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MASTER'S THESIS

Nowcasting the Real GDP Growth of the European Economies based on Machine Learning

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, July 22, 2023 Su Hazal Baylan

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Abstract

This thesis analyzes the nowcasting of quarterly GDP growth for nine European economies using a dynamic factor model and four different machine learning models. These machine learning models are as follows: Ridge, Lasso, Elastic Net, and Random Forest. The data includes ten hard and fifteen soft indicators for each country in order to calculate GDP for each nowcasting iteration for pre-covid and covid periods. For machine learning, models are fed with the extracted factors that are obtained from the dynamic factor model, and for all nowcasting models expanding window approach is selected to estimate nowcasting iterations. The empirical finding indicates t that overall machine learning models provide better forecasting accuracy compared to dynamic factor models and benchmark models for more stable periods, such as the period before Covid-19. On the other hand, for more volatile periods where the uncertainties are higher in economies, the dynamic factor model outperforms machine learning models in order to nowcast GDP growth. In addition to this, Random Forest is able to outperform all the alternative models for small economies such as Slovenia and Portugal for stable periods.

JEL Classification	C01, C33, C53, C83, E37
Keywords	Nowcasting, DFM, Ridge, Lasso, Elastic Net, Random Forest
Title	Nowcasting Real GDP Growth of the European Economies based on Machine Learning

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Acronyms

AIC	Akaike Information Criterion
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller Test
AR	Autoregressive Process
DFM	Dynamic Factor Model
DM	Diebold-Mariano Test
EM	Expectation-maximization algorithm
GDP	Gross Domestic Product
MLE	Maximum Likelihood Estimation
ML	Machine Learning
MF	Mixed Frequency
MIDAS	Mixed Data Sampling
NLS	Nonlinear Least Square
OLS	Ordinary Least Square
OECD	Organization for Economic Co-operation and Development
PACF	Partial Autocorrelation Function
PC	Principal Component
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
RSS	Residual Sum of Squares
SVM	Support Vector Machines
the U.S.	the United States
the U.K.	the United Kingdom
RF	Random Forest
NN	Neural Networks

Master's Thesis Proposal

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Motivation:
GDP growth is one of the most important macroeconomic indicators that allow us to determine the size of the economy and measure the macroeconomic well-being of the country. Especially in times of crisis, decreases in supply occur as a reflection of a fall in the worldwide demand. Thus, declines in the GDP growth of the countries are seen in the economies. In these periods, the substantiality of GDP growth is increasing, and it is widely used by central banks and policy makers to put the economy back on track (Dauphin et al., 2022). But we should not draw into conclusion that GDP is essential only in times of crisis. GDP growth still maintains its macroeconomic importance in periods when the economy is more stable.

One of the problems encountered while using GDP is that it cannot be obtained in a timely manner since it is calculated and published with a delay, usually on a quarterly basis. This problem leads to a lag problem. Also, due to the inability to access within the desired time, the accuracy of the forecasts may change and diverge (Kocenda and Poghosyan, 2020). In addition, accurate estimation of critical economic indicators and related data with appropriate methods is important for the success of the policies implemented by countries and economic programs prepared for the future (Banbura et al., 2013; Giannone, Reichlin, and Small, 2008; Kocenda and Poghosyan, 2020; Jansen, Jin and de Winter, 2016).

The method which is broadly used in the literature to overcome lag problem that mentioned in the above for GDP and GDP growth is forecasting and nowcasting methods. Studies successfully employed dynamic factors model developed by Giannone, Reichlin, and Small (2008) and they showed that DFM is suitable approach for nowcasting for different economies (Bok et. al., 2018; Banbura et al., 2013; Banbura and Saiz, 2020; Kocenda and Poghosyan, 2020; Lahiri and Monokroussos, 2013; Matheson, 2011).

Instead of more traditional methods, machine learning methods are another approach used in the literature for nowcasting. Cornec and Mikol (2011) used several machine learning algorithms to nowcast GDP in France. In more recent literature, Richardson, van Florenstein Mulder and Vehbi (2021) used gradient boosting, regularization techniques (ridge, lasso, and elastic net), support vector machine regression(SVM), and neural networks to nowcast GDP of New Zealand. Their empirical results showed that machine learning algorithms provide better forecast accuracy compared to AR and dynamic factor models. Similar studies employed machine learning algorithms for nowcasting single countries such as the US (Loermann and Maas, 2019; Soybilgen and Yazgan, 2021), Sweeden (Jönsson, 2020), Indonesia (Muchisha et. al.,2021), Turkey (Bolhuis and Rayner, 2020), Japan (Yoon, 2020). The recent studies employed machine learning algorithms mainly focused on a single country. However, a recently published study by Dauphin et al. (2022) includes nowcasting of multiple European countries (Austria, Hungary, Malta, Poland, Portugal, and Ireland)

GDP and GDP nowcasting is still broadly discussed and developing topic. The aim of this paper is to extend the literature on nowcasting in the following ways. Firstly, the study will employ several different machine learning algorithms in addition to the dynamic factor method which is broadly used. Secondly, the period will include the period after the covid-19, allowing us to monitor a more volatile period. Finally, the study will include a wider range of European countries than existing literature. Hence, it will allow us to compare the performance of different machine learning algorithms and traditional benchmark models within different economic sizes.

Methodology:

Several different machine learning methodologies can be used for nowcasting, include LASSO, Ridge, Elastic Net, Gradient Boosting, K nearest neighbor (KNN), Support Vector Machine (SVM), Random Forest (RF), Neutral Networks. This study aims to use Lasso, Ridge, Elastic Net and Random Forest.

1. Models

Autoregressive Model (AR)

As a benchmark, this study uses the AR model of order 1 to compare the performance of machine learning models.

Dynamic factor model

The methodology to extract the dynamic factors to nowcast quarterly GDP is proposed by Giannone, Reichlin, and Small (2008). In this study, two-step estimation introduced by Doz, Giannone, and Reichlin (2011) is selected because of its ability to handle missing values at the end of the sample overcome the problem of jagged edges.

Ridge Regression

Richardson et al. (2021) summarized the Ridge model as the following: The L2 regularization is used by the ridge regression in order to penalize the model. This penalization method allows us to decrease the complexity of the model and yet still be able to keep all variables in the model by approaching the coefficients of the model to zero.

Lasso Regression

The lasso regression is a very similar concept to ridge regression. Contrary to the Ridge method, Lasso uses the L1 penalization method. Moreover, the difference is that Ridge regression keeps all variables in the model. At the same time, Lasso allows extracting some variables outside of the model by allowing some coefficients to equal zero (Richardson et al., 2021).

Elastic Net Regression
Elastic Net is a combination of Ridge and Lasso methods. Thus, Elastic Net can convert some coefficients to zero at the same time method allows shrinkage of some coefficients (Richardson et al., 2021).

Random Forest

This study will employ Random Forest introduced by Breiman (2001), as a more complicated ML model compared to regularization methods. The results of the Ridge, Lasso Elastic Net, and Random Forest will be evaluated. According to their results and forecast accuracies, other possible machine learning methodologies that can be applied are the following: Support Network Machine (SVM), and Neural Networks (NN) and other possible machine learning methods which considered to be suitable for nowcasting.

2. Forecast evaluation methodology
The forecast accuracy of each model will be calculated by the root mean square error (RMSE) and mean absolute error (MAE).

3. Data
The hard and soft indicators of the selected European countries will be collected OECD database, FRED and nation level sources.

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1 Introduction

Many macroeconomic variables published within come certain publication lags, but an economy needs to be evaluated in real-time by policy makers and central banks in order to implement the correct monetary and economic policies (Chernis & Sekkel, 2017; Chernis et al., 2020; Loermann & Maas, 2019; Richardson et al., 2021, Kocenda & Poghosyan, 2020). On the other hand, among these macroeconomic variables, GDP is considered one of the most critical macroeconomic indicators that are required for the implementation of the right policy promptly (Botha et al., 2021, Richardson et al., 2021; Kocenda & Poghosyan, 2020). GDP growth is also considered an essential macroeconomic variable for policy implementations (Kocenda & Poghosyan, 2020). In addition to the fact that GDP is a quarterly variable, it has a publication that varies from country to country. For instance, in the nine countries included in this study, GDP has a publication lag of approximately 1.5 months. Due to this publication lags of GDP, this macroeconomic is not accessible anytime. To deal with the problem of this publication lag, the nowcasting method, which is similar to forecasting but uses only currently available data to forecast the current target variable, is widely used by many researchers and central banks to nowcast GDP growth (Chernis & Sekkel, 2017; Chernis et al., 2020, Richardson et al., 2021). Especially the availability of macroeconomic variables on time has become increasingly important during the Covid-19 pandemic. At the beginning of 2020, with the spread of Covid-19 across the globe, the economy globally has been affected profoundly. Unpredictability and uncertainty have risen in economies as well as macroeconomic variables. It has become remarkable again how important it is to assess economic activity in a timely manner to implement effective monetary and economic policies (Dauphin et al., 2022).

In this study, GDP growth nowcasting was carried out for nine European countries using five different nowcasting methods. These nowcasting methods are selected due to their ability to handle datasets with correlated variables with different frequencies since, due to the nature of economic data, many macroeconomic variables are highly correlated with each other (Dauphin et al., 2022). The dataset was constructed similarly for all nine countries to obtain comparable results. The dataset includes ten hard and 15 soft indicators as explanatory variables, where GDP growth is the target variable. On the other hand, two datasets were obtained for each of the selected countries. These datasets contain the same variables but different periods, and one dataset is 1995Q1-2019Q4, referred to as the pre-covid period in the following sections. The second period includes data between 1995Q1-2022Q3, referred to as the Covid period. The purpose of choosing these two datasets is to compare the effects of the covid-19 period, known as a more volatile period, on the forecasting accuracy of different nowcasting models compared to more stable times such as the pre-covid period. To nowcast GDP growth dynamic factor model introduced by Giannone et al. (2008) is employed in this thesis due to its ability to handle ragged edges and mixed frequency data. The alternative nowcasting models are four different machine learning models, namely as follows: Ridge, Lasso, Elastic Net, and Random Forest.

This study aims to nowcast GDP growth for different European economies with a dynamic factor model and four machine learning models to compare the root mean square error of these nowcasting models. Furthermore, AR(1) is selected as a more straightforward and traditional benchmark model. As stated previously, another aim of this study is to compare the forecasting accuracy of the models for more unstable periods to standard times. Also, this study will examine whether the performance of the nowcasting model will depend on the size of the economy. This study will extend the current literature in two ways: firstly, this study will examine nine different economies and forecast the accuracy of 6 different models, allowing for a more comprehensive study. Secondly, this study will examine two different periods, including covid and pre-covid, which will enrich the current nowcasting literature by including more recent periods that will allow to examine the effect of the more unstable period vs. normal times. The thesis is structured as follows: Chapter 2 presents a literature review related to different mixed-frequency approaches to nowcast. Chapter 3 gives more detailed information on the dataset and country selection used in this study. Chapter 4 presents the methodology of benchmark and nowcasting models, as well as model validation and model tuning of machine learning models. Chapter 5 describes the design of nowcasting and the selection of optimal factors and var lags. In Chapter 6, hypothesis testing and empirical findings of the out-sample period of the selected models are presented. Chapter 7 is the conclusion.

2 Literature Review

The following literature review section will review academic papers primarily conducted on GDP and GDP growth using nowcasting/forecasting methods. Nowcasting and forecasting are new concepts in the literature. Thus, it is worth noting that a considerable number of studies have been published on this subject in recent years. Moreover, many of these articles pointed out different elements and conclusions with their new perspective on this recently developing topic.

One of the most critical problems that GDP affects many policymakers and central banks is its delay (Chernis & Sekkel, 2017; Chernis et al., 2020; Loermann & Maas, 2019; Richardson et al., 2021, Kocenda & Poghosyan, 2020). The publication lag, which varies from country to country, is especially crucial in situations where macroeconomic policies need to be implemented more quickly. To forecast GDP, various macroeconomic variables are used as explanatory variables. However, these explanatory variables have a higher frequency (e.g., monthly, daily), while the target variable has a lower frequency. For this reason, macroeconomic forecasting methods with the ability to deal with mixed frequencies should be preferred. Thus, the literature suggests the most used methodologies to forecast GDP as follows: Bridge Equation Models, Dynamic Factor Models, Mixed-Data Sampling (MIDAS), Bayesian VAR, Mixed-Frequency VAR, and Machine Learning Tools.

2.1 Single Equation Approaches

2.1.1 Bridge Equations

The bridge equation links higher frequency explanatory variables (e.g., monthly) to lower frequency quarterly GDP growth by aggregating to produce short-term forecasts with the following equation:

$$y_t^Q = \mu + \sum_{i=1}^{k} \beta_i^j(L) x_{it}^{jQ} + \varepsilon_t^{jQ}$$

Where y_t^Q is GDP growth, j is the bridge equation, k for the vector of monthly indicators, x_{it}^{jQ} are quarterly aggregates of data, $\beta_i^j(L)x_{it}^{jQ}$ lag polynomial, μ intercept parameter.

The Bridge equation consists of two steps: The first step allows us to transform monthly data into quarterly by forecasting monthly indicators for the rest of the quarter to have quarterly aggregates. In the second step, the results of the first step are used as regressors, and the above equation is used to forecast GDP (Angelini et al., 2008).

The nature of GDP forecast would require a method with the ability to handle mixed-frequency data. Numerous studies used bridge equations to forecasting GDP growth, especially earlier studies in the literature for Canada (Zheng & Rossiter, 2006), Euro area (Angelini et al., 2008; Baffigi et al., 2004; Barhoumi et al., 2008; Diron, 2006; Rünstler & Sedillot, 2003), France (Darne & Charles, 2020), G7 countries (USA, Japan, Germany, France, UK, Italy, and Canada) (Golinelli & Parigi, 2007; Sedillot & Pain, 2003), Italy (Golinelli & Parigi, 2005); the U.S. (Kitchen & Monaco, 2003). On the other hand, Hoover & Perez (1999) and Krolzig & Hendry (2001) used bridge models to select data.

According to Baffigi et al. (2004), the bridge equation is an efficient technique because of its ability to compute earlier predictions of the National Account variables by allowing a combination of them with different short-term indicators. Furthermore, the author considered it as a "nowcast" rather than a forecast since it is able to provide an estimation of "present/now." Darne & Charles (2020) state that including various bridge models in the analysis provides a more precise interpretation of the data, while Bulligan et al. (2010) outline that the power of bridging to monthly data and quarterly GDP growth is crucial, especially in the period of deep and rapid changes to help us to understand the source of the change.

Antipa et al. (2012) compared the bridge and dynamic factor models and concluded that bridge models provide fewer forecast errors compared to dynamic factor models to forecast quarterly German GDP. Bencivelli et al. (2012) also showed that combining the bridge model with the Bayesian model averaging method leads to an improvement. Bridge equations perform better during less volatile periods than the small-scale factor model.

However, bridge equations have advantages and conveniences but suffer from certain limitations. Bridge equations are only can be used with a limited number of predictors as a small model (Angelini et al., 2008; Bencivelli et al., 2012; Diron, 2006; Giannone et al., 2008; Kitchen & Monaco, 2003).

2.1.2 Mixed Data Sampling (MIDAS)

As stated in the bridge equation section, according to Ghysels et al. (2004), bridge equations aggregate monthly data to have the same frequency as the explanatory variables. MIDAS suggests combining different frequency variables as one. According to the authors, MIDAS is defined as a regression of the parameterized reduced form that includes different variables with different sampling periods. The authors showed simple linear MIDAS regression as follows:

$$Y_t = \beta_0 + B\left(L^{1/m}\right)X_t^{(m)} + \varepsilon_t^{(m)}$$

Where Y_t is sampled at a fixed frequency and $X_t^{(m)}$ have different sampling frequencies than Y_t and $B\left(L^{\frac{1}{m}}\right) = \sum_{j=0}^{j max} B(j)L^{j/m}$ is the polynomial length of infinite in the operator $L^{1/m}$ which produces the value of $X_t^{(m)}$ lagged by j / m periods. Ghysels et al. (2004) concluded that MIDAS will result in more efficient estimations compared to other methods that are used to aggregate the series to the lowest frequency. On the other hand, the study pointed out the disadvantages of MIDAS: treatment of long memory, seasonality, fractional co-integration, estimation, and specification errors.

