NOWCASTING TURKISH GDP BY DYNAMIC FACTOR MODEL

İDRİS ALKIŞ

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NOWCASTING TURKISH GDP BY DYNAMIC FACTOR MODEL

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İdris Alkış

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DECLARATION OF ORIGINALITY

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ABSTRACT

Nowcasting Turkish GDP by Dynamic Factor Model

This study aims to nowcast, backcast, and forecast the quarter of Turkish Gross Domestic Product (GDP) growth by the dynamic factor model. Although GDP provides detailed information on economic activities, GDP data is released with a significant delay. This thesis constructs a real-time dataset of monthly economic activity indicators to measure the current GDP. Variables used in the estimation of the Turkish GDP are real, financial, and survey indicators. The dynamic factor model is utilized in the estimation because that model can tackle the issues of mixed frequency (quarterly and monthly variables in the dataset), ragged ends (nonsynchronous data publications), and missing data (the upper side of some indicators in the dataset is not same). The model developed by Giannone, Reichlin, Small (2008) and Banbura, Giannone, and Reichlin (2011) was adopted in the study. The thesis evaluates the performance of the dynamic factor model in nowcasting and the ARIMA Model in forecasting the quarterly Turkish real GDP growth rate for the period 2020-2021. Results show that the more data are released, the accuracy of the model increases in the dynamic factor model. On the other hand, no noticeable improvement was observed in the accuracy of the ARIMA model.

ÖZET

Türkiye Gayrisafi Yurtiçi Hasıla'nın Dinamik Faktör Model ile Şimdi Tahmini

Bu çalışma, dinamik faktör modeli ile Türkiye Gayri Safi Yurtiçi Hasıla (GSYİH) büyümesinin çeyreğine ilişkin şimdi tahminleri, geriye ve geleceğe dönük tahminleri amaçlamaktadır. GSYİH, ekonomik faaliyetler hakkında ayrıntılı bilgi vermesine rağmen, GSYİH verileri önemli bir gecikmeyle yayınlanmaktadır. Bu tezde, mevcut GSYİH'yi ölçmek için aylık ekonomik faaliyet göstergelerinden oluşan gerçek zamanlı bir veri seti oluşturuldu. Türkiye GSYİH tahmininde kullanılan değişkenler reel, finansal ve anket göstergeleridir. Tahminde dinamik faktör modelinden faydalanıldı çünkü bu model karışık sıklık (veri kümesindeki üç aylık ve aylık değişkenler), düzensiz uçlar (eşzamansız veri yayınları) ve eksik veriler (veri kümesindeki bazı göstergelerin başlangıcı aynı değil) problemleriyle başa çıkabilir. Çalışmada Giannone, Reichlin, Small (2008) and Banbura, Giannone and Reichlin (2011)'nin geliştirdiği model benimsenmiştir. Tez, 2020-2021 dönemi için üç aylık Türkiye reel GSYİH büyüme oranını tahmin etmede şimdi tahmin için kullanılan dinamik faktör modelinin ve ARIMA Modelinin performansını değerlendirmektedir. Sonuçlar, dinamik faktör modelinde ne kadar çok veri yayınlanırsa modelin doğruluğunun arttığını göstermektedir. Öte yandan, ARIMA modelin doğruluğunda gözle görülür bir gelişme gözlemlenmedi.

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CHAPTER 1

INTRODUCTION

Policymakers make decisions based on the state of the economy. The real and financial sectors also act according to the expansion or contraction of the economy. All economic agents including markets want to take action by making macroeconomic forecasts with the least error. Therefore, forecasting macroeconomic indicators are crucial for them. Forecasters have developed many models to make the best prediction. Developed models for economic projections have different periods as short, medium, and long term. These models are used for many macroeconomic indicators since the purpose of estimating these indicators is to accurately evaluate the state of the economy.

Economic growth is the main indicator that economists are most curious about. The most well-known indicator expressing economic growth in the economics literature is GDP. The biggest problem with GDP stems from the release schedule because GDP is announced approximately 60 days after the quarter ends, although it varies from country to country. The fact that GDP is announced late inevitably brings forecasting studies to the literature. Recently, nowcasting has started to gain more importance in forecast studies because policymakers are concerned about the current state of the economy and future state. Forecasting with available data is the characteristic of nowcasting studies.

In Banbura, Giannone, Modugno, and Reichlin (2013), one of the pioneering studies of nowcasting, nowcasting is identified as “the prediction of the present, the very near future, and the very recent past” (p. 2). This terminology, which was used for meteorology, later entered the economic literature (Banbura et al., 2013). The most distinct feature of nowcasting is that it works with real-time data.

Even though GDP is announced with significant delay, the nowcasting method can estimate the reference GDP by exploiting available variables at higher frequencies. Using these variables has advantages as well as disadvantages. The frequency of the indicators can be daily, weekly, or monthly, while GDP is quarterly. Using a higher frequency dataset with GDP induces the problem of mixed frequencies. Also, there may be no historical record of utilized data because some of them start to be recorded later. For this reason, nowcasting studies have to deal with the issue of missing data. Moreover, publishing the indicators on different dates causes an unbalanced data panel. This unbalanced dataset is called ragged or jagged edges (Banbura et al., 2013). Since the dynamic factor model can cope effectively with these issues and can be applied to large datasets (Banbura & Rünstler, 2007), we preferred this model in our study. To solve the curse of dimensionality, the dynamic factor model can summarize a large dataset with latent common factors.

In this study, we tried to estimate Turkey's GDP growth for the period 2020Q1-2021Q4 by using some hard, financial, and survey data. Our work also includes a backcasting scenario, as GDP was published 60 days after the quarter ended. The word backcasting in the literature is used when the quarter is over but the data has not yet been released.

