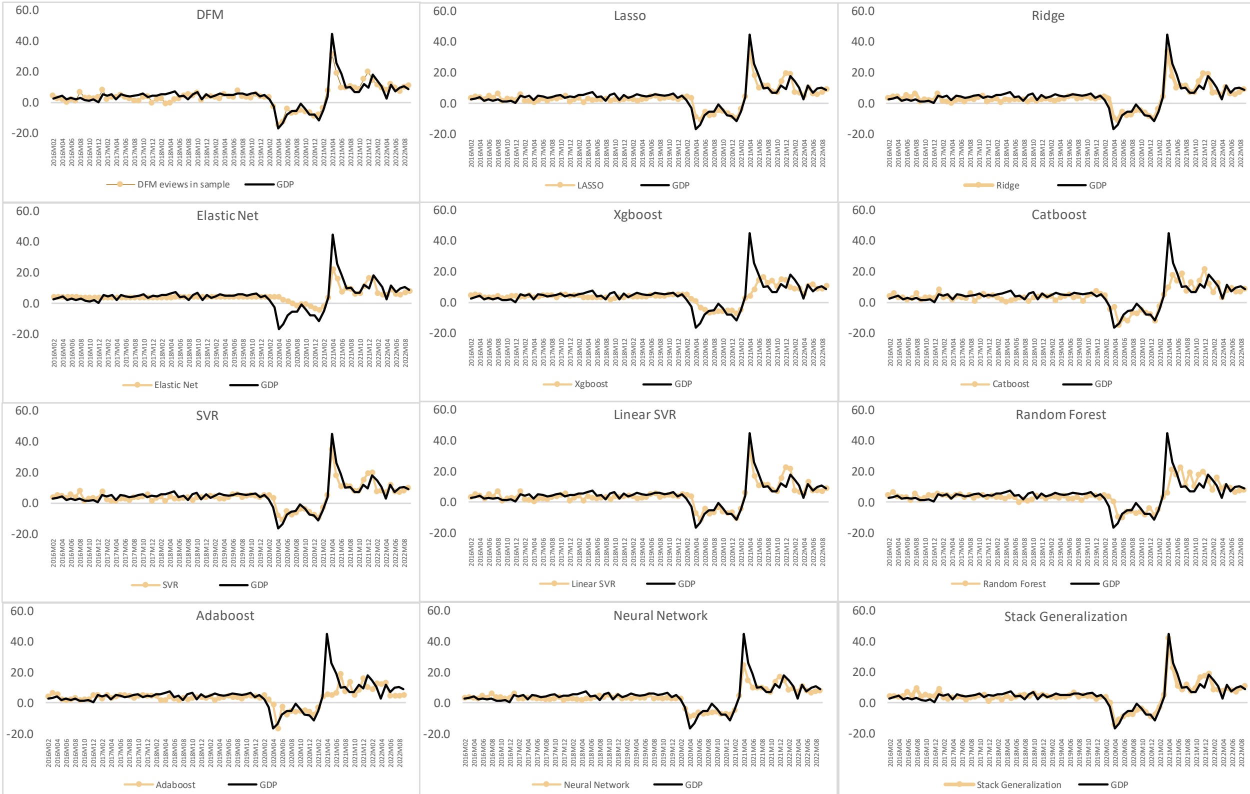
Source: Author Calculations

Table 4. Nowcasting Accuracy for Type two Data

Models	Type two data		Compared to AR (1)	
	RMSE	MDA	RMSE	MDA
AR(1)	5.71	66.2%	1.00	1.00
DFM	3.40	71.6%	0.60	0.92
LASSO	2.58	76.5%	0.45	0.87
Ridge	2.55	76.5%	0.45	0.87
Elastic Net	3.33	67.6%	0.58	0.98
Xgboost	5.28	70.6%	0.93	0.94
Catboost	4.56	73.5%	0.80	0.90
SVR	2.48	73.5%	0.43	0.90
Linear SVR	2.51	70.6%	0.44	0.94
Random Forest	5.23	70.6%	0.92	0.94
Adaboost	5.68	64.7%	1.00	1.02
Neural Network	2.58	66.2%	0.45	1.00
Stack Generalization	3.34	75.0%	0.59	0.88
Simple average	3.00	57.4%	0.53	1.15

Source: Author Calculations

Graph 8. Model Results for Type one Data



Source: Author Calculations

***Table 5.* Accuracy of Nowcasting for Type one Data**

Models	Type one data		Compared to AR (1)	
	RMSE	MDA	RMSE	MDA
AR(1)	5.71	66.2%	1.00	1.00
DFM	4.45	70.1%	0.78	0.94
LASSO	3.26	70.6%	0.57	0.94
Ridge	3.25	69.1%	0.57	0.96
Elastic Net	5.04	63.2%	0.88	1.05
Xgboost	6.04	64.7%	1.06	1.02
Catboost	5.38	66.2%	0.94	1.00
SVR	3.21	69.1%	0.56	0.96
Linear SVR	3.42	69.1%	0.60	0.96
Random Forest	5.94	63.2%	1.04	1.05
Adaboost	6.31	63.2%	1.10	1.05
Neural Network	3.74	61.8%	0.65	1.07
Stack Generalization	4.98	69.1%	0.87	0.96
Simple average	4.00	69.1%	0.70	0.96

Source: Author Calculations