MIDAS has been used in a considerable amount of forecasting studies as a popular alternative approach to estimate low-frequency target variables (e.g., quarterly GDP) by using higher-frequency observed predictors (e.g., monthly) (Ghysels et al., 2004, 2007, 2016), for the U.S. (Andreou et al., 2013; Aastveit et al., 2016; Clements & Galvao, 2008; 2009), Germany (Heinisch & Scheufele, 2018), Euro Area (Duarte, 2014), multiple industrialized countries(the U.S., France, and the UK) (Ferrara et al., 2014), Luxemburg (Marcellino & Sivec, 2021), Singapore (Tsui et al., 2018) and for regional economies such as regions of Germany (Claudio et al., 2020; Kuck & Sweikert, 2020), provincial Canada (Chernis et al., 2020).

Additionally, Foroni et al. (2011) suggested U-MIDAS as an alternative to MIDAS. U-MIDAS differs from MIDAS by using OLS, not NLS (nonlinear least square), and by not restricting the lag polynomials by a fixed functional form. Also, their results showed that U-MIDAS is a suitable method to nowcast/forecast GDP growth because U-MIDAS performs better in cases where the difference between sampling frequencies is not high.

Studies comparing MIDAS with different mixed data models have been frequently published in the literature. Fang et al. (2014) and Kuzin et al. (2011) compared MIDAS and MF-VAR, concluding that MIDAS performs better for shorter periods. Another study is conducted by Ramadani et al. (2021) to compare bayesian

MF VAR and U-MIDAS and found that these two approaches have similar statistical significance. A comparative study by Heinisch & Scheufele (2018) compared DFM and MIDAS with forecast combinations for Germany. Both models have similar prediction abilities and thus provide very limited evidence. Another study by Kuck & Schweikert (2020) found that single-predictor MIDAS is more robust for regional forecasts and outperforms DFM for a regional forecast for Baden-Wurttemberg, Germany.

Banbura et al. (2013) defined single equation approaches as MIDAS and bridge equations as “partial models.” Their study pointed out certain limitations in the literature as the ability to capture only a limited part of nowcasting because these models are not able to capture the flow once the data is published on a quarterly basis. Another problem addressed by authors about these partial models as they do not have a sufficient framework for the change in their impact as the nowcast becomes updated.

2.2 State-Space Approach

Another approach to deal with mixed frequency data is the state-space approach. This approach allows nowcasting using a multivariate dynamic factor model expressed in the state-space form (Banbura et al., 2013). State space models use filtering by extracting hidden states by including latent processes (Ghysels, 2011). The state-space representation allows researchers to have joint models, which are referred to as “joint state spaces.” Banbura et al. (2013) defined the main advantage of these joint models as the ability to link nowcasts to models derived from the news, which consists of statistical data releases. According to the authors, one of the problems arising in the nowcasting literature is “ragged/jagged edge” due to the publication lags and the difference between the last observation available in the series due to these lags. The state space approach allows using Kalman filtering to deal with this “ragged/jagged edge” problem due to its ability to handle missing data in the series.

2.2.1 Mixed- Frequency VAR (MF-VAR)

MF VAR models are considered another approach with the ability to handle mixed-frequency data. This approach is widely used in the recent literature to extract information from data releases with different publication frequencies, and as a state space approach, it allows for analysis jointly. According to Foroni & Marcellino (2013) and Sims (1980), MF VAR is able to characterize co-movements in macroeconomics. It is represented by the following equation by Mariano & Murasawa (2010):

$$s_{t_m} = \begin{pmatrix} z_{t_m} \\ \vdots \\ z_{t_m-4} \end{pmatrix}$$

$$s_{t_m} = Fs_{t_m-1} + Gv_{t_m}$$

$$\begin{pmatrix} y_{tm} - \mu_y \\ x_{t_m} - \mu_x \end{pmatrix} = HS_{t_m}$$

s_{t_m} is a monthly state variable where $z_{t_m} = \begin{pmatrix} y^*_{t_m} - \mu^*{}_y \\ x_{t_m} - \mu_x \end{pmatrix}$, tm is the latent month-on-month where unobserved GDP growth is equal to $y^*_{t_m}$and monthly indicator is equal to x_{t_m}, $\mu_y = 3\mu^*_y$ and $v_{t_m} \sim N(0, I_2)$. more overly, Mariano and Murasawa (2010) indicate that even though the data has missing observations, maximum-likelihood (MLE) techniques can be used to estimate the state space model. Estimation can be done using MLE with EM in addition to MLE.

Various studies used the mixed-frequency VAR method to nowcast GDP (Foroni & Marcellino, 2013; Botha et al., 2021; Fang et al., 2014; Ramadani et al., 2021). Similarly, Mittnik & Zadrozny (2004) forecasted German GDP with the Kalman filtering method and used VAR (2) models for monthly and quarterly to estimate quarterly GDP. Furthermore, they conclude that monthly models provide better results for short-term forecasts while quarterly models overperform in long-term GDP forecasts. Another study conducted by Kuzin et al. (2011) compared MIDAS to MF-VAR. Authors claimed that MF-VAR is not only able to GDP but also the indicator. On the other hand, authors argued MF-VAR as follows: Higher frequency information can increase the performance of MIDAS. In contrast, higher frequency data (e.g., daily) would increase the complexity of MF-VAR. More overly, MF-VAR suffers more from dimensionality problems. In some cases, MF-VAR is expected to perform better than MIDAS. Nevertheless, their study provides limited evidence about whether MIDAS or MF-VAR should be chosen over each other.

As used in MIDAS, bayesian techniques used with Mixed frequency VAR often appear in the recent literature as an alternative approach to classical Mixed frequency VAR models. Chiu et al. (2011) developed a Bayesian estimation of mixed frequency-VAR to create alternative draws for the unknown parameters and unobservable data. Moreover, the authors criticized MF VAR with Kalman filtering due to its inability to handle unobservable data at different frequencies. On the other hand, the Bayesian method is able to deal with multiple irregular missing series compared to Kalman filtering. In addition to this, as previously argued, MF-VAR suffers from dimensionality. In order to deal with the problem of the high dimensionality of parameter spaces, Schorfheide & Song (2011) suggest MF-VAR equipped with Minnesota prior and estimated with the Bayesian method. According to the authors, the main advantage of using monthly information in VAR models to nowcast GDP is that these VAR models allow tracking the economy closer in real-time. On the other hand, authors also described Bayesian MF-VAR with Minnesota prior and Bayesian methods as a helpful tool to deal with the problem of parameter space dimensionality. Bayesian MF-VAR is a combination of prior distribution and likelihood function and is shown by the authors as the following equation of VAR form:

$$z_t = F_1(\Phi) z_{t-1} + F_c(\Phi) + v_t \qquad v_t \sim iid\ N\ (0, \Omega(\Sigma))$$

$$y_t = M_t \wedge_z z_t$$

Where M_t is a sequence of matrices that makes the selection of the time t variables observed in period T. They use Minnesota prior for shrinking the VAR coefficients toward a random walk by mixing dummy observations into the sample estimation. These dummy variables allow authors to generate correlations between VAR parameters. Also, they conclude that monthly information significantly improves forecast performance for the short-term forecasting quarter. However, they conclude that monthly information provides no advantages for longer-term horizons such as one or two years.

2.2.2 Factor MIDAS

Factor MIDAS uses factor estimation methods for unbalanced datasets. These datasets are considered unbalanced due to their publication lags. Factor MIDAS is considered an appropriate approach that can be used in forecasting and nowcasting studies to estimate GDP by using variables with a higher frequency than the target variable (e.g., GDP) (Marcellino & Schumacher, 2010; Gul & Kazdal, 2021; Kim & Swanson 2017). As discussed in the MIDAS section above, MIDAS combines variables with different frequencies using a single equation. Thus, it is specified as a partial model in the literature. Factor MIDAS works with estimated factors instead of using regressors from a single or relatively small group of macroeconomic indicators to forecast. Factor MIDAS combines classical MIDAS and factor estimation approaches (Marcellino & Schumacher, 2010). Thus, it would be correct to classify Factor MIDAS as a state space approach than other factor models because of the factor estimation used by factor MIDAS. Marcellino & Schumacher (2010) introduced the basic Factor MIDAS equation as an extension to MIDAS approach by the following equation:

$$y_{t_q} + h_q = y_{t_m} + h_m = \beta_0 + \beta_1 b(L_m, \theta)\hat{f}^{(3)}_{t_m+w} + \epsilon_{t_m} + h_m$$

Forecast horizon is $h_q = h_m$ /three and where polynomial $b(L_{m,}\theta)$ is equal to exponential Almon lag with $b(L_m, \theta) = \sum_{k=0}^{K} c(k, \theta)\, L_m^k$. And factor $(\hat{f}^{(3)}_{t_m+w})$ and its monthly lags are related to the quarterly variable $(y_{t_q} + h_q)$ directly. One of the problems arising from forecasting GDP is ragged/jagged edge data due to the missing data at the end of the sample. To overcome this problem, the authors used different factor estimation methods: Vertical alignment DPCA (VA-DPCA), EM algorithm with Principal Component Analysis (EM-PCA), and state space model Kalman filter estimator of the factors (KFS-PCA). These methods were chosen due to their ability to deal with ragged data. The authors conclude that the choice of factor estimation method provides insufficient evidence on which method performs better. However, Factor MIDAS can exploit information from large data sets of indicators. Thus, It can easily overcome the problem of small models such as Bridge Equations.

2.2.3 Dynamic Factor Model (DFM)

In addition to state space approaches such as MF-VAR and Factor MIDAS, the dynamic factor model, another estimation method frequently encountered in the literature, is widely used by researchers and central banks to forecast macroeconomic variables. Numerous studies applied the dynamic factor model to forecast GDP for different economies such as Luxemburg (Marcellino & Sivec, 2021), Armenia (Poghosyan & Poghosyan, 2021), the Euro Area (Proietti & Giovanneli, 2021; Jansen et al., 2016), New Zealand (Richardson et al., 2021), China (Jiang et al., 2017), Slovakia (Toth, 2017), Turkiye (Soybilgen & Yazgan, 2017), and Portugal (Dias et al., 2015). Dynamic Factor Model, which was introduced by Giannone et al. (2008) to forecast/nowcast GDP popularly used among empirical papers for different countries and regions such as South Africa (Botha et al., 2021), the US (Soybilgen & Yazgan, 2021), multiple European Countries (Austria, Hungary, Ireland, Malta, Poland, Portugal) (Dauphin et al., 2022), Baden-Württemberg, Germany (Kuck & Schweikert, 2020), Old and new European Countries (Kocenda & Poghosyan, 2020), Canada (Chernis & Sekkel, 2017), provinces of Canada (Chernis et al., 2020), the US (Loermann & Maas, 2019; Camacho and Martinez-Martin, 2014; Longo et al., 2022), Germany (Heinisch & Scheufele, 2018), Mexico (Caruso, 2018), BRIC countries (Brazil, Russia, India, China) and Mexico (Dahlhaus et al., 2015), Czech Republic (Rusnak, 2013), China (Yui & Chow, 2011).

Giannone et al. (2008) suggested using a two-step estimator applied by Doz et al. (2011), where their two-step estimator combines Kalman filtering techniques with principal components. The authors apply Kalman filtering to extract the common factors. Doz et al. (2011) showed the dynamic factor models as the following:

$$X_t = \Lambda_0^* F_t + \xi_t$$

Where Λ_0^* is the n x r matrix of factor loadings, F_t are common factors, ξ_t is an idiosyncratic component.

Botha et al. (2021) conclude that DFM performs better to extrapolate the direction of GDP growth for the future. Similarly, according to Chernis & Sekkel (2017), DFM outperforms MIDAS and Bridge models before the first publication of monthly GDP. They obtain similar results, and the DFM is more accurate than MIDAS and Bridge for the second month of the quarter. Various studies have shown that dynamic factor models perform well concerning forecasting accuracy (Heinisch & Schuefele, 2018; Dauphin et al., 2022). Moreover, a comparative study by Chernis et al. (2020) concludes that the dynamic factors model performs comparably to the MIDAS model. Also, their obtained results showed that DFM outperforms traditional benchmark models.

Similarly, Dauphin et al. (2022) conclude that the dynamic factors model outperforms traditional benchmark models such as AR (1). On the other hand, they have shown that DFM performs better during stable times, while other approaches, such as machine learning models, might be considered more suitable during crisis periods. On the contrary, Kuck & Schweikert (2020) found that simple MIDAS performs better compared to the dynamic factor model for Baden-Württemberg. However, it should not be forgotten that Baden-Wüttemberg is not a country but a regional economy. The forecast performance of different models may differ according to the country and the size of the economy. Rusnak (2013) used the DFM model to forecast a relatively small economy like the Czech Republic.

Moreover, he concludes that dynamic factor models perform well in terms of the ability to make forecasts six quarters ahead. Thus, it can be concluded that DFM is a suitable forecasting tool for longer horizons. Another advantage of DFM that the author claims is its ability to use the latest available data. Another paper by Dahlhaus et al. (2015) concludes that a dynamic factor model is an appropriate tool to nowcast GDP Growth of relatively small, emerging economies. Another result that they show is that DFM performs accurate results during the crisis period. Botha et al. (2021). Caruso (2018) compared their DFM results with the institutional forecasts of the IMF. Their conclusions about DFM are similar results to previous studies, and the dynamic factor model is able to perform good forecast accuracy. Further sections will cover the dynamic factor model methodology in more detail.

2.3 Machine Learning Methods (ML methods)

Machine learning is another method that has become popular, especially in recent years, and is still developing. However, machine learning methodologies appear in different fields. It is frequently encountered in forecasting and nowcasting studies, which have been published relatively recently. However, a specific ML method for nowcasting studies does not come to the forefront compared to others in the literature. The results of studies that include and compare different machine learning methods to nowcast GDP for different sized economies and countries are promising. Dauphin et al. (2022) list the advantages of using machine learning as follows: Because ML methods are much better than other traditional methods in capturing patterns in data, they are able to provide much better forecast performance than traditional methods. At the same time, one of the most essential features of the machine learning method to become so widespread and popular is that it is able to limit overfitting. Lastly, ML methods divide datasets into testing and training samples (Dauphin et al., 2022). This method trains testing samples and aims to have as low a forecast error as possible.

For these reasons, different machine learning methods are used in nowcasting studies, such as Lasso, Ridge, ElasticNet, Support Vector Machine (SVM), Random Forest (RF), and Neural Networks (NN). Ridge, Lasso, and Elastic Net are called regularization techniques. Furthermore, these techniques have only minor differences. These methods decrease the complexity of data for the models with many features (Richardson et al., 2021). Several studies have used Lasso, Ridge, and Elastic Net as their selected machine learning method to nowcast GDP, for New Zeland (Richardson et al., 2021), for multiple countries (Austria, Hungary, Ireland, Malta, Poland, and Portugal) (Dauphin et al., 2022). While Few studies applied only LASSO for South

Africa (Botha et al., 2021) and the US (Babii et al., 2021). Additionally, several studies adopted different additional ML approaches such as support vector machines (SVM) (Dauphin et al., 2022), Random Forest (Soybilgen & Yazgan, 2021; Marcellino & Sivec, 2021; Yoon, 2020), gradient boosting (Richardson et al., 2021; Yoon, 2020), neural networks (Loermann & Maas, 2019; Tkacz, 2001; Longo et al., 2022). Studies showed that ML outperforms DFM and other traditional methods (Richardson et al., 2021; Babii et al., 2022; Loermann & Maas, 2019), while Dauphin et al. (2022) and Longo et al. (2022) conclude that ML methods are better to capture turning points in data. Thus, it can be concluded that machine learning techniques are an appropriate method to nowcast/forecast different economies. However, the suitable ML methods will depend on the data and selected periods. Therefore, many studies employed not only multiple selected ML applications to enable the comparisons. In the later sections of this study, the selected machine-learning methods will be presented and discussed more elaborately.