Real data is a solid source of data on GDP growth but has a considerable lag time after the end of the respective month. For instance, the employment and the unemployment rate in Turkey are released around 45 days after the end of the month. Although survey data especially confidence indexes gives more information about the future of the economy, it is released earlier than many hard indicators. Since the timeliness of survey data is valuable for nowcasting studies, we include these indicators in our dataset. Financial data reflecting the current market conditions and expectations have daily and hourly frequencies but we will use monthly data in our study.

We also will apply the ARIMA model to forecast Turkish GDP. Our aim is to observe whether there is an improvement in the performance of the model over time.

The flow of the study is as follows. Chapter 2 describes a literature review on the dynamic factor model and nowcasting studies. Chapter 3 describes the dataset and data preprocessing for the collected variables. Chapter 4 covers our empirical exercise and presents its results. Finally, Chapter 5 summarizes the main findings of the performance of the two models and outlines the limitations of the thesis and presents recommendations for future studies.

CHAPTER 2

LITERATURE REVIEW

The current chapter is dedicated to a literature review of dynamic factor models and nowcasting studies. Historically, dynamic factor models have been used to construct an index of economic activity, and are now used for nowcasting studies. Moreover, the chapter glances at conventional nowcasting models that try to predict GDP. Finally, this chapter contains recent studies on the Turkish economy using the dynamic factor models.

2.1 Historical backgrounds of dynamic factor models

GDP is the best descriptive signal for the performance of an economic condition. Because GDP has a considerable lag time after the end of the relevant quarter and contains insufficient information on the course of the economy (Aruoba & Sarikaya, 2013; Çelgin, 2020), economic indexes are constructed as an alternative measure. The aim of the indexes provides to detect economic contraction and expansion periods. The literature on the index model trying to track current economic activity is based on the notion that macroeconomic variables co-move strongly (Forni, Hallin, Lippi & Reichlin, 2000).

Stock and Watson (1989) stated that Mitchell, Burns, and their colleagues prepared the indexes for indicating the condition of macroeconomic activity. Mitchell and Burns explain the coincident and leading economic indexes with the "reference cycle", many economic activities draw similar patterns in terms of general recessions, contractions, and revivals. Since this definition has not a sufficiently mathematical framework, one cannot reach certain conclusions from swings in the index. Also, their definitions of expansions and recessions have drawn widespread criticism. Stock and Watson (1989) revise coincident economic indicators (CEI), leading economic indicators (LEI), and create the recession index (RI) as a new index upon the US data from 1959 to 1988. Their variables for constructing the coincident economic indicator are industrial production, real personal income less transfer payments, real manufacturing and trade sales, and employee-hours in nonagricultural establishments. CEI expresses the comovements in different macroeconomic variables by compositing in a single indicator. They alleged that many macroeconomic variables can be addressed by a single common, unobserved indicator, that is the “state of the economy”. The proposed LEI shows the forecast of six months growth rate of CEI by using seven leading variables. RI is constructed for the probability of a recession over the next six months by using four coincident and seven leading variables. These alternative indexes are constructed with the dynamic factor model.

According to Mariano and Murasawa (2002), Stock and Watson (1989) model has two deficiencies. Firstly, their index does not include GDP, the quarterly indicator. Secondly, the index does not provide sufficient economic interpretations. For this reason, Mariano and Murasawa (2002) combined both GDP and monthly variables to construct a coincident indicator for the U.S. economy. They use maximum likelihood analysis to overcome mixed frequency and ragged end problems. Consequently, they extend the work of Stock and Watson (1989).

In a nutshell, Stock and Watson (1989) construct economic activity index with the help of the dynamic factor model while Mariano and Murasawa (2002) contributed to the literature by including higher frequency variables into the estimation.

Index studies for the current “state of the economy” with the help of the dynamic factor model paved the way for macroeconomic short-term forecasting studies. The word nowcasting in the sense of short-term forecasting thus entered the economics literature. GDP replaces the state of the economy as an unobserved variable in the nowcasting literature. Nowcasting literature has a peculiar position in forecast studies with its intrinsic features. It ables to forecast the current and previous unreleased quarter of GDP growth by utilizing higher frequency variables. While most other studies are based on some fundamental judgments, nowcasting does not involve any judgment. Another feature of nowcasting provides iterative predictions since estimations are updated as data comes in.

Results in the literature support several general assumptions. The accumulation and the expansion of pieces of information help to increase the accuracy of nowcasting GDP. The accuracy of nowcasting improves as indicators are released. The timeliness of survey and financial variables is extremely important at the beginning of the measured quarter because real data is not available meanwhile. However, the impact of survey data on GDP estimations decreased at the end of the quarter.

2.2 Conventional methodologies on nowcasting

Nowcasting studies were performed through different econometric models. The conventional ones are bridge equations and Mixed-Data Sampling (MIDAS) models. These are used frequently in policy institutions and central banks.

Bridge equations stem from time aggregation. In this model, the monthly variables are aggregated quarterly (converted to a lower frequency by averaging or by taking a representative value) and applied to the bridge equation. GDP growth is estimated in two steps. Firstly, the monthly indicators are estimated in isolation and then aggregated. Secondly, the aggregated values are used as regressors to estimate the GDP of the current quarter (Angelini, Mendez, Giannone, Rünstler & Reichlin, 2008).

With the temporal aggregation method, the high-frequency variables are reduced to the same frequency as the low-frequency variables but several potential information included in high-frequency variables can be disappeared. To avoid problems with temporal aggregation and to use variables with different frequencies, MIDAS (Mixed Data Sampling) regression model was developed to analyze within the same model (Foroni & Marcellino, 2013).

MIDAS uses a low-frequency dependent variable and high-frequency independent variables together in a one-equation model. In the MIDAS model, a low-frequency variable is estimated by using independent variables at different frequencies. Autoregressive distributed lag (ARDL) models are used to predict the target variable. With this approach, variables with their original frequencies can be used. Therefore, the aggregation problem is not realized (Foroni & Marcellino, 2013).