3 Data

The importance of the methodology chosen in the nowcasting studies was emphasized earlier. Another crucial issue as important as methodology is the selection of the variables to have accurate forecasts, especially for the nowcasting papers. For instance, the RMSE values of nowcasting studies conducted in similar periods for the same countries may differ due to the inclusion of different variables in the dataset. For this reason, the variables used in this study are selected based on the variables suggested and successfully employed by the current literature for the nowcasting studies. As stated in the literature review chapter, nowcasting studies are used as an estimation tool that has become very popular, especially by the central banks of the countries. Although it is a very popular topic among academics since the central banks broadly use this method, nowcasting studies primarily focus on single countries. Considering the literature, the nowcasting paper published by Kocenda & Poghosyan (2020) comes to the fore among the nowcasting studies focusing on multiple countries and comparing a broad range of nowcasting and short-term forecasting methods.

This study will employ a dataset containing a similar set of hard and soft indicators suggested by Kocenda & Poghosyan (2020) in their recently published study, including the periods between 1995Q1 and 2018Q4. However, the covid-19 period, which has taken place in the recent past, has affected the world on a global scale and is not included in the study of the authors. First, the presenting study will extend the current literature by suggesting implementing different machine learning methods, which will be discussed in the methodology chapter. In addition to extending the methodology, this study will enrich the dataset from the period between 1995Q1 and 2022Q3, including the effects of the Covid-19 pandemic. The expanded dataset, including Covid-19, will allow observing the performance of the same selection of DFM and machine learning models to be evaluated during highly volatile periods.

On the other hand, this study aims to compare the performance of the selected methods where the volatility of macroeconomic indicators does exist. For such a comparison to be possible, the study will employ another dataset with the same variables. The second dataset, “pre-covid,” will only include the period until 2019Q4 to cover the period before Covid-19. The pre-covid period will allow the performance of DFM and machine learning models to be evaluated in macroeconomically more stable periods. Thus, these two different datasets will contribute to the literature by comparing the performances of different models for different-sized countries with more stable and unstable periods. The further chapters will provide more detailed information regarding the covered period for each selected country.

Hard indicators mainly consist of the production of different sectors, such as the manufacturing industry, total industry, energy, and construction. Also, the hard indicators include the number of registered cars, dwelling permits, and monthly growth of exports and imports. Soft indicators consist of surveys of consumer opinion and surveys of business tendencies. The detailed description and selection of hard and soft indicators are presented in Table 1 and

Table 2. All hard and soft indicators are collected at a monthly frequency from OECD. As shown in

Table 2, soft indicators include business surveys, and the current literature suggests that the inclusion of business surveys in the data set positively impacts the results and performance of nowcasting studies. Lahiri & Monokroussos (2013), who studied the role and the importance of surveys of the Insitute for Supply Management (ISM) in the U.S., concluded that ISM business surveys are leading to an increase in the performance of nowcasting.

Similarly, Chernis & Sekkel (2017) findings show that ISM business surveys are an essential element of nowcasting. For this reason, it is believed that the inclusion of business surveys as soft indicators in this study will be expected to positively affect the results of the GDP nowcasts for different European countries. Another advantage of soft indicators is that they do not have a publication lag because survey data, as the name suggests, are collected through surveys. Unlike hard indicators, data from business surveys and consumer opinions are available at the end of the current month. The data of the hard indicators in the reference month and the previous month is not available due to the 45 days of publication lag of hard indicators shown in Table 1.

In addition to 10 hard and 15 soft indicators, another data included in the dataset is quarterly GDP data. Similar to hard and soft indicators, quarterly GDP data is collected from OECD data. Considering the given dataset, linking lower frequency (e.g., quarterly GDP) and higher frequency variables (such as hard and soft indicators) will be presented and discussed in more detail in chapter 4 and chapter 5. The collected real GDP data assumes constant prices. Thus, real GDP is at the national currency level.

Table 1: Description of Hard Indicators

Symbol	Description of Hard Indicators	Frequency
PRMNTO01	Production in Total Manufacturing s.a., Index, 2015 = 100	Monthly
PRINTO01	Production of total industry s.a., Index, 2015 = 100	Monthly
PREND401	Production of electricity, gas, steam, and air conditioning supply s.a., Index, 2015 = 100	Monthly
PRCNTO01	Production of total construction s.a., Index, 2015 = 100	Monthly
SLRTTO01	Total retail trade (Volume) s.a., Index, 2015 = 100	Monthly
SLRTCR03	Passenger car registrations s.a., Index, 2015 = 100	Monthly
WSCNDW01	Work started for dwellings s.a., Index, 2015 = 100	Monthly
XTIMVA01	Imports in goods, s.a., growth previous period	Monthly
XTEXVA01	Exports in goods, s.a., growth previous period	Monthly
ODCNPI03	Permits issued for dwellings s.a., Index, 2015=100	Monthly

Source: OECD Data

Another point to be noted about GDP data is that two different methods stand out regarding how the GDP variable will be used in nowcasting studies. Because the GDP data is subject to two revisions before the final GDP value is published, due to these revisions, there are generally two prominent uses regarding the way the GDP variable is included in the dataset. One of these methods is to use data vintages that take revisions into account (Soybilgen & Yazgan, 2021; Kuck & Sweikert, 2020; Rusnak, 2013). Another alternative suggested in the literature is to use only the second revision of GDP while not considering the previous revisions (Chernis et al., 2020; Kocenda & Poghosyan, 2020).

Studies that only used second revisions were able to obtain successful forecast accuracy of nowcasting. Consequently, the presented study considers only the second revisions of GDP, and other revisions are ignored due to the limited access to information on previous revisions. Thus, only the final revision figures are taken into account for GDP data.

Table 2: Description of Soft Indicators

Symbol	Description of Soft Indicators	Frequency
BSPRTE	Manufacturing, production tendency, balance s.a.	Monthly
BSPRFT	Manufacturing, production future tendency, balance s.a.	Monthly
BSEMFT	Manufacturing, employment future tendency, balance s.a.	Monthly
BSCI	Manufacturing, confidence indicators, balance s.a.	Monthly
BCEMFT	Construction, business situation, activity, future tendency, balance s.a.	Monthly
BCCI	Construction, confidence indicators, balance s.a.	Monthly
BCBUTE	Construction, business situation, activity, tendency, balance s.a.	Monthly
BRBUTE	Retail Trade, business situation, activity, tendency, balance s.a.	Monthly
BRBUFT	Retail Trade, business situation, activity, future tendency, balance s.a.	Monthly
BRCI	Retail Trade, confidence indicators, balance s.a.	Monthly
BREMFT	Retail Trade, employment future tendency, balance s.a.	Monthly
BVBUTE	Services (excl. retail trade), business situation, activity, tendency, balance s.a.	Monthly
BVCI	Services (excl. retail trade), confidence indicators, balance s.a.	Monthly
BVEMFT	Services (excl. retail trade), employment future tendency, balance s.a.	Monthly
BVEMTE	Services (excl. retail trade), employment tendency, balance s.a.	Monthly

Source: OECD Data

"Another factor taken into account when selecting the data and number of variables in this study is that models with a moderate number of variables (e.g., between 10 and 30) perform similarly to models with a larger number of variables (e.g., more than 100)." (Alvarez et al., 2016). When the results found by Alvarez et al. (2016) are compared to a number of variables obtained in this study, a total of 26 variables is expected to perform well for the scope of this nowcasting study.

Table 3: Description of Soft Indicators per Country

	Belgium	Czech Republic	Denmark	Finland	France	Hungary	Italy	Portugal	Slovenia
Exports	X	X	X	X	X	X	X	X	X
Imports	X	X	X	X	X	X	X	X	X
Construction Future Tendency	X	X	X	X	X	X	X	X	X
Construction Conf. Indicator	X	X	X	X	X	X	X	X	X
Construction Tendency	X	X	X	X	X	X	X	X	X
Retail Trade Future Tendency	X	X	X	X	X	X	X	X	X
Retail Trade Tendency	X	X	X	X	X	X	X	X	X
Retail Trade Conf. Indicators	X	X	X	X	X	X	X	X	X
Retail Trade Employment Future Tendency	X	X	X	X	X	X	X	X	X
Manufacturing Conf. Indicators	X	X	X	X	X	X	X	X	X
Manufacturing Employment Future Tendency	X	X	X	X	X	X	X	X	X
Manufacturing Future Tendency	X	X	X	X	X	X	X	X	X
Manufacturing Tendency	X	X	X	X	X	X	X	X	X
Services Tendency	X			X	X		X	X	X
Services Future Tendency	X			X	X		X	X	X
Services Employment Future Tendency	X			X	X		X	X	X
Services Employment Tendency	X			X	X		X	X	X
Dwelling Permits	X			X	X			X	
Total Construction Production		X		X	X	X	X		X
Energy Production		X		X	X	X	X		X
Total Industry Production	X	X	X	X	X	X	X	X	X
Total Manufacturing Production	X	X	X	X	X	X	X	X	X
Registered Cars	X		X						X
Total Retail Trade	X	X	X	X	X	X	X	X	X
Start of dwellings			X						

Source: OECD Data

As mentioned in the literature section, current literature has a particular constraint about comparative nowcasting studies on multiple countries. As previously stated, this study aims to obtain an accurate nowcast for different sizes of economies for volatile and less volatile periods. Thus, including several countries is one of the critical elements to enrich the results and build a comparative study. The list of selected European countries that have been included in this study is as follows: Belgium, Czech Republic, Denmark, Finland, France, Hungary, Italy, Portugal, and Slovenia. However, since several countries will be included, the accessibility of the data varies from country to country. Therefore, a more detailed data description of each country will be provided in Table 3. In addition to the variety of data, the periods of the dataset will as well vary by country. The selected periods for both pre-covid and covid periods will be provided for each country will be given in Appendix A.

4 Methodology

4.1 Benchmark Models

Simpler models are frequently used in the literature as benchmark models to measure and compare the performance of more complex and advanced models such as machine learning.

As a benchmark, this study uses the autoregressive model (AR) of order 1 in order to make comparisons.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + u_t$$

Where y_t is quarterly GDP growth, α_0, $\alpha_1$and, α_2 stands for parameters, and the residual term is shown as u_t

4.2 Dynamic Factor Model

This study follows the DFM methodology for nowcasting, which has been introduced by Giannone et al. (2008). The dynamic factor model is illustrated in more detail with the following notation to obtain the factor structure for monthly indicators and stationary (unobserved) variables.

$$x_t = \mu + \lambda_{i1} f_{1,t} + .. + \lambda_{ir} f_{r,t} + \epsilon_{it} \text{ , i =<1,…,n}$$

The above equation can be rewritten as follows:

$$x_t = \mu + \Lambda f_t + \epsilon_t$$

x_t is a vector of standardized stationary monthly variables, f_t and *r* unobserved common factors with unit variance and the mean value of zero. Where Λ is n x r the factor loadings and ϵ_t is a vector of idiosyncratic dimension N component modeled as AR (1) process, uncorrelated with f_t at any leads and lags. Giannone et al. (2008) have made two important assumptions for the above model. The first is assuming that GDP, which enables the use of common factors, is not dependent on variable-specific dynamics. In addition, the other assumption is that monthly indicators and GDP are jointly normal.

As stated in the earlier sections, nowcasting is the process of estimating less frequently published data, such as quarterly GDP, based on present data, including higher frequency indicators (such as daily and monthly variables). Generally, when considering the nowcasting method by its nature, datasets with different publication frequencies, so-called mixed-frequency datasets, are used. One of the challenges frequently encountered in the literature for nowcasting is the ragged edge or jagged edge problem (Giannone et al., 2008; Kocenda & Poghosyan, 2020). The missing observations at the end of the sample period are called jagged edges in the literature (Kocenda & Poghosyan, 2020). Especially in the nowcasting studies, the jagged edge problem is encountered frequently because many variables with different publication dates are used together to accurately predict macroeconomic data.

Nevertheless, some variables are publicly available in the current quarter. On the contrary, some of the variables with more publication lags are accessible in the later months of the current quarter or might be unavailable during the quarter due to the lag in their publication. Thus, this will lead to missing variables at the end of the quarter, which is called a ragged or jagged edge problem. E.g., the dataset has been used in this study of hard and soft indicators. As already discussed in the data section. The soft indicators consist of business surveys available at the beginning of the month.

On the other hand, the selected hard indicators have approximately 45 days of publication lags, depending on the country. Therefore, the jagged edge problem will also be encountered in this study.

For this reason, when the methodologies that may be suitable for this study are evaluated, the dynamic factor method introduced by Giannone et al. (2008) is selected as an appropriate methodology for the presented dataset. Because the chosen methodology to cope with the jagged edge problem will have an important role. To deal with the jagged edge problem, Giannone et al. (2008) suggested a two-step estimator to extract dynamic factors introduced by Doz et al. (2011). The suggested procedure to extract common factors will be explained in more detail in the next section.

4.2.1 Extracting Common Factors

Common factors can be found by applying principal component analysis. However, there should be no missing observation in the used dataset for applying PCA. As discussed earlier, the datasets used are unbalanced by the nature of economic forecasting. Considering the ragged/jagged edge problem of the dataset two-step procedure with Kalman filtering is found to be a more suitable approach to extracting common factors (Kocenda & Poghosyan, 2020). Because one of the main highlights of the two-step estimator approach is that it can cope with the jagged edge problem, another alternative approach suggested by the literature to a two-step estimator with Kalman Filtering is the expectation-maximization (EM) method. EM uses maximum likelihood to estimate, and this method can deal with any pattern of missing observation, not only the ragged edge. However, the unbalanced part of the dataset is only at the end of the sample period. Therefore, a two-step procedure with Kalman filtering is selected as a suitable method to handle the nature of the dataset.

4.2.2 Two-step procedure with Kalman Filtering

The dynamic factor model in state-space form has the following representation by Doz et al. (2011).

$$x_{t_m} = \Lambda f_{t_m} + \xi_{t_m}; \quad \xi_{t_m} \sim \mathbb{N}(0, \textstyle\sum_{\epsilon_{t_m}})$$

Where f_{t_m} is common factors, Λ represents the matrix of factor loadings and ξ_t shows idiosyncratic factors, where f_{t_m}, ξ_{t_m} and x_{t_m} are stationary processes. The model needs to have a state-space form in order to be able to apply the two-step procedure with the Kalman filter.

Soybilgen & Yazgan (2017) shows the unobserved common factors that follow the vector autoregression process (VAR) as in the following notation.

$$f_{t_m} = \sum_{i=1}^{p} A_i f_{t_{m-\mathrm{i}}} + B\eta_t; \quad \eta_{t_m} \sim \mathbb{N}(0, I_q)$$

According to authors state that the two-step procedure for estimating the model's factors is used to estimate the factors when the model's parameters are unknown. The two-step procedure is explained in detailed as follows:

- In the first step, estimators of parameters and estimators of the factors ($\tilde{f}_{t_m}$) are calculated by using principal component analysis (PCA)

The following principal component analysis will be discussed to better understand the application of the DFM method. PCA is defined as a data reduction technique that has been successfully used in numerous studies. "The PCA method transforms the correlated variables into uncorrelated variables by converting to the principal components." (Adler and Golany, 2001). One of the advantages of this method is that it allows extracting information from the set of used variables, and by using the components, PCA avoids multicollinearity (Lafi & Kaneene, 1992). PCA is constructed by the weights that maximize the variance of each component while keeping the components uncorrelated (Jolliffe & Cadima, 2016).

On the other hand, it should be noted that the PCA method can only handle the balanced data part of data (Soybilgen & Yazgan, 2021). Thus, the missing observations or ragged edges of the dataset are disregarded during the application of principal component analysis. As discussed in the previous data part, the dataset of this study suffers from a jagged edge problem. "The dynamics of the model can be estimated through the application of weighted regressions in order to utilize the cross-sectional heteroscedasticity of the idiosyncratic components, and the dynamics of the factors can be obtained through Kalman smoother." (Doz et al., 2011). This Kalman method is considered useful for handling the unbalanced part of the data (Soybilgen & Yazgan, 2021).

- "The second step is the step in time where the Kalman smoother is applied, and the PCA replaces true values of parameters estimates that have been calculated in the first step. Moreover, preliminary estimates of factors are used to compute the dynamics of the factors. The estimated parameters from the first step are projected onto the observations." (Doz et al., 2011)

There are two specific cases where the Kalman filter can be used to obtain dynamics of the common factors are shown and explained by Doz et al. (2011) as follows:

$$\Omega_0^{R3} = \{\Lambda_0, A_0(L), \sqrt{\psi_0} I_n\}$$

$$\Omega_0^{R4} = \{\Lambda_0, A_0(L), \Psi_{0d}^{1/2}\}$$

Furthermore, the state space form of the model is denoted as:

$$X_t = (\Lambda_0\ 0 \ldots 0)\begin{pmatrix} G_t \\ G_{t-1} \\ \vdots \\ G_{t-p+1} \end{pmatrix} + \xi_t$$

The covariance matrix of ξ_t should be equal to the $\sqrt{\psi_0} I_n$ and $\Psi_{0d}^{1/2}$ for both Ω_0^{R4} and Ω_0^{R3} equations. Moreover, both Kalman smoother computes the following equation whereas R = R3 or R4:

$$G_{t/T,R} = Proj\Omega_0[G_t | X_s, s \leq T]$$

The Kalman smoother is calculated iteratively for each t.

4.2.3 Linking monthly factors to quarterly GDP growth rates

As stated in the data section, the dataset used in this study consists of 25 hard and soft indicators. These hard and soft indicators are published monthly, where the target variable of the study, GDP, is published at a lower frequency (e.g., quarterly). Therefore, the target and explanatory variables of this thesis have different frequencies. In order to link higher frequency variables to lower frequency variables, the extracted common factors, described in the previous section extraction section, are used as explanatory variables in the simple OLS in order to nowcast GDP.

$$\hat{y}_{t_q} = \alpha + \beta \hat{f}_{t_q}$$

$\hat{f}_{t_q}$ stands for quarterly aggregations of f_{t_m}. In the further sections, the application of the nowcasting method and linking the different frequency methods will be discussed in more detail in Chapter 5.

4.3 Machine Learning Models

4.3.1 Ridge Regression

Ridge regression is a regularisation technique, also called the shrinkage method, together with Lasso and Elastic Net, and is represented by the following form.

$$\beta_{Ridge} = argmin \left[\sum_{i=1}^{l} (y_i - \beta_O - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right]$$

λ is a hyperparameter, also called as tuning parameter. The first part of the regression shown above is similar to the OLS. However, in the part where the lambda coefficient is located, the adjustment parameter allows penalizing the betas obtained from the first part of the equation. The penalty L2 regularisation where the Ridge method is used is called regularisation. These L2 regularization coefficients square how many beta parameters the regression has and multiply them by lambda for tuning (Richardson et al., 2021). As a result of this penalty process, the method continues to keep the variables in the model. However, penalization makes the coefficients of these variables less effective by approaching them as zero. Finding a suitable value for the lambda value is provided by cross-validation. Although the Ridge method is very similar to OLS, it is expected to achieve better results than OLS due to its penalization method. Especially this method is found to be more effective since because it reduces dimensionality problems where models have more variables or within models that include more correlated variables.

4.3.2 Lasso Regression

As stated previously, the lasso, which is similar to the ridge method, is shown as follows:

$$\beta_{Lasso} = argmin\left[\sum_{i=1}^{l}(y_i - \beta_O - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda\sum_{j=1}^{p}\left|\beta_j\right|\right]$$

As can be seen, when comparing the ridge and lasso equations, the only difference between the two methods is that Ridge uses L2 regularization, while lasso uses L1 regularization. As mentioned in the L2 method, the penalty is squared; in the L1 method, the absolute values of the penalty coefficients are taken. Another difference between Lasso and Ridge was that the coefficients in the Ridge regression approached zero. Therefore, all the variables were still kept in the model. In Lasso, depending on the size of the lambda hyperparameter, some coefficients are approached to zero, while some coefficients are converted to zero. Thus, Lasso regression allows some variables to be extracted from the model by its penalty method (Richardson et al., 2021).

4.3.3 Elastic Net Regression

The third and last regularization method, the Elastic Net is described as follows:

$$\beta_{Ridge} = argmin\left[\sum_{i=1}^{l}(y_i - \beta_O - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda\sum_{j=1}^{p}(1-\alpha)\beta_j^2 + (\alpha)\left|\beta_j\right|\right]$$

As can be seen from the above formulation, Elastic Net is a combination of Ridge and Lasso methods. In other words, the method combines of L1 and L2 regularizations. Therefore, Elastic Net can convert some coefficients to zero and shrink some coefficients (Richardson et al., 2021). Elastic Net has an alpha parameter that is not found in Ridge and Lasso. The user determines the selection of this parameter, similar to the selection of the lambda parameter in the Ridge and Lasso methods, and the most appropriate parameter is again selected by the cross-validation method.

4.3.4 Random Forest

The Random Forest method, one of the tree-based machine learning methods, was first found in the literature by Breiman (2001). However, the Random Forest method has emerged as a result of the combination of two different methods in the literature for Random Forest. One of these methods is called bagging, also known as bootstrap aggregating, which was introduced by Breiman (1996). The other method used is the Random subspace method which was introduced by Ho (1998).

In simpler terms, the logic applied in the bootstrap method is to create a tree by selecting random samples from our dataset. Then, these selected samples are returned to the dataset, and a tree is obtained again by randomly selecting new samples. Bootstrapping continues to create trees by creating different observation clusters so that the randomly selected number of n observations is less than the number of observations of the dataset (Breiman, 1996). The random subspace method follows the same method in terms of randomization logic. Random subspace randomizes the selected variables (Ho, 1998), while bootstrapping randomizes observations. The random subspace method occurs by randomly choosing the variables that are found to be more informative among all the variables.

Random Forests are formed by the bootstrapped aggregating of decision trees (Soybilgen & Yazgan, 2021), and decision trees are shown with the following notation (Hastie et al., 2009; Soybilgen & Yazgan, 2021):

$$g(f) = \sum_{m=1}^{M} c_m \mathbb{1}(f \in R_m)$$

Where R_m stands for the M regions split of feature space, and f is denoted as the factors used in the model. The indicator function, which results in 1 when the arguments are true and 0 when they are false, is shown as follows$\mathbb{1}$. The optimal estimator is chosen as one that minimizes RSS.

The Random Forest method summarized by Hastie et al. (2009) and Soybilgen & Yazgan (2021) as the following:

Firstly, the number of bootstrapped training sets denoted as B is obtained from the dataset. However, it should be noted that the random selection of variables is also considered in this data split, as described above. Therefore, this approach reduces the variance and avoids overfitting problems compared to decision trees. As a second step, the bootstrapped data is used to estimate a regression tree by using the randomized factors. The best split is determined when n_{min} (the minimum node size) is attained for each terminal node of the decision tree. As a final step, these first two operations are reiterated as many times as the number of bootstrapped training datasets. Thus, B decision trees are obtained using the described method. However, estimation is obtained by taking the average of these bootstrapped decision trees where predictions are required to obtain our target variable, quarterly GDP, for this study. The averaging of B decision trees is shown as the following notation (Soybilgen & Yazgan, 2021):

$$\hat{y}_{t_g+h_q|t_q} = \frac{1}{B}\sum_{b=1}^{B} \hat{g}_{RF}^{(b)}\left(\hat{f}_{t_q+h_q|t_m}\right)$$

Furthermore, estimation is obtained through the following notation:

$$\hat{y}_{t_g+h_q|t_q} = \frac{1}{B}\sum_{b=1}^{B} \hat{g}_{BG}^{(b)}\left(\hat{f}_{t_q+h_q|t_m}\right)$$

Where m is the number of factors in RF and $\hat{g}_{RF}^{(b)}(\hat{f})$ is denoted as the obtained bootstrapped decision trees and $\hat{g}_{RF}^{(b)}(f)$ is the estimated regression tree that is described in the second step.

4.3.5 Model Validation and Tuning

In machine learning studies, different model validation methods are recommended in the literature, such as train/test split, cross-validation, rolling window, and expanding window. However, due to the nature of the time series dataset, other approaches come to the fore in the literature instead of separating the dataset only as train and test split. Due to the nature of time series and nowcasting studies, the normal test/train split is chosen to be the less appropriate method. Therefore, in order to avoid overfitting problems, the train/test split is done by using expanding estimation window as applied by several studies (Soybilgen & Yazgan, 2017; 2021).

Since this study was conducted by using a similar dataset and selection of countries to Kocenda & Poghosyan (2020), another reason for choosing the recursive method is that authors applied a similar expanding estimation window approach during their nowcasting design process in order to decide in-sample out sample separation. Consequently, this study also applied a very similar approach to Kocenda & Poghosyan (2020) during the nowcasting design to decide the appropriate in-sample and out-sample approaches successfully applied. However, this study aims to advance the work of Kocenda & Poghosyan (2020) by adding machine learning methods to compare the performance and forecast accuracy of the dynamic factor model and several machine learning approaches. Therefore, since the expanding window was preferred during the nowcast design of the dynamic factor model, the same method was used for model selection and model validation in machine learning.

In the expanding estimating window approach, the dataset is first divided into two as train and test split, as is commonly used in machine learning. However, in each next nowcasting round, the train split is increased by one more observation. In other words, the number of observations in the training dataset is increased by one observation in each new nowcasting iteration. The design of the expanding estimating window will be discussed in more detail in Chapter 5.

Another method used in machine learning studies is model tuning. Model tuning aims to increase the performance of the model by optimizing the hyperparameters. In the section where machine learning methods were explained in more detail earlier, the lambda parameter in the ridge and lasso method and its function in the regression were discussed. Model tuning represents the fit of the model with this optimal parameter value, by finding the optimized value of hyperparameters. In order to eliminate the problem of overfitting, the range of the hyperparameters is selected from the suggested literature. The value ranges to find optimal hyperparameters are as follows: λ_{Ridge} is set between 0.01 and 0.099, λ_{Lasso} is between 0.001 and 0.9, $\lambda_{Elastic\ Net}$ is between 0.1 and 0.9, and $\propto_{Elastic\ Net}$ is set between 0.9, as applied by Richardson et al. (2021). For the Random Forest, this study employs a similar range of hyperparameters to Soybilgen & Yazgan (2021). It estimates the optimal hyperparameters for all employed machine learning algorithms for each nowcasting period.

5 Nowcasting Design

5.1 Data Transformation and Preprocessing

After the data collection from the OECD database, another important point that needs to be taken into consideration is to have the stationarity variables as it is known from the econometric framework. Also, in the nowcasting literature, variables are assumed to be stationary. Thus, the first step of the analysis design should begin with the stationarity tests. In order to determine whether the dataset is stationary, there are multiple methods, such as the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF), which are considered more visual techniques. Another method that can be used statistically is the Augmented Dickey-Fuller test (ADF) to test the unit root. The obtained dataset is examined for stationarity, and the ADF results conclude that most of the variables are not stationary by not rejecting the null hypothesis.

Several methods are suggested in the existing literature to convert non-stationary data to stationary ones, such as differencing and logarithmic transformation (Kocenda & Cerny, 2014). This study applied differencing method in order to make stationarity. However, during the implementation of the differencing, the value differences among the indicators should be taken into account. Similarly to Kutman (2022), the percentage values are differenced by percentage change, and numeric value variables are differenced by absolute value. The dataset presented in Chapter 3 has two sets of variables in terms of value. For instance, export and import variables classified as complex indicators are variables with percentages values. On the other hand, the dataset also consists of numeric value variables such as GDP.

Firstly, the obtained GDP data is a numeric value. However, as the name of the study suggests. This study aims to nowcast the real GDP growth of the economies. Thus, the GDP should convert into GDP growth by calculating the percentage change between the reference and previous quarters. Since the purpose of this study is quarterly GDP nowcast, instead of considering the year-over-year change of the variables, the quarter-over-quarter growth of all variables has been taken into account. In order to calculate quarterly growth, the percentage change between the reference quarter and three months before the reference month is calculated for the percentage value variables. Furthermore, the reference month numeric value variables differ from the previous three months to make the data stationary.

After the differentiation steps were completed for all necessary variables, it was found that the data became suitable for the stationarity assumption after re-running the steps ACF, PACF, and ADF test steps, which were applied initially to check whether the mean and variance are constant over time.

After obtaining stationary data, the following step is to apply a data preprocessing technique known as standardization. The standardization is applied to the whole stationary dataset to transform the variables into one common scale and obtain correct parameters through regression. Thus, unit variance and zero mean for the whole dataset are obtained to follow the assumption.

5.2 Design of the Nowcasting with DFM

As suggested in the machine learning literature, the dataset is similarly split into two as train and test also in nowcasting studies that used dynamic factor models. The train and test split are an essential feature since it allows the performance evaluation of the model to capture accurate predictions of the future. During the literature review, the dataset is split into train and test data, especially machine learning studies, to avoid the problem of overfitting. On the other hand, this method is also broadly used in nowcasting studies that have applied dynamic factor models. Because the aim of the nowcasting studies is quite similar to short-term forecasting, as discussed previously, the only difference between the nowcasting and forecasting studies is that nowcasting studies include the current data.

In contrast, forecasting methods include only past data. Since nowcasting is also forecasting at some level, as the literature suggests, it should not be a coincidence that train and test split is an appropriate approach in nowcasting studies. The collected dataset presented in Chapter 3 is split into two subsets: in-sample and out-sample.

In this study, the chosen nowcasting exercise and in-sample/out-sample split is follow the same logic as Kocenda & Poghosyan (2020). As described in the previous data chapter, the period of data varies depending on the country. A detailed table of the pre-covid and covid period can be found in Appendix A for each country.

Considering that the total number of observations is different for all the countries mentioned above, the separation of train and test was made for all countries separately. For a more detailed explanation, the dataset of Belgium for the pre-covid period is taken as an example. The dataset starts from 1995 Q1 to 2019 Q4. After data transformation, the data becomes between 1995 Q2 to 2019 Q4. Thus, for hard and soft indicators published monthly, the total number of observations is 297 (296/3 = 99 quarters in total). In order to obtain an in-sample split of 70% of the dataset, the total quarterly observations are multiplied by 0.70, and fractional results are rounded up. In the case of Belgium, 99 quarterly observations are multiplied by 0.70, and the result 69.3 is rounded up to 69 observations to determine the training dataset. Thus, the dataset used to train the dataset that allows optimization of the parameters and learning the patterns of the given dataset is the first 207 monthly observations of the Belgium pre-covid data. The remaining 90 observations of the data are called the out-sample set, where the predictions of the in-sample set will be tested. According to the 70/30 split, the model should produce 30 nowcasting rounds to nowcast quarterly GDP (90/3 = 30) for Belgium. The nowcasting rounds started from 2012Q3 (beginning of the in-sample period) until 2019Q4 (end of the out-sample). However, at each next nowcasting iteration, the in-sample period is increased by three observations (or one quarter)

Another point that needs to be considered for the construction of this nowcasting exercise is that each of the nowcasting rounds of the model is designed in a way that this nowcasting is constructed at the final month of the quarter to predict the GDP growth of the previous quarter. Because the purpose of this nowcasting is to calculate a GDP growth prediction and compare it to actual GDP growth in order to compare the performance of the predictions, however, it will not be possible to compare predicted and actual data when trying to estimate a GDP for the next quarter in the current period. Therefore, while designing GDP nowcasting, it is assumed that the data is collected in the final month of the test period, as suggested by Kocenda & Poghosyan (2020).