2.3 Pioneering nowcasting studies using dynamic factor models

Dynamic factor models are useful for nowcasting, due to the issues of "the mixed frequency of variables, the non-synchronous release, the curse of dimensionality, and the unbalancedness of datasets" (Akkoyun & Günay, 2012).

There has been extensive literature on nowcasting with dynamic factor models. As Banbura, Giannone, Modugno, and Reichlin (2013) point out that various versions of dynamic factor models have been applied for different economies (for the United States (Lahiri & Monokroussos, 2011); for the Euro Area (Angelini, Banbura, & Rünstler, 2010; Banbura & Modugno, 2010; Banbura & Rünstler, 2011; Camacho

& Perez-Quiros, 2010); for Germany (Marcellino & Schumacher, 2010)) by central banks and other policy institutions, for example, at the European Central Bank (ECB, 2008) and the International Monetary Fund (Matheson, 2011).

In this section, the most prominent examples of nowcasting literature are introduced in chronological order. For detailed literature on the dynamic factor model, the study of Barhoumi, Darne, and Ferrera (2013) can be examined. In the next chapter, we will only explain the model developed by Giannone, Reichlin and Small (2008) and Banbura, Giannone, and Reichlin (2011) which is the model we will adopt. Giannone et al. (2008) summarize the information of the monthly released data into only dynamic factors. These monthly estimated factors are transformed into quarterly factors and then they are regressed to GDP.

While other pioneering studies use a small number of economic variables in their model, Giannone, Reichlin, and Small (2006) work with a large dataset contained around 200 macroeconomic indicators of the U.S. economy. The outstanding feature of the method is that the nowcast can be applied to large datasets. To exploit the information in a broad number of data releases, the model summarizes these with a few common factors. In this model, the mixed frequencies and jagged edges are evaluated as a problem of missing data. The statistical model combines principal components with the Kalman filtering technique which can cope with the problem of missing data. The system is represented by a state-space form which is based on two types of equations: measurement equations and transition equations. Additionally, Giannone et al. (2006) remarked that their model allows to nowcast GDP and also to observe the contribution of new releases of data on the accuracy of the nowcast. They scrutinized whether the marginal contribution of a block of releases arises from timeliness or its quality. They concluded that if the timeliness of blocks is ignored, the contribution of hard data increases.

Banbura and Rünstler (2007) assert that the dynamic factor model is insufficient in the role of the individual series. This is a general criticism of factor models. For this reason, they conduct contribution analysis to measure the weights of the individual monthly indicators in the forecast. Their dataset compromises 76 monthly real activity, survey, and financial data for nowcasting the Euro Area GDP. Because of the differences in publication lags of real, survey, and financial data, to observe their sole contributions to the forecasts is ambiguous. When ignoring differences in publication lags, they find that real activity data are the most contributor to GDP. However, its significant lags make the soft data make non-negligible in earlier estimations.

Besides, Boivin and Ng (2006) made a study to learn whether using more time series to extract the factors would give better results. Boivin and Ng (2006), in their empirical study, revealed that 40 series were better than 147 series. Accordingly, the study shows that the extension of the dataset by adding new indicators does not improve the estimation. Also, Banbura and Modugno (2010) create three scales of datasets for comparison among them. The small scale consists of 14 series including real indicators of activity and financial series. The medium scale contains 46 series while the large scale compromises of 101 series. The study shows that the accuracies of the small and medium scales beat the large scale dataset for Euro Area GDP.

Empirical results in the literature demonstrate that the survey data plays a key role to improve the estimation at the beginning of the quarter because of its timeliness. However, the contribution of the survey decreases as real variables become available for that quarter. Also, these empirical studies show that more information helps in increasing the prediction of the model as the nowcasts are updated, although not absolute.

Thanks to the good forecast performance of the dynamic factor model, leading central banks started periodically nowcasting reports on their websites, although not their official forecasts. The New York Fed Staff Nowcast starts the nowcast for a reference quarter one month before until one month after the end of the quarter and also its model produces the impact of all data series on GDP growth. Its publications are updated each week based on released data. In September 2021, they notified visitors to suspend the nowcast reporting because of the uncertainty arising from the COVID-19 and volatility in the data. They state that they are working on methodological improvements to overcome the problems (https://www.newyorkfed.org/research/policy/nowcast.html). The Atlanta Fed GDPNow says that its model imitates the methods of the U.S. Bureau of Economic Analysis to estimate real GDP growth. The GDPNow forecast utilizes 13 elements that form GDP. The GDPNow model estimation is updated weekly on hand economic data for the measured quarter. For their detailed model, they direct the working paper of Higgins (2014). He combines the bridge equation approach and Bayesian vector autoregressions with the factor model approach used by Giannone, Reichlin, and Small (2008) (https://www.atlantafed.org/cqer/research/gdpnow).

2.4 Recent studies on nowcasting Turkish GDP

So far, the studies of the economic activity index model and nowcasting literature are summarized. From this point on, recent studies about Turkey will be introduced.

Çelgin (2020) constructed a monthly economic activity indicator to track the retrospective economic rise and fall and to assess the course of the Turkish economy for the period 1988-2020 with the dynamic factor model. Her work contains five types of variables: hard data including GDP, soft data, trade, employment, and financial variables. She selected the variables by using the hard-thresholding method. She considered economic conditions as an unobserved variable. The study concludes that monthly economic activity indicator can catch economic shrinkage periods and can flash the current course of Turkish economic activity.

Soybilgen (2015) applied the dynamic factor model to nowcast quarter over quarter, year over year, and annual Turkish GDP growth rates with 15 variables including real, soft, and financial data for the period between 2008Q1- 2013Q4. He finds that the dynamic factor model is better than univariate models and professional forecasters. As is expected, real variables are the most contributor to nowcasting GDP especially in later periods. Also, his study shows that financial variables are as important as soft data for nowcasting GDP.

Soybilgen and Yazgan founded the website of simditahmin.com for Turkey in 2019. On this website, the prediction model of Modugno, Soybilgen, and Yazgan (2016) are adopted. They update weekly the nowcasting. Also, other macroeconomic indicators are nowcasted (https://www.simditahmin.com/).

Barlas et al. (2021) use the data of Garanti BBVA Bank transactions to grasp the economic activity in real-time in Turkey. They regenerate the quarterly national accounts aggregate consumption and investment with the help of the Bank transactions database, which contains all monetary transactions between Garanti BBVA clients including individuals and firms. They also use these two series, which they denominated as the Big Data information, to nowcast Turkish GDP. They compare the dynamic factor model (DFM) and Bayesian vector autoregressive model (BVAR) with some machine learning models by utilizing 13 series including real, soft data and their own prepared big data activity indices (consumption and investment). They applied models between January 2016 and December 2020.

They find that the nowcasting accuracies of the BVAR and DFM broadly outperform compared machine learning models. Even though they do not observe a prevailing model in terms of the accuracy, the accuracy of DFM is steadily increasing as data are released. They finally deduced that the big data information has a significant contribution to the beginning of the nowcasting process, when the traditional hard data is not available. However, when hard data become plentiful the big data information becomes negligible.

In brief, several monthly, weekly, or daily indicators are used for nowcasting of GDP growth. As with most of the papers in the literature, in this thesis, we will use monthly variables by using the dynamic factor model for the nowcasting of Turkish GDP. We will explain our econometric model and the details of our dataset in the next chapter.

CHAPTER 3

RESEARCH METHODOLOGY

The current chapter is dedicated to the theoretical part and the methodology of the thesis. Initially, the chapter contains the description of dynamic factor model, determining the number of factors and shocks to the factors, and the EM algorithm. We used the dynamic factor model for nowcasting, while we applied the ARIMA model as the benchmark model for forecasting. In last section, the dataset for the thesis is presented. The collection process, and descriptive statistics for the collected variables are explained.

3.1 Dynamic factor model

The dynamic factor model is a dimension reduction technique (Doz & Fuleky, 2019), which estimate a set of fewer unobserved factors underlying observed variables in population. Since many macroeconomic variables can be summarized by a few unobserved variables, we prefer to use this model. The dynamic factor model adopted in this thesis is based on the studies of Giannone et al. (2008) and Banbura et al. (2011). This version of the model reduces the information contained in several monthly time series by transforming into quarterly factors and these are used in a regression against GDP. The general representation of the dynamic factor model is:

$$x_t = \lambda f_t + \epsilon_t \tag{3.1}$$

In Equation 3.1, $x_t = [x_{1,t}, x_{2,t}, \cdots, x_{n,t}]'$ denotes the vector of monthly observable variables standardized to zero mean and unit variance for t = 1, 2, ...T where t refers to the time index. f_t is the r×1 vector of the unobserved (latent) common factors. λ is the n × r matrix containing factor loadings at time t. These weights load on the unobserved factors. $\epsilon_t = [\epsilon_{1,t}, \epsilon_{2,t}, \cdots, \epsilon_{n,t}]'$ is the n × 1 vector of the idiosyncratic component which involves the shocks to the factors. The dynamics of the common factors, f_t , is modeled as a stationary vector autoregression process:

$$f_t = A_1 f_{t-1} + A_2 f_{t-2} + \cdots + A_p f_{t-p} + u_t \qquad u_t \sim i.i.d.\ N(0, Q)$$

where A_1, A_2, .., A_p have dimension r × r.

The meaning of the Equation 3.1 is that the unobserved factors f_t load the x_t through λ (Valk, Mattos & Ferreira, 2019). λf_t is named as the common component which models the common shocks (Mokas, 2016).

3.1.1 The problem of mixed frequency

In order to nowcast a quarterly Turkish GDP, we adopt the model proposed in Mariano and Murasawa (2003) which models quarterly GDP by monthly variables. In Equation 3.2, X_t^M is the value of the unobservable monthly GDP and X_t^Q is the quarterly value of GDP for t = 3, 6, 9 ...T.

$$X_t^Q = X_t^M + X_{t-1}^M + X_{t-2}^M \tag{3.2}$$

The equation 3.2 says that the quarterly GDP (X_t^Q) is equal to the sum of the unobservable monthly GDP. The change in quarterly GDP can be expressed in Equation 3.3:

$$x_t^Q = X_t^Q - X_{t-3}^Q \tag{3.3}$$

The differences of the monthly variable are depicted in Equation 3.4:

$$x_t^M = X_t^M - X_{t-1}^M \tag{3.4}$$

By using the calculation of Mariano and Murasawa (2003), we bring that:

$$x_t^Q \approx \frac{1}{3}(X_t^M + 2X_{t-1}^M + 3X_{t-2}^M + 2X_{t-3}^M + X_{t-4}^M) \tag{3.5}$$

We adopt the study of Bai and Ng (2002) and Bai and Ng (2007) to determine the number r of factors and the number of shocks q to the factors in Equation 3.1.

3.1.2 Estimation

To estimate dynamic factors, Two-Stage approach and Expectation-Maximization Algorithm (the EM Algorithm) are preffered mostly in the literature. Firstly, the Two-Stage approach estimates the unobserved and the loadings by Principal Components Analysis. To cope with the missing values and outliers, Kalman smoothing is used to re-estimate the factors (Mokas, 2016). We adopt the second estimation technique, the EM Algorithm, developed by Banbura and Modugno (2010) for estimating unobserved common factors and missing values. The EM Algorithm assume that the number of shocks to the factors q is equal to the number of factors r. The EM Algorithm has more restrictive assumption than the Two-Stage method in terms of that the number of common shocks q can not be specified (Valk et al. , 2019).