Thus, the variables with approximately 45 days of publication lag (e.g., hard indicators) at the selected point of time should not be available for the last two months of the quarter. Thus, the dataset should have a ragged edge at the end of the training period. At each of the nowcasting periods, it is assumed that the current period is the last month of the beginning of the out-sample and the nowcasting round aims to predict current GDP growth. Going back to the Belgium example, following the previous assumption, the current period is assumed to be 2012 Q3 for the first round of the nowcasting. The first round of nowcasting aims to predict the assumed to be current GDP of 2012 Q3. Thus, the variables with the publication lag have missing variables for M8 and M9 2012, while the whole data is available in M7 2012 due to approximately 45 days of. DFM is constructed for each nowcasting period mentioned above using all data from train periods. The first round of nowcasting will be obtained as follows. Firstly, the dynamic factor model is applied for hard and soft indicators between Q2 1995 to 2012 Q3. The period of the dynamic factor model includes the period in which the train data is included, plus the first quarter of the beginning of the out-sample period. The reason for this will be explained in more detail shortly. It should be noted that the Kalman filter is applied only to the balanced part of the data. At the same time, the factors of the model are obtained for the entire period, including the period with missing variables.

In the next step, the main focus is linking quarterly and monthly variables, as described in the methodology section. The factors obtained through dynamic factors using monthly published data are collected at monthly levels. However, the GDP variable is only available at a quarterly frequency. In order to link these monthly factors to quarterly GDP, this study will employ the method described by Soybilgen & Yazgan (2021) in the following way: Quarterly factors are obtained through the monthly factors extracted from the applied dynamic factor model by extracting the factors calculated for the last month of each quarter. In other words, the factors of the third month of each quarter are extracted from the dynamic factor model. These extracted factors are considered as the quarterly factors of the dataset discussed in the data section.

In the next step, the extracted quarterly factors are used as the explanatory variables of the regression, while the GDP variable is used as the dependent variable. Moreover, these variables are regressed by the simple OLS to determine the parameters of the model. The extracted quarterly factors and quarterly GDP regressed in simple OLS are between 1995 Q2 to 2012 Q2, which is precisely equal to only the in-sample period, excluding the next quarter, Q3 2012, which is included in DFM. This is because the first round of the nowcasting aims to predict the GDP of 2012 Q3. The parameters obtained from the described OLS regression are used as the parameters of 2013 Q3, and extracted factors for 2012 Q3 are used as the independent variables of the model to predict the 2012 Q3 GDP.

However, for each next nowcasting round, the number of in-sample observations is increased by one observation. In other words, the same logic is used for the next, second round of nowcasting is constructed in the same way as the first one. Nevertheless, to explain briefly, the second round in-sample period is extended to 1995 Q2 to 2012 Q3, and the aim is to nowcast GDP for 2012 Q4. Thus, DFM was applied between 1995 Q2 and 2012 Q4, and the quarterly factors are extracted from the model. The parameters obtained from OLS from the factors and GDP between 1995 Q2 and 2012 Q3 followed the same logic as the first round to predict the GDP growth of 2012 Q4. And so on, the same logic is applied till the end of the nowcasting rounds. Following the same logic, a GDP forecast for Belgium until the end of 2019 was calculated using 30 nowcasting rounds for the pre-covid period.

The same logic applies to all the countries in pre-covid and covid periods. However, the number of nowcasting rounds (again, 30% of the data) is higher than pre-covid datasets for each country, while the application method is the same as described for the Belgium example.

5.3 Selection of Optimal Factors

The detailed methodology of DFM is described in Chapter 4; in this section application of the dynamic factor model and selection of the optimal combination of static, dynamic factors, and VAR lag will be discussed.

The first step to determining the optimal dynamic and static factors is to determine var lags. The number of lags to be tried in determining the current lag has been chosen as similar to the lag numbers used in studies with similar datasets in the literature (Kocenda & Poghosyan; 2020). However, Akaike information criteria, one of the information criteria methods, was used to find the most suitable lag order for our dataset among these var lag orders suggested by the literature (Kocenda & Cerny, 2014). The appropriate number of lags is selected from the lowest AIC obtained.

To find the optimal combination of factors, firstly, the number of the eigenvalues above 1 is determined to select the number of static factors. Similarly to Kocenda & Poghosyan (2020), the maximum number of static factors model should be less or equal to the number of eigenvalues above one. In comparison, the appropriate number of the dynamic factor should be less or equal to the static factors. In order to obtain the optimal combination of dynamic and static factor, each possible combination of dynamic and static factors are used to obtain the dynamic factor, and the DFM with the lowest RMSE value is selected as the optimal combination of factor (Kocenda & Poghosyan, 2020). The most appropriate combination of factors is shown in Table 3 and Table 4 for all the selected counties for both datasets.

Table 4: Optimal Combination of Dynamic and Static Factors

	Pre-Covid Period			Covid Period		
	No of Dynamic Factors	No of Static Factors	Explained Variance (%)	No of Dynamic Factors	No of Static Factors	Explained Variance (%)
Belgium	5	6	55%	5	6	85%
Czech Republic	1	5	53%	1	1	63%
Denmark	4	7	52%	2	7	68%
Finland	4	5	73%	5	5	72%
France	6	6	81%	6	6	94%
Hungary	6	6	71%	4	6	88%
Italy	4	5	82%	5	5	94%
Portugal	5	5	62%	1	5	81%
Slovenia	3	5	85%	1	4	87%

The optimal factor combination is selected according to the lowest RMSE value obtained after selecting Var lag according to AIC criteria. After careful consideration of RMSE and AIC results in order to decide var lag, optimal dynamic and static factors. The factors obtained from the optimal dynamic factor model for the pre-covid dataset are as follows: Belgium 18 factors, Czech Republic 20, Denmark 21, Finland 20, France 18, Hungary 18, Italy 10, Portugal 20, Slovenia 10. For the covid dataset, the number of extracted factors are as follows: Belgium 18 factors, Czech Republic 3, Denmark 21, Finland 20, France 18, Hungary 18, Italy 20, Portugal 5, Slovenia 12.

5.4 Design of Nowcasting with Machine Learning

As explained in more detail in the methodology section, three regularization techniques and one Random Forest, known as one of the bootstrapped decision tree techniques, were applied as a machine learning method in this study.

While setting up machine learning models, one of the most important features of the machine learning models that are used in this study is that, instead of using the stationary data that is used to obtain the dynamic factors model, we obtained from all of the four machine learning methods are fed with the factors obtained through DFM. Soybilgen & Yazgan (2021) suggested and successfully applied this method.

For all ML methods, the number of nowcasting rounds arranged for each method varies according to the countries. However, the nowcasting rounds and estimation periods are identical in every DFM and ML method. At the same time, the train/test split was selected as 70%/30% for both dynamic factors and all machine learning methods. However, due to the avoidance of overfitting and the inadequacy of separating only train/test split in nowcasting studies. As explained in more detail in the nowcasting design with the DFM section above, the expanding window has also been applied for ML methods, quite similar to the applied method in DFM. In this method, the test and train split in the first round are separated as 70% and 30% as specified, but for each next nowcasting round, the test split is extended to cover the following observation. Continuing from our example of Belgium, 1995 Q2 to 2012 Q2 is the first test split to predict 2012 Q3 GDP. In the second round of nowcast, the test split is extended to 1995 Q2 to 2012 Q3 to estimate 2012 Q4, and this method continues to repeat until it reaches the final estimation of GDP, in Belgium case, 2019 Q4. The hyperparameter tuning is conducted as it is described in the methodology section.

6 Empirical Findings

Six different models were applied, and these models can be classified under three main headings: Benchmark models, dynamic factor models and machine learning algorithms. The study uses the AR (1) method as a benchmark model. AR(1) model is also known as a more straightforward and traditional method frequently used as a benchmark in literature. For nowcasting methods, this study employed five different nowcasting models: One dynamic factor model and four different machine learning models. Four different machine learning methods were chosen to nowcast quarterly GDP growth, namely as the following: Ridge, Lasso, Elastic Net, and Random Forest.

Also, in this section, the following hypotheses will be examined whether sufficient empirical findings will be obtained to reject these null hypotheses:

Hypothesis 1: Machine learning does not provide more accurate forecasting during less volatile periods compared to dynamic factor model

Hypothesis 2: Machine learning does not provide more accurate forecasting during less volatile periods compared to benchmark model.

Hypothesis 3: Random Forest does not have lower RMSE value compared to regularization methods during less volatile periods.

Hypothesis 4: Machine learning does not provide more accurate forecasting during volatile periods compared to dynamic factor model

Hypothesis 5: Machine learning does not provide more accurate forecasting during volatile periods compared to benchmark model.

Hypothesis 6: Random Forest does not have lower RMSE value compared to regularization methods during more volatile periods.

Hypothesis 7: Performance of machine learning methods does not differ among relatively small economies.

Due to the nature of the nowcasting method, the only data available at the current quarter is included for nowcasting models to predict the GDP growth of the current quarter. The purpose of applying multiple nowcasting methods, including four different ML algorithms to compare the accuracy of different nowcasting models to determine which model provides better forecast accuracy for different countries for pre-covid and covid periods.

In this study, datasets are collected datasets from 9 different countries. In addition, while there are two datasets for each of these nine countries, one including the covid period and one covering the pre-covid period until the end of 2019 was used. Including different nowcasting models presented in this study will be valuable for two reasons. One because of the variations between countries and another because different models may come to the fore in more volatile periods such as the Covid-19 period.

The selection of var lag, optimal and dynamic factors for each 18 datasets is obtained as described in section 5. This study's forecasting accuracy was evaluated by comparing RMSE values for all countries and datasets. Moreover, the better-performing model is selected based on the lowest RMSE value compared to the alternative benchmark and nowcasting models. The RMSE values of the models obtained for all countries are given in Table 5 for the pre-covid period and Table 6 for the Covid period as the critical evaluation method of the selected models.

Table 5: Out-Sample RMSE results for the pre-covid period

	AR (1)	DFM	Ridge	Lasso	ENet	RF
Belgium	**0.261**	0.294	0.337	0.339	0.335	0.304
Czech Republic	0.654	0.589	**0.587**	0.587	0.586	0.646
Denmark	**0.537**	0.602	0.696	0.568	0.581	0.564
Finland	**0.592**	0.616	0.604	0.628	0.598	0.644
France	0.333	0.289	**0.266**	0.269	0.276	0.313
Hungary	0.685	**0.457**	0.491	0.469	0.471	0.494
Italy	0.326	0.362	0.287	**0.285**	0.285	0.296
Portugal	0.552	0.461	0.455	0.453	0.484	**0.433**
Slovenia	0.793	0.636	0.672	0.676	0.676	**0.602**

Note: Models with the lowest RMSE value are shown in bold

Table 5 shows that in 5 out of 9 countries, machine learning models outperform the alternative benchmark and dynamic factor models during the less volatile pre-covid period. The exceptions are Belgium, where AR(1) outperforms all alternative nowcasting models with 0.26 RMSE value, and Denmark, where AR(1) obtains reduced RMSE result that varies between 5% and 12% compared to the alternative nowcasting models. Similarly, the Finland benchmark model obtains the best forecast accuracy with 0.59. However, comparing the RMSE values of Finland, it should be noted that the difference between RMSE values obtained from Ridge and Elastic Net is only 1-2% lower compared to DFM. Thus, these ML models can also be considered a powerful alternative to the benchmark model. It should also be considered that better results can be obtained from Elastic Net than alternatives with different variable selections. Hungary is the only country where DFM outperforms the benchmark and alternative ML nowcasting with the lowest RMSE of 0.45. Similarly, Elastic Net and Lasso models have second and third-best forecast accuracy compared to the outperforming nowcasting model.

The results of the six countries where the machine learning model beats the alternative dynamic factor models, and benchmarks are evaluated. Results of 2 countries out of 9 indicate that the Random Forest model provides the best forecasting accuracy among alternative ML models. Results from the Czech Republic, France, and Italy show that regularization methods (Ridge, Lasso and Elastic Net) provide better forecasting accuracy than the alternatives. However, for the Czech Republic, although Ridge regression provides the best forecasting accuracy, the RMSE results of alternative models such as Lasso and DFM indicate that these models can also be considered alternative nowcasting methods since the difference is below 1%, which is considered less nominal. Hypotheses 1 and 2 are rejected since ML methods provide better forecasting accuracy overall. On the other hand, the results indicate that there is not sufficient evidence to reject Hypothesis 3. Considering the RMSE average of the ML methods where the ML method outperforms compared to RMSE results of ML methods, Ridge provides 1.2% lower RMSE, while Random Forest provides 1.6% higher RMSE.

This study considers Slovenia and Portugal as small economies in terms of their GDP. For small economies, Random Forest is the best-performing model among the alternatives for less volatile periods. On average, RF reduces RMSE value by 30% compared to the benchmark model, DFM, and ML alternatives, respectively by 30%, 6% and 7%. Thus, Hypothesis 7 is rejected since RF is able to reduce forecast error by 7% compared to other ML nowcasting models.

Before discussing the empirical finding of the Covid period, it should also be taken into account the significant increase in RMSE values among all nine selected countries is considered as expected as datasets started to include the Covid-19 period (until 2022 Q3).

Table 6 shows the out-sample RMSE results for the Covid period, which is considered more volatile than the pre-covid period due to the rise in the uncertainty level of the economies. One of the aims of this study is to compare the performance of different nowcasting methods under more uncertain periods such as covid. In Table 6, the substantial increase in RMSE is more visible than in Table 5. RMSE values have risen as expected at the beginning of the paragraph. Compared to Table 5, with the inclusion of the corona period, significant changes are seen in best-performing models, as in RMSE values. The dynamic factor model performs best in 7 out of 9 countries by surpassing benchmark and machine learning models. The two exceptional countries are Italy and Hungary, where Ridge regression beats nowcasting with the dynamic factor model with a 10% lower RMSE result for Italy and 20% for Hungary.

Table 6: Out-Sample RMSE results for the Covid period

	AR (1)	DFM	Ridge	Lasso	ENet	RF
Belgium	2.950	**2.063**	2.880	2.638	2.592	2.929
Czech Republic	2.203	**1.920**	1.921	1.939	2.057	2.118
Denmark	1.753	**1.227**	1.625	1.605	1.648	1.685
Finland	1.568	**1.230**	1.389	1.427	1.252	1.471
France	4.126	**2.504**	2.790	2.804	2.815	4.221
Hungary	3.469	2.004	**1.811**	1.833	1.971	2.928
Italy	3.751	2.358	**1.950**	2.359	2.157	3.563
Portugal	4.114	**2.578**	3.148	3.097	3.061	3.916
Slovenia	3.664	**1.789**	2.480	2.701	2.821	3.453

Note: Models with the lowest RMSE value are shown in bold

The RMSE difference between DFM and Ridge for the Czech Republic is also only -0.001. Therefore, similarly to the pre-covid period, the Ridge model can perform better with different datasets. However, Hypothesis 4 is not rejected since the overall dynamic factor model provides much better nowcast performance in terms of better forecast accuracy for the volatile Covid period.

Compared to the benchmark model in 9 countries out of 9, machine learning models improved forecast accuracy. Thus, this thesis is able to collect sufficient evidence to reject Hypothesis 5 as per the RMSE results shown in Table 6. On the other hand, Hypothesis 6 is accepted since RF is not able to provide lower RMSE during covid period compared to other ML methods.

Table 7: Out-Sample Normalized RMSE results for the pre-covid period

	AR (1)	DFM	Ridge	Lasso	ENet	RF
Belgium	**0.947**	1.066	1.224	1.229	1.218	1.104
Czech Republic	1.038	0.935	**0.932**	0.932	0.931	1.026
Denmark	**1.097**	1.230	1.423	1.162	1.188	1.153
Finland	**1.008**	1.049	1.029	1.071	1.020	1.097
France	0.980	0.852	**0.784**	0.792	0.814	0.921
Hungary	1.244	**0.831**	0.893	0.852	0.856	0.897
Italy	1.057	1.174	0.930	0.927	**0.925**	0.961
Portugal	1.374	1.149	1.133	1.128	1.206	**1.078**
Slovenia	1.278	1.025	1.083	1.089	1.089	**0.970**

Note: Models with the lowest RMSE value are shown in bold

In addition to RMSE, normalized RMSE is suggested by Kocenda & Poghosyan (2020) as another comparative approach that compares the performance of different models. Normalized RMSE is calculated by the RMSE values already obtained and presented in Table 5 and Table 6 divided by the standard deviation of Actual GDP growth of the respective out-sample period. The results of normalized RMSE are shown for the pre-covid period in Table 7. The normalized RMSE of the covid period for the out-sample period is presented in Table 8. Kocenda & Poshosyan (2020) stated that normalized RMSE allows to reduce of the nowcasting variation by allowing to identify of the effect of the economy. The normalized RMSE for the pre-covid out-sample period is presented in Table 7 and Table 8 for the Covid period. The outperforming models remain the same as RMSE results in Table 5 and Table 6.

Table 8: Out-Sample Normalized RMSE results for the Covid period

	AR (1)	DFM	Ridge	Lasso	ENet	RF
Belgium	0.985	**0.689**	0.961	0.881	0.866	0.978
Czech Republic	0.980	**0.854**	0.855	0.863	0.915	0.942
Denmark	0.992	**0.694**	0.919	0.908	0.932	0.953
Finland	0.988	**0.775**	0.875	0.899	0.789	0.926
France	0.985	**0.598**	0.666	0.669	0.672	1.007
Hungary	0.987	0.570	**0.515**	0.521	0.561	0.833
Italy	0.984	0.618	**0.511**	0.619	0.566	0.934
Portugal	0.987	**0.619**	0.756	0.743	0.735	0.940
Slovenia	0.987	**0.482**	0.668	0.728	0.760	0.930

Note: Models with the lowest RMSE value are shown in bold

Recalling Table 5 and Table 6, this study concluded that during the Covid period, the forecast accuracy dropped significantly due to higher uncertainty and significant changes in the economies. The normalized RMSE for the Covid period is almost half of the normalized RMSE of the Covid period, as shown in Table 7 and Table 8. As stated previously, normalized RMSE takes standard deviation into account. As the uncertainty rises during the Covid period, the standard deviation of GDP growth has also risen. During Q1 2022, when the covid-19 pandemic spread across the world, all countries in the dataset experience negative GDP growth. This economic downsizing became much more significant within Q2 2022, where the GDP growth reduced between -9% and -15% for all nine countries where the standard deviation of GDP growth increased significantly.

Nevertheless, for all nowcasting models to adjust and perceive these rapid and unexpected changes requires time. Thus, the models obtained higher forecast errors compared to normal times. The fact that the normalized RMSE is much lower in the covid period compared to the pre-covid period may indicate that the increase in RMSE during covid may result from these higher nowcasting errors by taking the higher standard variation of GDP growth into account.

The RMSE and normalized RMSE findings of the pre-covid period align with Kocenda & Poghosyan (2020), who conducted a comparative study for similar datasets and countries. Their RMSE and normalized RMSE results align with the findings in Table 5 and Table 7.

For the Covid period, there is a limitation in the literature on such a comprehensive study, including the same countries and the Corona period. The study that resembles this thesis most is conducted by Dauphin et al. (2022) to nowcast the GDP of 5 different European economies with a dataset until 2021Q1 for the same benchmark and nowcasting models. In their study, the percentage increase between covid and pre-covid periods aligns with the RMSE increase for the Covid period compared to the pre-covid period. Several studies conclude that ML performs better during more volatile times than DFM (Dauphin et al., 2022; Soybilgen & Yazgan, 2021). On the contrary, the empirical findings of this thesis suggest that DFM reduces forecast errors compared to machine learning. These differences in results can be due to the size of the variables since Dauphin et al. (2022) included 20-60 variables in their study. In contrast, this study only includes 25 indicators to nowcast GDP. Only for Hungary, the results of this thesis align with Dauphin et al. (2022) that the Ridge model outperforms the alternatives for Hungary.

Diebold-Mariano test is suggested by the various nowcasting studies (Chernis et al., 2020; Kocenda & Poghosyan, 2020; Rusnak, 2013; Kuck & Schweikert, 2020) in order to test the statistical significance of RMSE results attained from various nowcasting models. In this study, the Diebold-Mariano test introduced by Diebold & Mariano (1995) is conducted, and for the calculations of loss differential squared forecasting errors of each model are subtracted by the squared forecasting errors among the alternatives which allow obtaining to cross-model test results for best-performing model based on the results of best-performing models in Table 5 and Table 6 vs. the alternative nowcasting and benchmark model at 1%, 5%, 10% significance levels.

Comparing the results obtained from the Diebold-Mariano test for pre-covid period nine countries. In Belgium, AR(1) outperforming model is statistically significant compared to all nowcasting models at all significance levels. The only exception is that AR(1) is statistically insignificant to RF at a 1% significance level. Therefore, AR(1) is considered a better model for to nowcast the GDP growth of

Belgium. On the other hand, the Ridge model is statistically significant to AR(1) in the Czech Republic. However, as the test suggests, DFM can have good results as Ridge for the Czech Republic. For Denmark, the benchmark model outperforms all of the alternative nowcasting methods. The only exception is that the Elastic Net is statistically insignificant. Thus, Elastic Net can be considered an alternative nowcasting method to AR(1). For Finland, AR(1) model only outperforms Random Forest at all significance levels. Thus, DFM and other ML methods remain as alternative nowcasting models. For Hungary, DFM is statistically significant to RF and Enet. Again similarly, the remaining machine learning models, such as Lasso and Ridge, can be good as DFM. For Portugal, RF is statistically significant to all alternative models. Thus, RF is considered to be a better fit for Nowcast. For Slovenia, Italy, and France, all of the outperforming models are statistically insignificant to all alternatives. In summary, most of the models suggest insignificant results. Moreover, this insignificant result indicates no impactful evidence for these outperforming models that they should be preferred over the alternatives.

For covid period, again DM test was conducted separately for nine countries. For Belgium, DFM is statistically significant to Lasso and Enet. However, RF, Ridge, and benchmark can provide good results and DFM. For Denmark, DFM is statistically significant to all ML and benchmark models. Similarly, for Slovenia, DFM outperforms all alternative ML models and benchmarks. The only exception is the Random Forest model. The results for other countries are statistically insignificant. Thus, similarly to the covid period, there is insufficient evidence to decide which model is better. Machine learning and benchmark models can still be considered alternatives to DFM, except for Denmark, where DFM outperforms all the models.

Kocenda & Poghosyan (2020) concluded that nowcasting is statistically insignificant for most countries compared to the AR model. Also, the authors concluded that there is insufficient evidence to decide which model is a better fit to forecast GDP growth which aligns with the results obtained from DM findings of this thesis. Ashley (2003) concluded that the statistically insignificant results of the compared models could result from an evaluation sample with less than 100 observations.

There are relatively few studies dealing with the Covid-19 period in the literature. In addition to this, most nowcasting studies are conducted in single countries. Therefore, this study aims to extend the current literature by including the covid-19 period for nine different countries.

In summary, for the less volatile period, such as the pre-covid period in this study, machine learning models provide better forecast accuracy in five countries out of 9. Therefore, ML models are considered an appropriate method to nowcast to reduce nowcast errors that lead to better nowcast predictions. On the contrary, for the Covid period, the DFM model outperforms ML and benchmark models overall.

However, ML methods can still be considered as alternatives to DFM. Moreover, according to the Diebold-Mariano test for most countries for both periods, test results were found to be insignificant. Thus, there is insufficient evidence to conclude that outperforming models statistically provides better results than their alternatives. However, the publishing lag of GDP is an important limitation for many central banks and policymakers to implement correct policies. Therefore, even though the results are statistically insignificant, it can be concluded that ML models can reduce the forecast accuracy of nowcasting during less volatile periods.

Moreover, DFM provides better forecast accuracy for the periods where uncertainties are rising. Insufficient observations for the DM test can drive insignificant test results due to data limitations. According to Table 5 and Table 6 results, the outperforming nowcasting models can be interpreted as appropriate models. Detailed figures of actual and predicted GDP growth can be found in Appendix B.

In the meantime, the success of these models can be compared again with different countries and datasets, without forgetting that alternative nowcasting models can be as good as outperforming nowcast models, keeping in mind that ML models can still be considered as alternatives due to insignificant statistical results.

Generally, DFM for less volatile periods and ML methods for more stable economies should be considered appropriate tools to forecast GDP growth even though there is no statistical evidence. Especially considering these models' ability to predict GDP growth without publication lag and their ability to provide better forecast accuracy is worth to considering these models as suitable methods to nowcast.

7 Conclusion

Macroeconomic indicators need to be assessed instantaneously to carry out correct policies economy, and GDP is considered to be one of the most important macroeconomic variables for such policy implementations (Botha et al., 2021, Richardson et al., 2021; Kocenda & Poghosyan, 2020).

In this thesis, several nowcasting models were employed in order to nowcast the GDP growth of 9 different European economies for two different periods, one including covid-19 pandemic during 2022 and one excluding. In the analysis, 25 hard and soft indicators are used as explanatory variables. GDP growth variable is used as the target variable, and only final GDP revisions are taken into account due to data limitations. The dynamic factor and machine learning models are calculated by expanding window estimations, and 70% and 30% percent in-sample and out-sample data splits are used to determine the initial train/test split.

This thesis observes that for most countries, the machine learning model provides better nowcasting accuracy compared to the alternative dynamic factor model in terms of RMSE for more stable periods based on the results shown in the empirical finding section. Additionally, For the small economies such as Portugal and Slovenia in this study, the Random Forest provides better forecast accuracy of nowcast among the nowcasting alternatives. Thus, compared to other machine learning methods, Random Forest is the most appropriate nowcasting method for small economies such as Portugal and Slovenia based on root mean square error reduction. For the period when uncertainty and GDP growth variation have risen, the dynamic factor model is reducing nowcasting errors more than machine learning models. Thus, the author concludes that the dynamic factor model is the more appropriate tool to nowcast GDP growth in more volatile periods.

Findings suggest that Normalized RMSE achieves significantly lower results for the Covid period compared to the pre-covid period indicating that the higher RMSE values for the Covid period are proven to be based on higher GDP growth variation experienced by the countries in the dataset.

The author cannot conclude that the outperforming model is statistically significant for many countries using the Diebold-Mariano test. However, it is thought that the underlying reason for this statistical insignificance can be explained by the insufficient number of observations for the DM test. Thus, the author concludes that even though the statistical significance remains ambiguous for most countries, the outperforming models for their respective periods are suitable methods to nowcast GDP growth. Since these models are able to provide good forecasting accuracy, another fact that should not be ignored is that although it has not been statistically proven, these models are able to estimate GDP growth with strong predictions and can be considered a powerful tool for many central banks and policymakers to take quick actions to implement correct policies at the correct time without any publication delays. Another concluding remark of the author is that the dynamic factor model and machine learning models should still be considered alternatives, especially in volatile periods since model models can obtain similar root mean square errors for several countries.

This comparative study makes room for different researchers and possible extensions. Further studies can focus on including different variables that compare the same models employed in this study and may obtain different outperforming models with better forecasting. On the other hand, alternative machine learning models can be employed to compare more alternative nowcasting models. A similar study can be conducted for more than nine countries included in this study. Finally, a similar study can evaluate the performance of MIDAS as an alternative mixed-frequency approach to the dynamic factor model.

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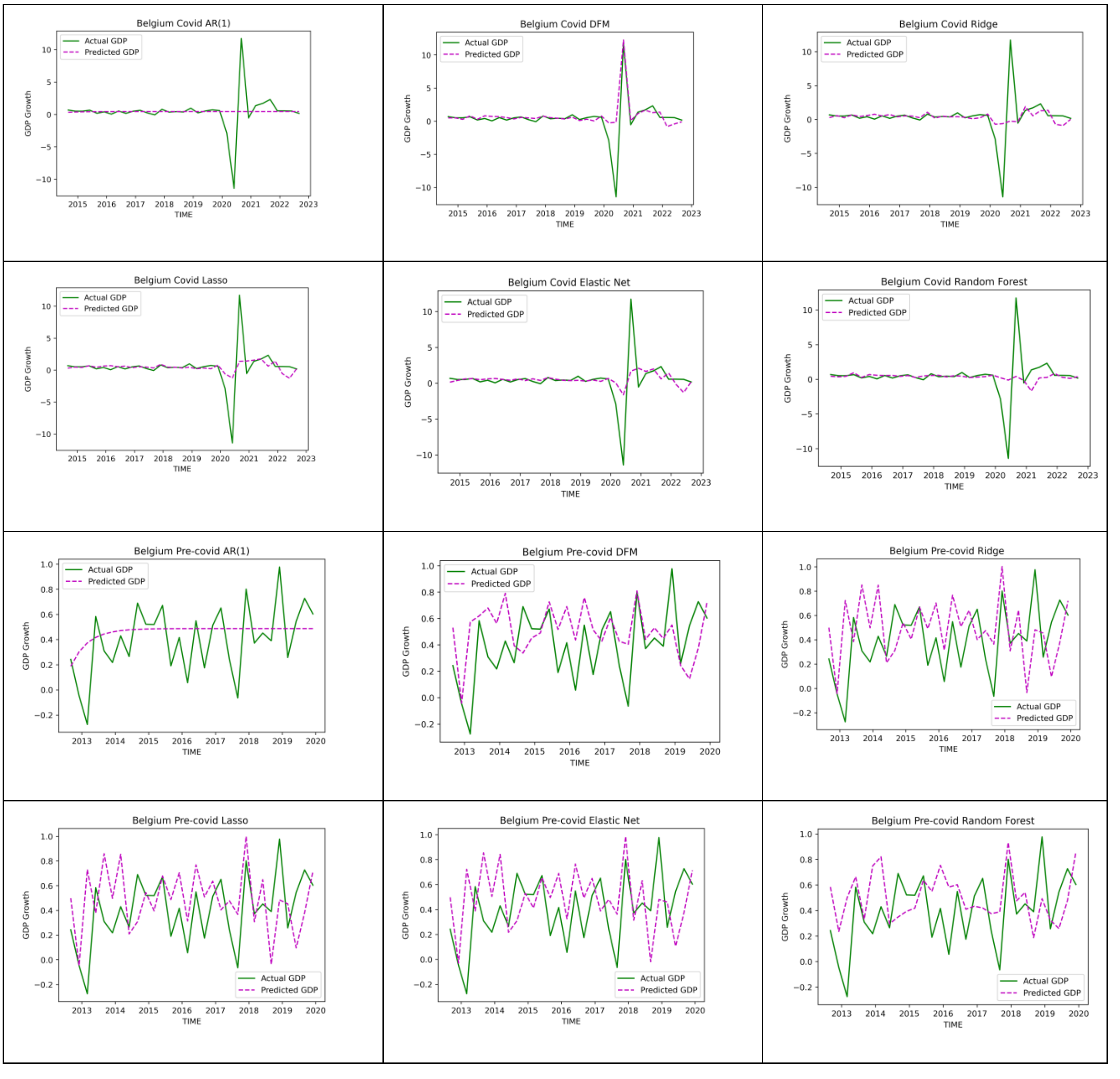
Appendix A: Detailed Data Period

Table 9: Detailed Data Period

	Pre-Covid	Covid
Belgium	1995Q1-2019Q4	1995Q1-2022Q3
Czech Republic	1996Q1-2019Q4	1996Q1-2022Q3
Denmark	1998Q1-2019Q4	1998Q1-2022Q3
Finland	1997Q3-2019Q4	1997Q3-2022Q3
France	1995Q1-2019Q4	1995Q1-2022Q3
Hungary	1996Q2-2019Q4	1996Q2-2022Q3
Italy	1998Q1-2019Q4	1998Q1-2022Q3
Portugal	1997Q3-2019Q4	1997Q3-2022Q3
Slovenia	1995Q1-2019Q4	1995Q1-2022Q2