3.2 The univariate benchmark: ARIMA model

As can be seen from what has been said so far, the thesis focuses on nowcasting. The aim of nowcasting studies is to predict the current target indicator, mostly the GDP. Forecasting, on the other hand, tries to predict the future value of the target indicator based on historical time series. In time series analysis, Autoregressive Integrated Moving Average (ARIMA) methodology is most prevailing for forecasting. We will forecast Turkish GDP by using ARIMA model based on its own past values. Because of that, it is called univariate time series forecasting in the literature. The equation of ARIMA model is:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \cdots + \beta_P Y_{t-p} \epsilon_t + \phi_1 \epsilon_{t-1} + \cdots + \phi_q \epsilon_{t-q} \qquad (3.6)$$

In Equation 3.6, Y_t is the predicted GDP, $Y_{t-1} \ldots Y_{t-p}$ are the lags of past GDP upto p lags, $\epsilon_{t-1} \ldots \epsilon_{t-q}$ are the lagged forecast errors upto q lags and α is constant or intercept.

The biggest noticeable difference between the two methods is that the dataset used for GDP estimation are different. Nowcasting utilizes from different indicators while the ARIMA model only uses historical values of GDP. The estimation periods of nowcasting and forecasting are also different. The first allows estimations on a monthly basis, while the other forecasts quarter to quarter. As a result, the performance of two models will be evaulated seperately.

3.3 The dataset and its description

The section provides the description of the collected variables. The dataset includes in total 25 publicly available indicators for the Turkish economy. We categorize the dataset into three blocks, namely “real data”, “financial data” and “survey data” depending on their content. Eleven of them are real data including quarterly real GDP, seven series are financial data and, last seven series are survey data. Except for GDP, which is quarterly data, all series have the monthly frequency. Even though the series are relatively short, the first observation at the dataset starts with January 2010 and the dataset finishes at December 2021. The constructed dataset includes the main variables available for the Turkish economy.

Table 1 depicts variables, their affiliated groups, the applied transformations (1 represents monthly rate of change, 2 represents monthly difference, 7 represents quarterly rate of change), their units, their delays, institutions or people by which indicators are released. TSI refers to the Turkish Statistical Institute. AIA refers to the Automotive Industry Association. ADA refers to the Automotive Distributors

Association. TEA refers to Turkey Electricity Administration Inc.. CBRT refers to the Central Bank of the Republic of Turkey. EIA refers to the Energy Information Administration. BAT refers to the Banks Association of Turkey. TR refers to Thomson Reuters. In delay column, some series are marked as minus because they were announced before the end of the month. In other words, it shows how many days before the end of the month the data was announced.

Caldara and Iacoviello create the geopolitical risk index (GPR) covering geopolitical tensions and events. In the new version, which has been published since 1985 and can be accessed from websites, 10 newspapers were used. According to this index created for 39 different countries, the higher risk signals to “low investments, stocks and employment” (Caldara and Iacoviello, 2022). Since these factors are related to economic growth, we decided to add the index to our dataset.

As an example, Table 2 shows the structure of our dataset for the nowcasting exercise of the Q1-2020 at January. The dataset involves both monthly and quarterly variables, containing ragged ends and missing observations. In the table, N/A means not available while + means that data are available and TBA represents that the data will be announced. GDP is depicted in the last month of the quarter.

The public availability and the timeliness of the series was critical for us when creating our dataset. The target variable of this study is the seasonally adjusted quarter-on-quarter growth rate for the Turkish GDP.

Table 1. The Description of the Dataset

Group	Series Name	Transformation	Units	Delay	Released by
Real	Export (EX)	1	Thousand TL	30	TSI
Real	Import (IMP)	1	Thousand TL	30	TSI
Real	Home Sales (HSALES)	1	Units	15	TSI
Real	Employment (EMP)	2	Thousands of Persons	45	TSI
Real	Unemployment Rate (UNEMP)	2	%	45	TSI
Real	Consumer Price Index (CPI)	1	Index	5	TSI
Real	Producer Price Index (PPI)	1	Index	5	TSI
Real	Vehicle Production (VPROD)	1	Units	30	AIA
Real	Auto Sales (ASALES)	1	Units	30	ADA
Real	Electricity Consumption (Daily) (ECONS)	1	MWh	5	TEA
Financial	Europe Brent Spot Price FOB (Dollars per Barrel) (EUBR)	1	Units	2	EIA
Financial	Total Domestic Credit Volume (TDOMCR)	1	Thousand TL	30	CBRT
Financial	Credit Card Spending (CRSPEN)	1	Thousand TL	30	CBRT
Financial	BIST100 (BIST)	1	Index	0	CBRT
Financial	Mortgage Credits (MORTCR)	1	Millions TL	30	BAT
Financial	Nonperforming Loan (NPL)	1	Millions TL	30	BAT
Financial	Credit Default Swap (CDS)	1	Index	0	TR
Survey	Capacity Utilization Rate of Man. Industry (CURMI)	2	%	-3	CBRT
Survey	Consumer Confidence Index (CCI)	1	Index	-5	TSI
Survey	Geopolitical Risk Index (GPR)	1	Index	0	Caldara & Iacoviello
Survey	Service Confidence Index (SCI)	1	Index	-5	TSI
Survey	Construction Confidence Index (CONCI)	1	Index	-5	TSI
Survey	Industrial Production Index (IPI)	1	Index	-5	CBRT
Survey	Real Sector Confidence Index (RSCI)	1	Index	-5	CBRT
Real	Gross Domestic Product (GDP)	7	Thousand TL	60	TSI

Table 2. The Structure of the Dataset at January 2020

TIME	EX	IMP	HSALES	…	TDOMCR	CRSPEN	…	NPL	CDS	CURMI	…	RSCI	GDP
2010-01	N/A	N/A	N/A	…	+	N/A	…	+	+	+	…	+	N/A
2010-02	N/A	N/A	N/A	…	+	N/A	…	+	+	+	…	+	N/A
2010-03	N/A	N/A	N/A	…	+	N/A	…	+	+	+	…	+	+
2010-04	N/A	N/A	N/A	…	+	N/A	…	+	+	+	…	+	N/A
…	…	…	…	…	…	…	…	…	…	…	…	…	…
2012-01	N/A	N/A	N/A	…	+	N/A	…	+	+	+	…	+	N/A
2012-02	N/A	N/A	N/A	…	+	N/A	…	+	+	+	…	+	N/A
2012-03	N/A	N/A	N/A	…	+	N/A	…	+	+	+	…	+	+
2012-04	N/A	N/A	N/A	…	+	N/A	…	+	+	+	…	+	N/A
…	…	…	…	…	…	…	…	…	…	…	…	…	…
2014-01	+	+	+	…	+	N/A	…	+	+	+	…	+	N/A
2014-02	+	+	+	…	+	N/A	…	+	+	+	…	+	N/A
2014-03	+	+	+	…	+	+	…	+	+	+	…	+	+
2014-04	+	+	+	…	+	+	…	+	+	+	…	+	N/A
…	…	…	…	…	…	…	…	…	…	…	…	…	…
2019-10	+	+	+	…	+	+	…	+	+	+	…	+	N/A
2019-11	+	+	+	…	+	+	…	+	+	+	…	+	N/A
2019-12	+	+	+	…	+	+	…	+	+	+	…	+	TBA
…	…	…	…	…	…	…	…	…	…	…	…	…	…
2020-01	TBA	TBA	TBA	…	TBA	TBA	…	TBA	+	+	…	+	N/A
2020-02	TBA	TBA	TBA	…	TBA	TBA	…	TBA	TBA	TBA	…	TBA	N/A
2020-03	TBA	TBA	TBA	…	TBA	TBA	…	TBA	TBA	TBA	…	TBA	TBA

CHAPTER 4

EMPIRICAL RESULTS

The chapter is devoted to the empirical part of the thesis. Initially, we prepared our dataset for nowcasting and forecasting exercises. For this reason, we applied seasonality and stationarity test. To apply the scenarios we had drawn for nowcasting, we replicate the codes that Valk et al. (2019) had prepared on R. The empirical results of the dynamic factor model and ARIMA were presented and interpreted. Finally, the root mean squared error (RMSE), mean squared error (MSE) and mean absolute error (MAE) are used to measure the performance of two models.

4.1 Design of the empirical nowcasting exercises

Our aim is to present the results of forecasts, nowcasts and backcasts of the quarter-over-quarter Turkish GDP growth rate between 2020Q1 and 2021Q4 period. In a word, we estimated the past, current or future values of Turkish GDP.

For each quarter, seven estimations are made, each at the end of the month. Three of them are forecast, three are nowcast and one is backast. As there are eight quarters in two years, 56 exercises totally were performed. As in the literature, we use the term backcasting for estimation the value of a yet unpublished GDP by using the indicators after the end of that quarter. The term nowcasting, if we repeat, estimates the GDP growth rate by using the available indicators within the measured quarter.

If we clarify our exercises by way of illustration (see Figure 1), suppose we want to apply the exercises for the the second quarter of 2021. If the exercises are made during the first quarter of 2021, the estimations are named as the forecast period. If the exercises are applied during the second quarter of 2021, this period is the nowcast. Finally, if the exercise is applied after the second quarter of 2021 and the GDP is unknown, then this estimation period is classified as the backcast. As is seen in Figure 1, backcasting is implemented once because GDP is officially announced next month (at the end of August) for the second quarter of 2021.

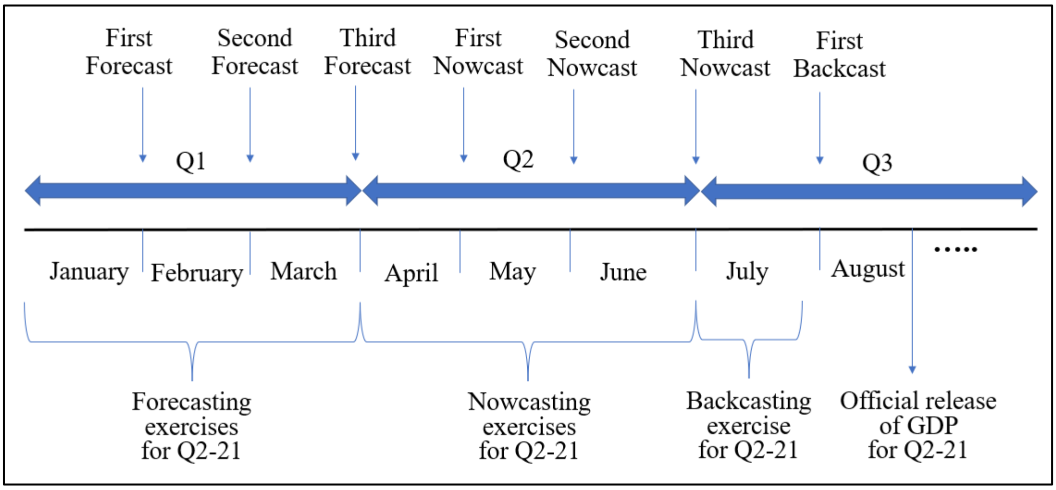

Figure 1. The illustration of the exercises for the second quarter of 2021

The exercises are recursive even the dataset has a fixed starting point but as data are announced, its last point moves forward. Our dataset starts at January 2010, while it spans to December 2021 for the last scenario. The dataset of the model are updated before each exercise at the end of each month. All exercises are applied based on the dynamic factor model.

4.2 Data transformation

To apply the exercises, firstly, we test the seasonality and the stationarity of the dataset. Our first data preprocessing is whether the variables have seasonality. We applied Webel-Ollech (WO) Seasonality Test for all indicators. Because “Auto Sales”, “Electricity Consumption (Daily)”, “GDP”, “Home Sales”, “Industrial Production Index” and “Vehicle Production” identify the seasonality, we seasonally adjust those economic indicators by Tramo-Seats. Since other indicators do not identify the seasonality, we use their original forms.