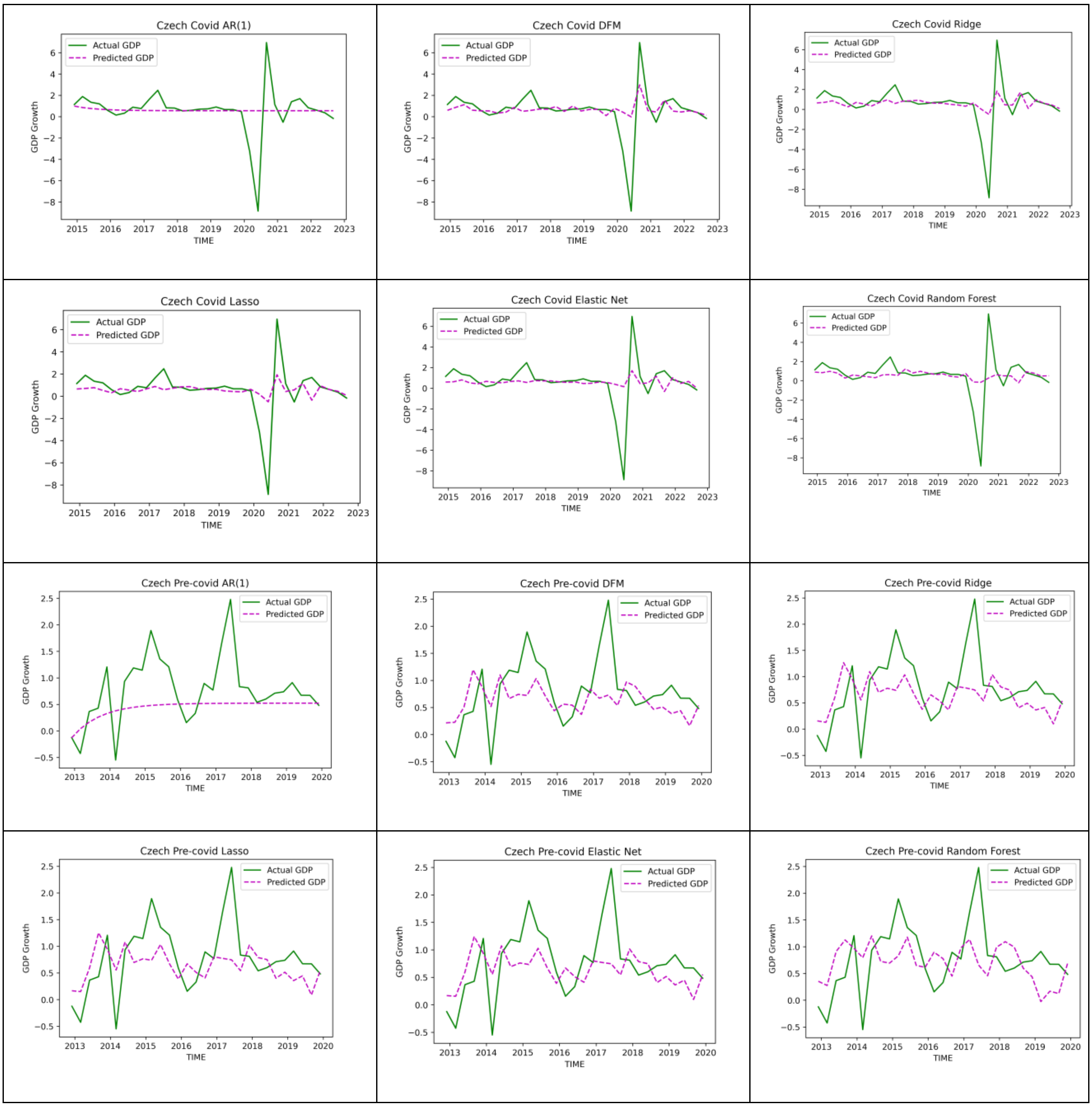
Appendix B: Out-sample Predicted GDP Growth vs. Actual GDP Growth

Figure 1: Belgium - Predicted GDP Growth vs. Actual GDP Growth



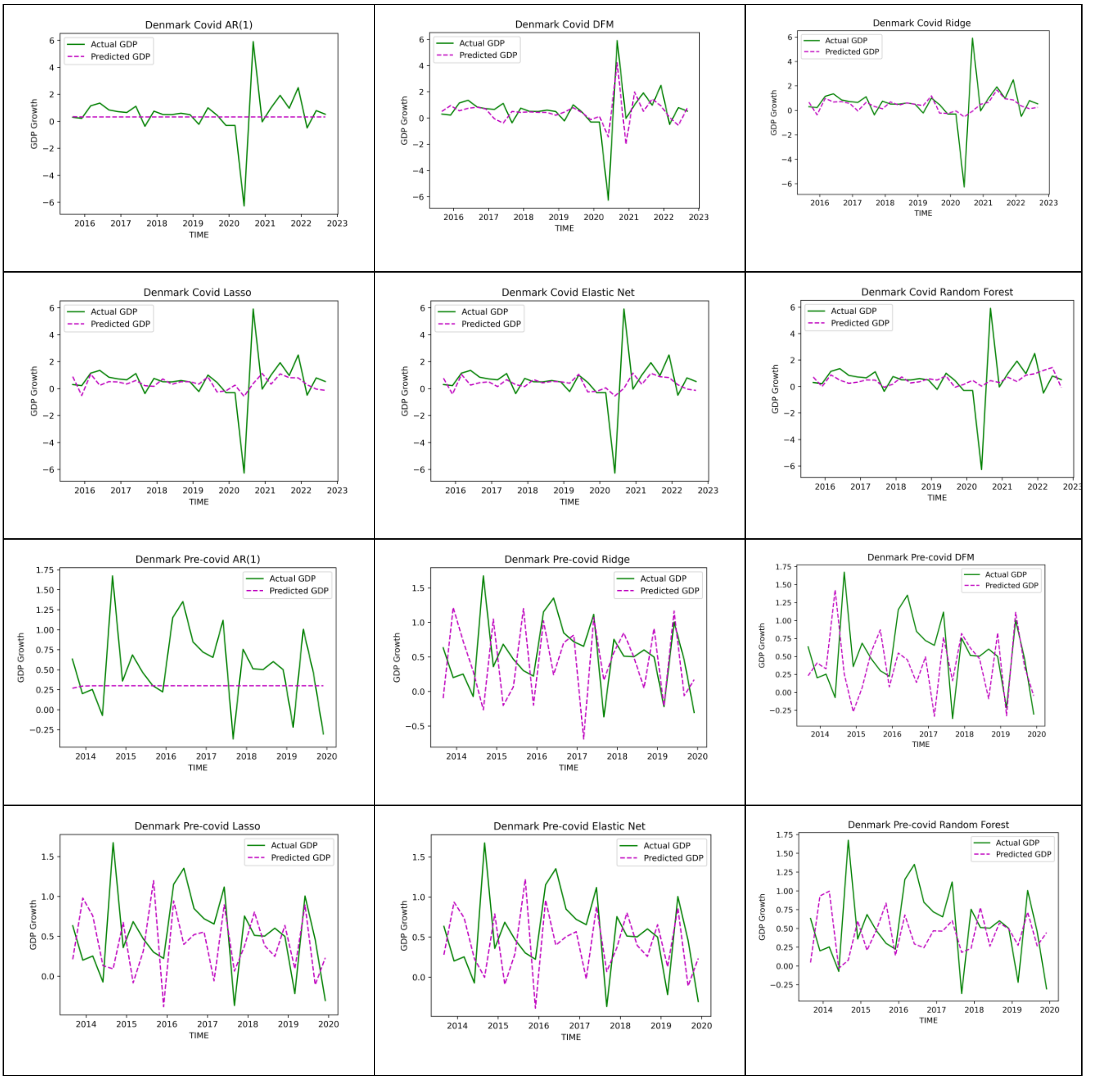
Appendix B: Out-sample Predicted GDP Growth vs. Actual GDP Growth

Figure 2: the Czech Republic - Predicted GDP Growth vs. Actual GDP Growth



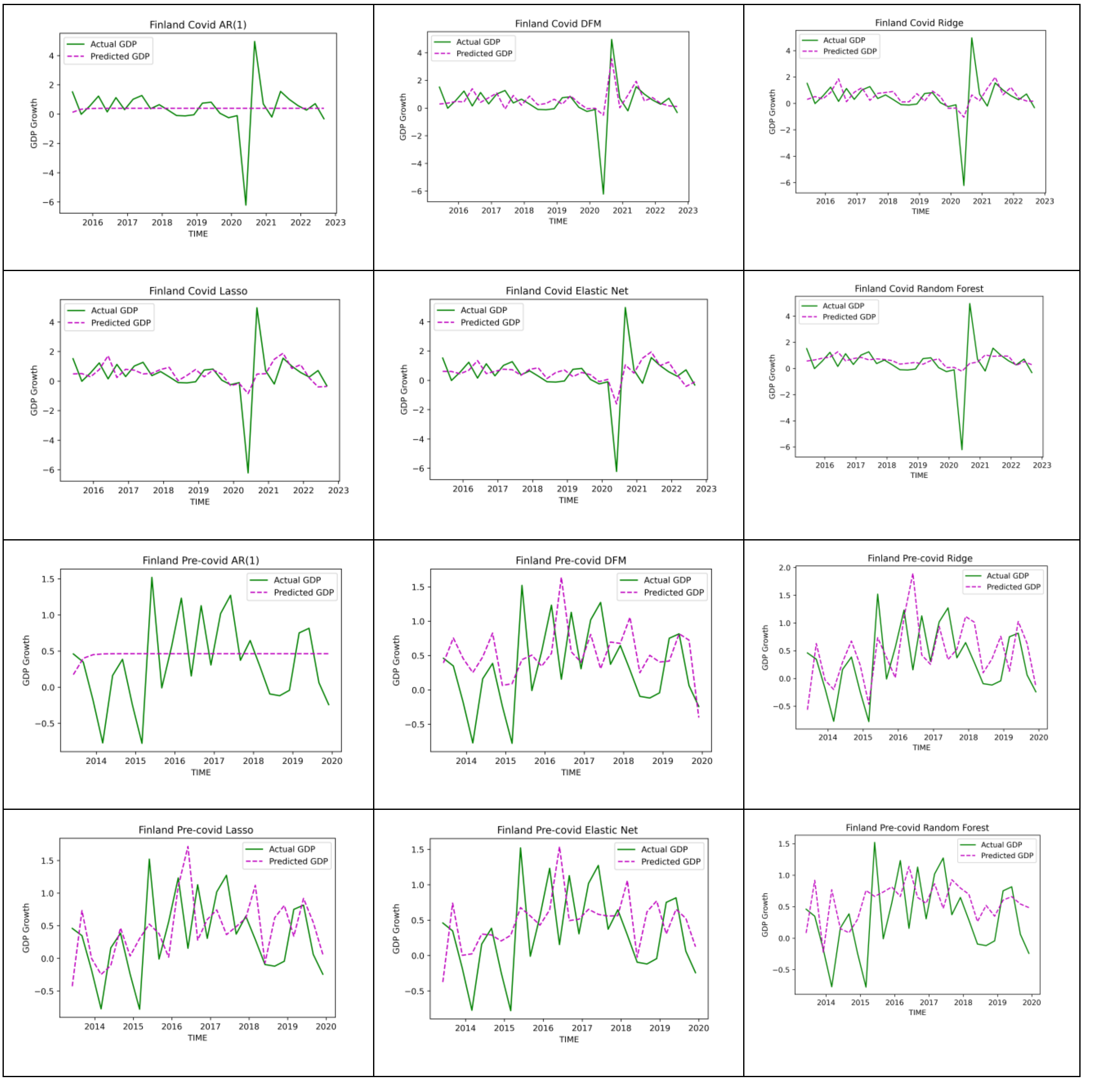
Appendix B: Out-sample Predicted GDP Growth vs. Actual GDP Growth