After seasonality test, we transform all indicators to stationarity form. Phillips-Perron Unit Root Test is applied for all time series. The null hypothesis (H_0) of the test is that the series contain a unit root while the alternative hypothesis (H_1) has no unit root. The test results after the series were differenced are given in Table 3. Since the p-value of all indicators is smaller than a critical size (0.05), the null can be rejected and the series appears the stationarity.

Table 3. Stationarity Test for All Indicators

Phillips-Perron Unit Root Test	p-value
Auto Sales	0.03413
BIST100	0.01
Consumer Confidence Index	0.01
Credit Default Swap	0.01
Construction Confidence Index	0.03973
Consumer Price Index	0.01
Credit Card Spending	0.03389
Capacity Utilization Rate of Manufacturing Industry	0.01
Electricity Consumption (Daily)	0.04723
Employment	0.01
Europe Brent Spot Price FOB (Dollars per Barrel)	0.01
Export	0.01
Gross Domestic Product	0.01
Geopolitical Risk Index	0.01
Home Sales	0.01
Import	0.01
Industrial Production Index	0.01
Mortgage Credits	0.01
Nonperforming Loan	0.01
Producer Price Index	0.0154
Real Sector Confidence Index	0.01
Service Confidence Index	0.01
Total Domestic Credit Volume	0.01
Unemployment Rate	0.01
Vehicle Production	0.01

In last step, we adopt the approach of the Expectation-Maximization to estimate the parameters, the unobserved common factors and the missing values. We do not discard any series which are the observations are missing from the database.

After estimation, we check the autocorrelation for residuals by applying Durbin-Watson Test. The test statistic for the Durbin-Watson test is computed in Equation 4.1.

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2} \tag{4.1}$$

where *T* is the total number of observations and e_t is the t^{th} residual from the regression model. The test statistic result (*d*) is always between 0 to 4. If *d* is equals to 2, it shows no autocorrelation. If *d* is smaller than 2, it demonstrates positive serial correlation, and if *d* is bigger than 2 depicts negative serial correlation. The null hypothesis (H_0) of the test is that there is no correlation among the residuals while the alternative hypothesis (H_1) is that the residuals are autocorrelated. Since *d* in our test is 2.04, we cannot reject the null hypothesis and conclude that the residuals in this regression model are not autocorrelated.

4.3 The selection of parametrizations

In order to select the best estimation, we compared the errors by changing the number r of dynamic factors and the lag order p of the factors. Since the number r of dynamic factors equals to the number q of shocks to the factors in the EM Algorithm, we do not change the parameter of the q seperately. As an example, the RMSE, the MSE and the MAE of the third forecast and of the third nowcast were compared to choose the best parameters. As can be seen in Table 4, r = 1, p = 1 parameters gave significantly better results. For this reason, we assigned the parameters as r = 1, p = 1 in all our work.

Table 4. The Comparison of the Numbers of the Parameters by the Statistical Errors

2020-2021	Third Forecast			Third Nowcast		
	RMSE	MSE	MAE	RMSE	MSE	MAE
r=1, p=1	0.061297	0.003757	0.051427	0.054765	0.002999	0.046822
r=2, p=1	0.071669	0.005136	0.064915	0.071337	0.005089	0.06609
r=1, p=2	0.076588	0.005866	0.070218	0.07653	0.005857	0.069647

4.4 The performance of the model

To measure the performance of the model, we will depict the RMSE, the MSE and the MAE for the period of 2020Q1-2021Q4 in Table 5, 6 and 7.

As it can be seen in Table 5, 6 and 7, seven exercises were applied for each quarter of 2020 and 2021. The first three are the forecasts, the next three are the nowcasts, and the last one is the backast. Our expectation in line with the literature is that the errors of the forecast period will be the highest and then the errors of the nowcast period are higher than the backcast.

As can be seen in Table 5, which shows the year 2020, all forecast errors are higher than the nowcast errors but the backcast errors are higher than the nowcast errors. We can conclude that the performance of the nowcast period are better than the forecast and ever the backcast periods in 2020.

In Table 6, which shows the year 2021, the results are more evident. The biggest error was in the first month of the forecast period, and the errors are decreasing with each subsequent months. As expected the backcast has given better results than the nowcast period.

In Table 7, where the performance of the model is evaluated as overall, the biggest error is in the forecast period, and the errors are decreasing gradually with each next months in the nowcast and the backcast periods. Naturally, the least error realized in the last exercise, in other words in the backast period.

It can be said that the model gives the expected results in general. It seems that 2020 is not as successful as 2021. Due to COVID19, the model may have deviated in 2020 but more research is needed for this assumption.

Table 5. The Errors of the Model for Successive Horizontal Estimation of 2020

2020	First Forecast	Second Forecast	Third Forecast	First Nowcast	Second Nowcast	Third Nowcast	Backcast
MSE	0.0020	0.0019	0.0020	0.0015	0.0013	0.0018	0.0019
MAE	0.0334	0.0338	0.0356	0.0323	0.0327	0.0376	0.0390
RMSE	0.0444	0.0439	0.0453	0.0386	0.0361	0.0427	0.0439

Table 6. The Errors of the Model for Successive Horizontal Estimation of 2021

2021	First Forecast	Second Forecast	Third Forecast	First Nowcast	Second Nowcast	Third Nowcast	Backcast
MSE	0.0060	0.0059	0.0055	0.0057	0.0049	0.0042	0.0040
MAE	0.0709	0.0704	0.0673	0.0701	0.0610	0.0561	0.0549
RMSE	0.0777	0.0766	0.0739	0.0758	0.0700	0.0646	0.0631

Table 7. The Errors of the Model for Successive Horizontal Estimation between 2020Q1 and 2021Q4

Overall	First Forecast	Second Forecast	Third Forecast	First Nowcast	Second Nowcast	Third Nowcast	Backcast
MSE	0.0040	0.0039	0.0038	0.0036	0.0031	0.0030	0.0030
MAE	0.0521	0.0521	0.0514	0.0512	0.0468	0.0468	0.0469
RMSE	0.0633	0.0624	0.0613	0.0602	0.0557	0.0548	0.0544

4.5 The impact of survey data on the model

When making the estimations, the quality of the data is as important as its timing. In the nowcasting literature, the effect of the data type on the estimations was frequently studied. In this section, we will test the effect of survey data on the estimations. We have taken the dataset we have used in our study as a base dataset. We will compare the performances of our base dataset with new dataset, which does not include survey variables. In parallel with the results in the literature, our aim is to observe the contribution of survey data at the beginning of the estimation and whether its effect decreased towards the end of the quarter. According to our hypothesis, since the base dataset contains survey data, we expect it to give a lower error than the dataset without survey data in the beginning of the estimations. Towards the end of the quarter, since the survey data will be negligible, it is expected that there will be no significant difference in the performance of the two datasets. We used the t-test to test the hypothesis.