Figure 3: Denmark - Predicted GDP Growth vs. Actual GDP Growth



Appendix B: Out-sample Predicted GDP Growth vs. Actual GDP Growth

Figure 4: Finland - Predicted GDP Growth vs. Actual GDP Growth



Appendix B: Out-sample Predicted GDP Growth vs. Actual GDP Growth

Figure 5: France - Predicted GDP Growth vs. Actual GDP Growth

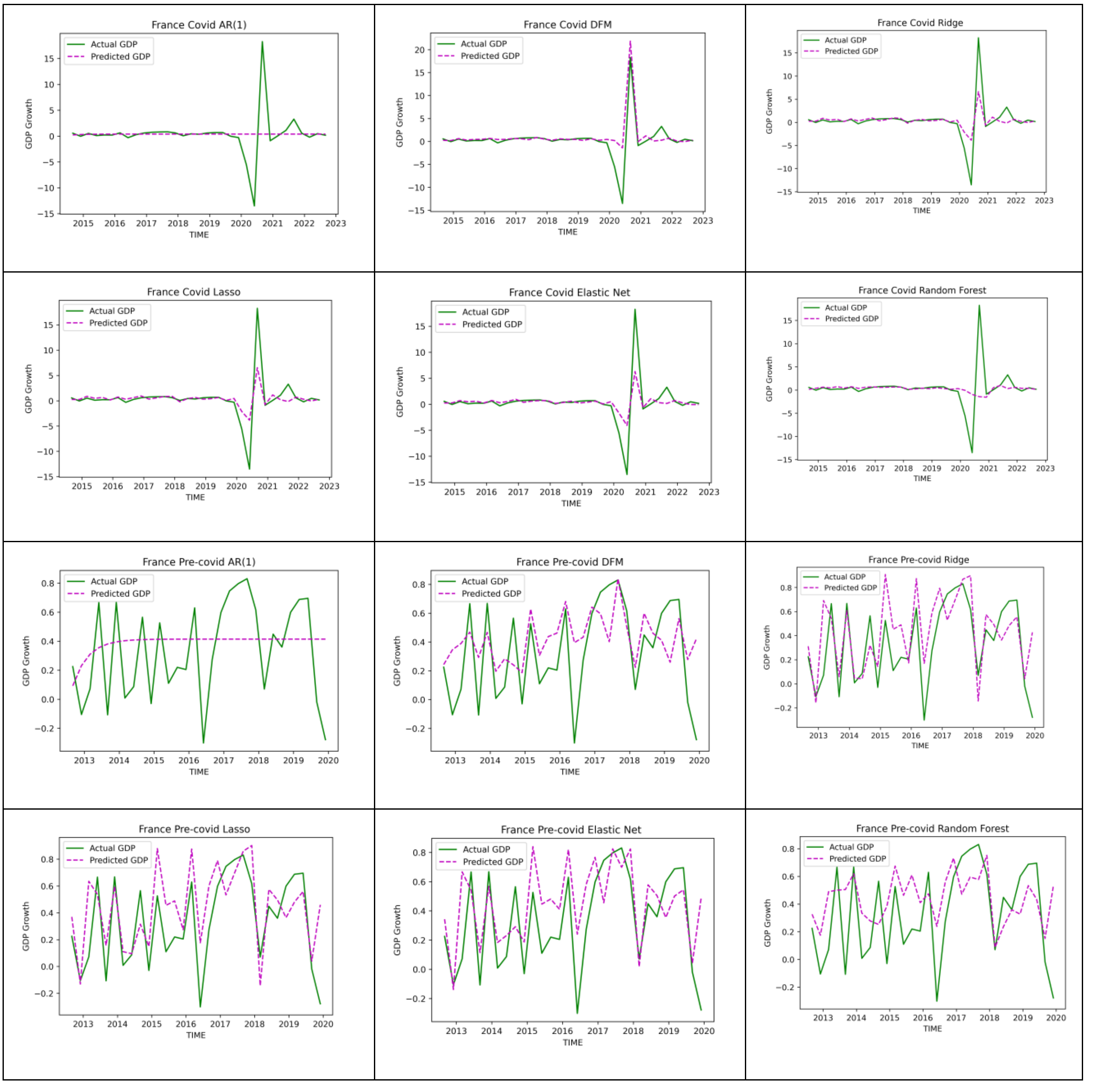
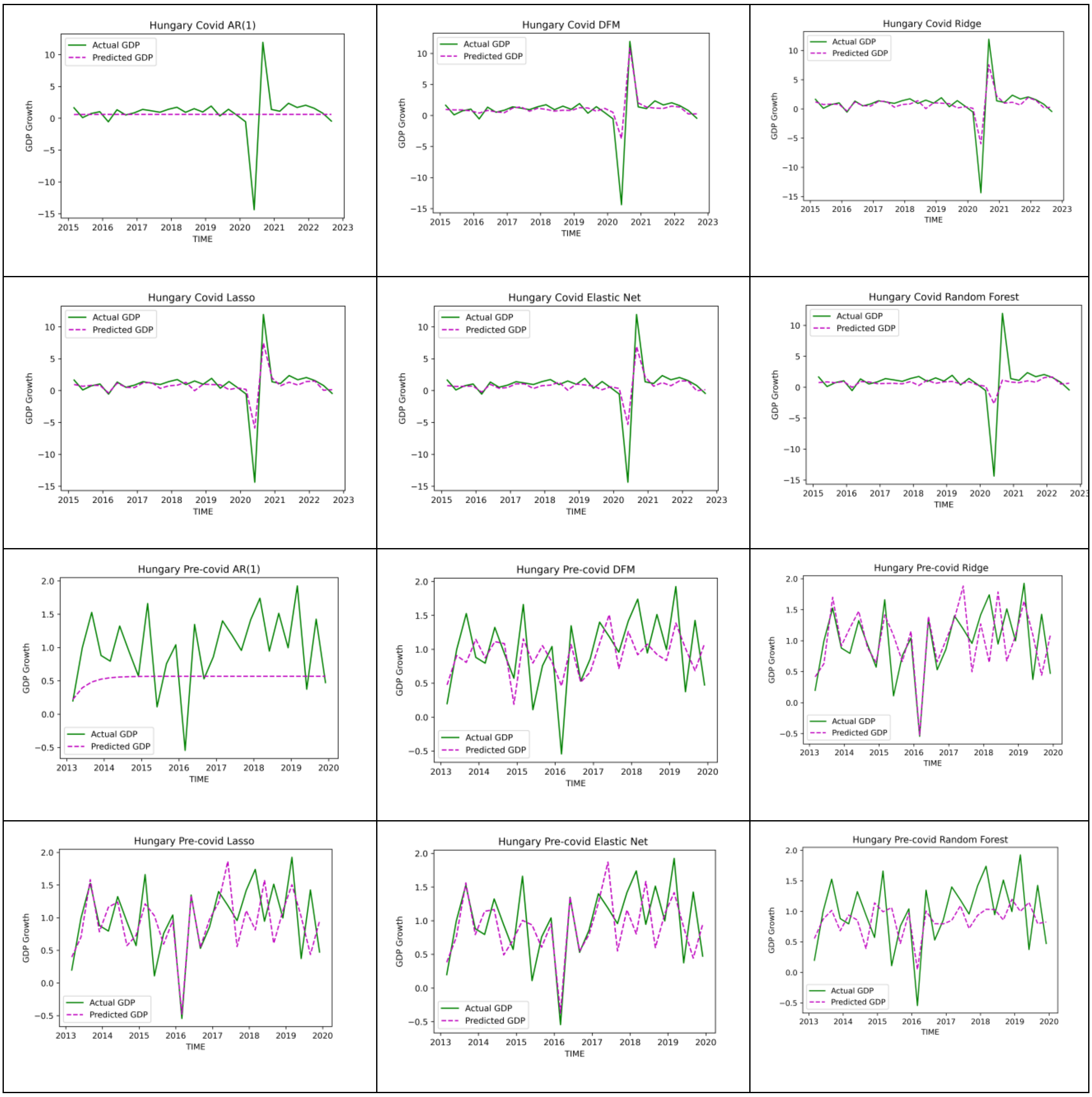


Figure 6: Hungary - Predicted GDP Growth vs. Actual GDP Growth



Appendix B: Out-sample Predicted GDP Growth vs. Actual GDP Growth

Figure 7: Italy - Predicted GDP Growth vs. Actual GDP Growth

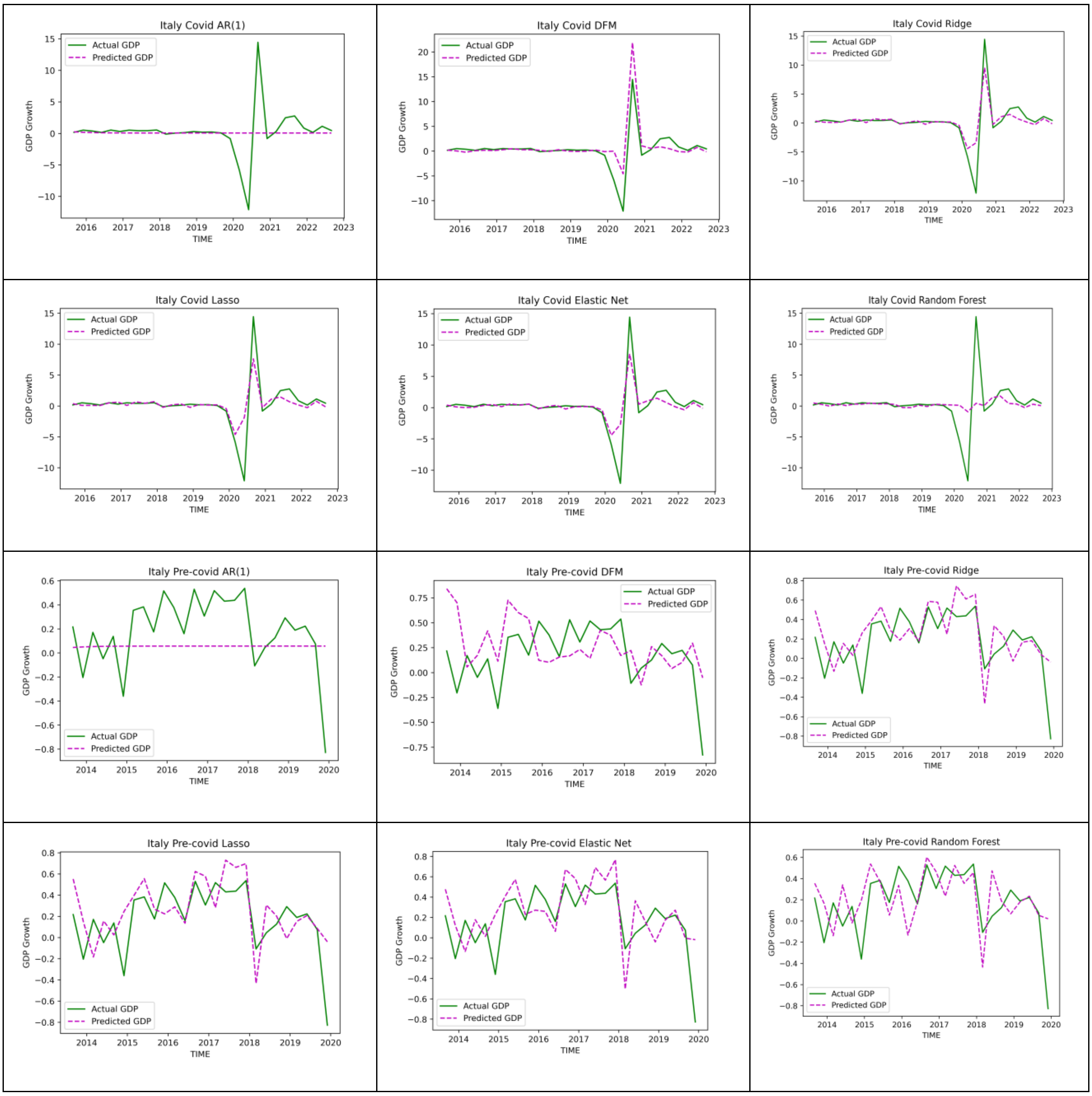


Figure 8: Portugal - Predicted GDP Growth vs. Actual GDP Growth

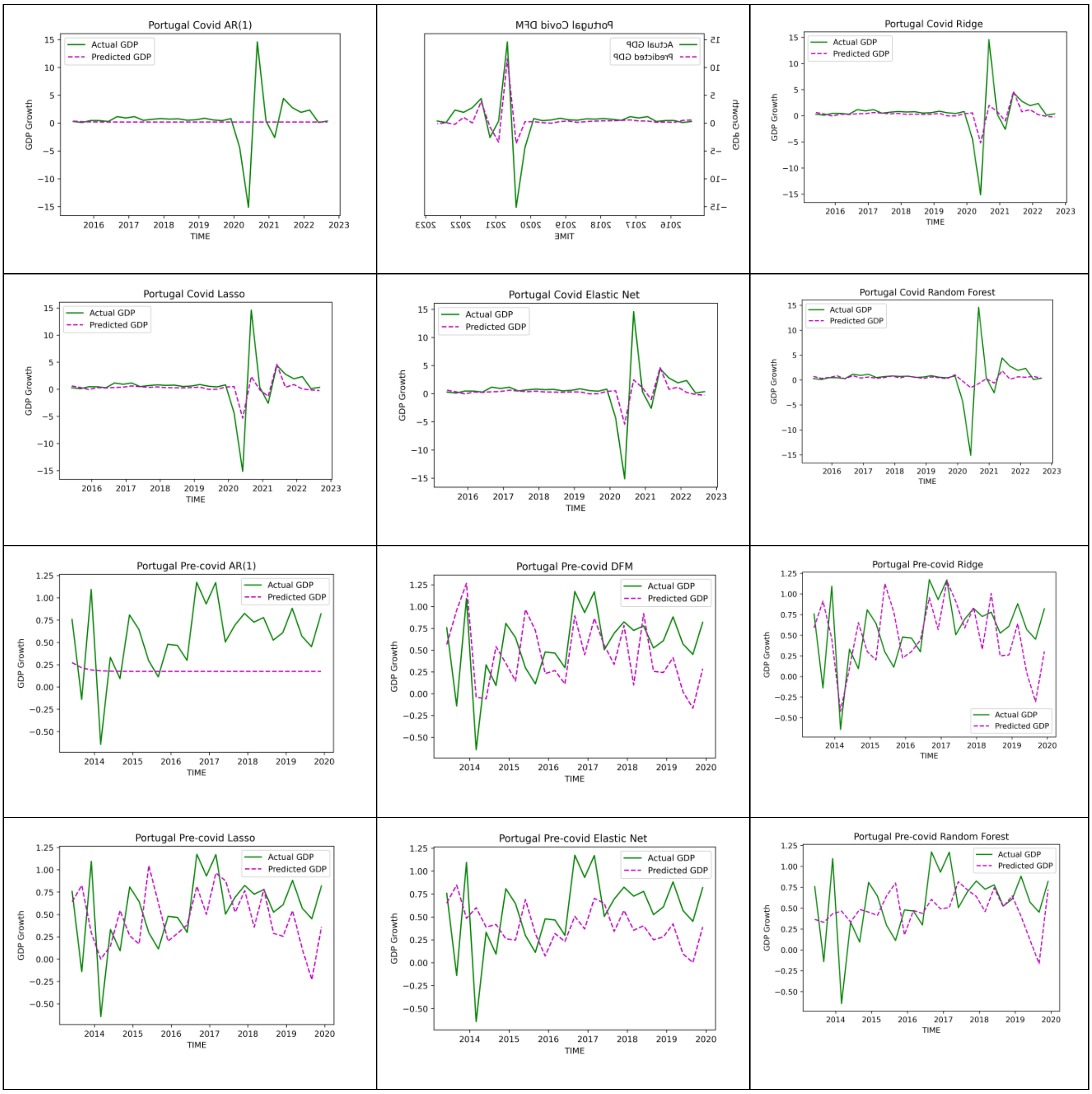
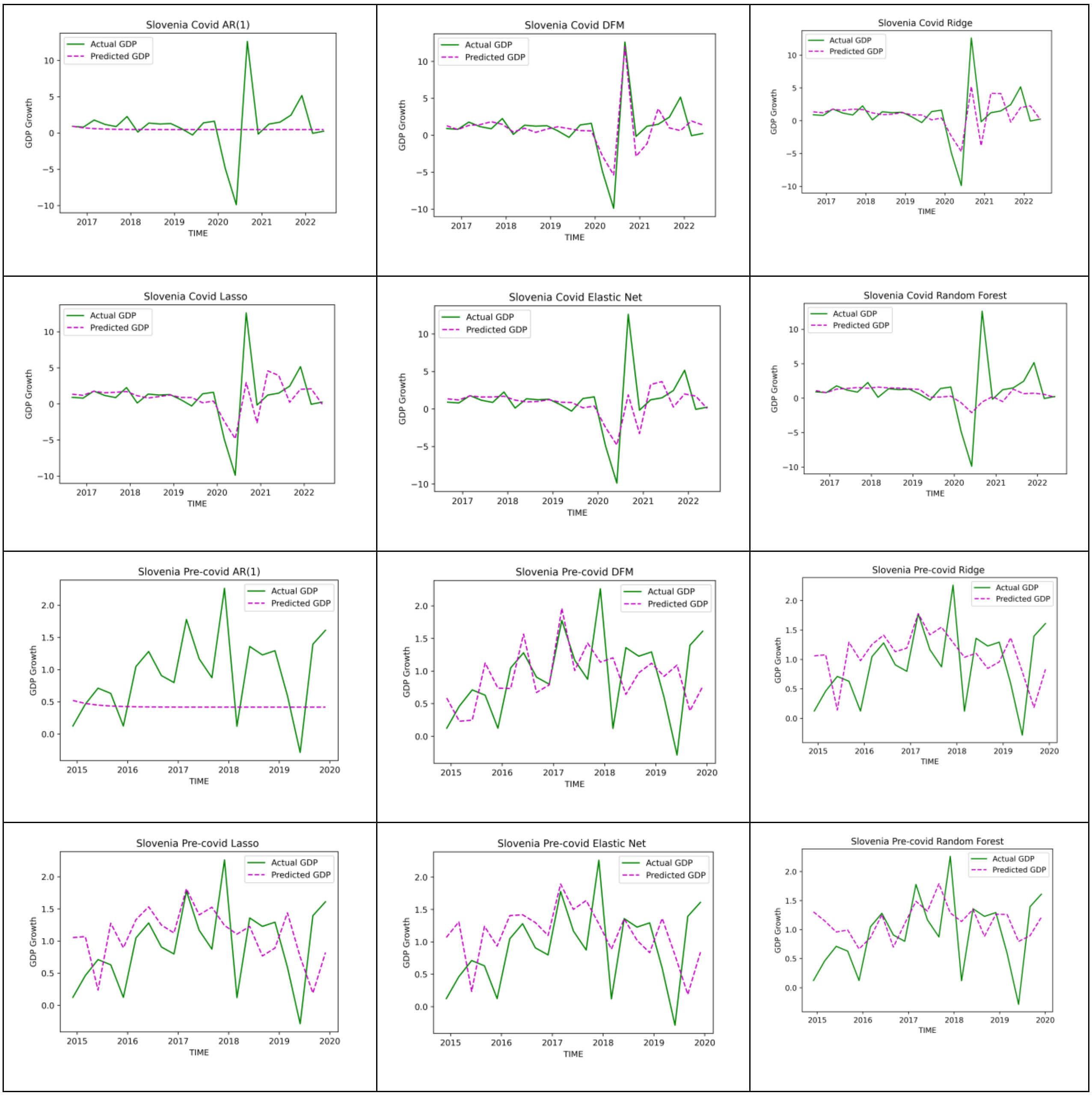


Figure 9: Slovenia - Predicted GDP Growth vs. Actual GDP Growth



Appendix C: Data and Codes

In this thesis, for application dynamic factor model R programming language is used. Also, for the applications of machine learning models, plots, data-preprocessing, and DM test, Python programming language is used with the following packages: pandas, numpy, statsmodels, scikit-learn, matplotlib. The data and codes will be provided upon request.