Before applying the t-test, we performed a normality test for the residuals which are the difference between the residuals of two datasets. The p-value of the Jarque-Bera normality test is 0.38902. Since this p-value is not less than 0.05, we fail to reject the null hypothesis. We have sufficient evidence to say that the residuals are normally distributed so we can apply t-test for the residuals.

We used t-test to test our hypothesis to determine whether there is a significant difference between the values. A paired t-test is performed since it can compares the same values for different datasets at the same estimation time. The values in this study are the residuals, the squared residuals and the absolute errors of two datasets. As seven estimations were made for each quarter, we compared seperately the errors of two datasets seven times.

One-tailed hypothesis tests are used because we expect the errors of the base dataset are lower than the the errors of the new dataset without survey data. The null hypothesis (H_0) is no significantly difference between two errors. If the p-value is lower than 0.05, we reject H_0 and then accept the alternative hypothesis (H_1) which shows a statistically significant difference between two errors.

As it can be seen in Table 8, the null hypothesis cannot rejected because all the values of the estimations are greater than 0.05, so there is no significant difference between two errors. As a result, the absence of survey data does not statistically affect the performance of the model. However, during the forecast period, the p-value sharply drops, we can infer that the effect of the survey data descends as closer to the measured quarter. Although studies in the literature show that the contribution of survey data at the end of the quarter is lower than at the beginning of the quarter, we cannot track a clear difference in our case.

Table 8. One-Tailed t-test Between Reference Dataset and the New Dataset without Survey Data

p-value	First Forecast	Second Forecast	Third Forecast	First Nowcast	Second Nowcast	Third Nowcast	Backcast
Residuals	0.4159	0.1454	0.0606	0.2245	0.0512	0.2547	0.1371
Squared Residuals	0.3972	0.0592	0.0427	0.3596	0.2168	0.3124	0.4939
Absolute Error	0.3004	0.0804	0.0741	0.3213	0.2777	0.3045	0.4745

4.6 Forecasting with ARIMA model

In this model, we only use historical data of quarterly GDP. We will apply the same scenario like in the nowcasting exercises. As each quarter is announced, we will forecast the next quarters. Our dataset starts with the first quarter of 2010. Suppose that we are at the first quarter of 2020 and forecast that quarter based on historical time series. Since forecasting exercises does not allow to estimate the GDP at every month like in the nowcasting exercises, the forecast scenarios were applied after each quarter was announced. Therefore the considerable difference between two model is the estimation frequency. For the consistency, we compare the two models seperately. The reason we include the ARIMA model in this study is to observe the change of the errors as each estimation is applied.

The data transformation methodology of the nowcasting in Section 4.2 was also applied for the forecasting. The seasonality problems are seen respectively in Figure 2 and Figure 3. Seasonally adjusted GDP time series with Tramoseats can be seen in Figure 4 and Figure 5.

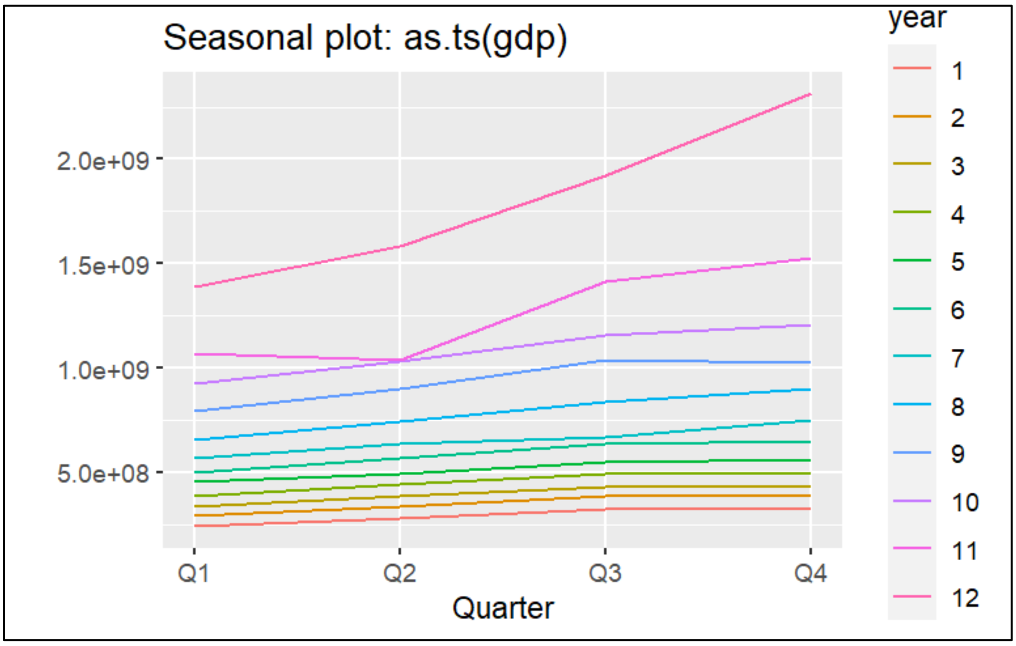

Figure 2. The seasonality by years

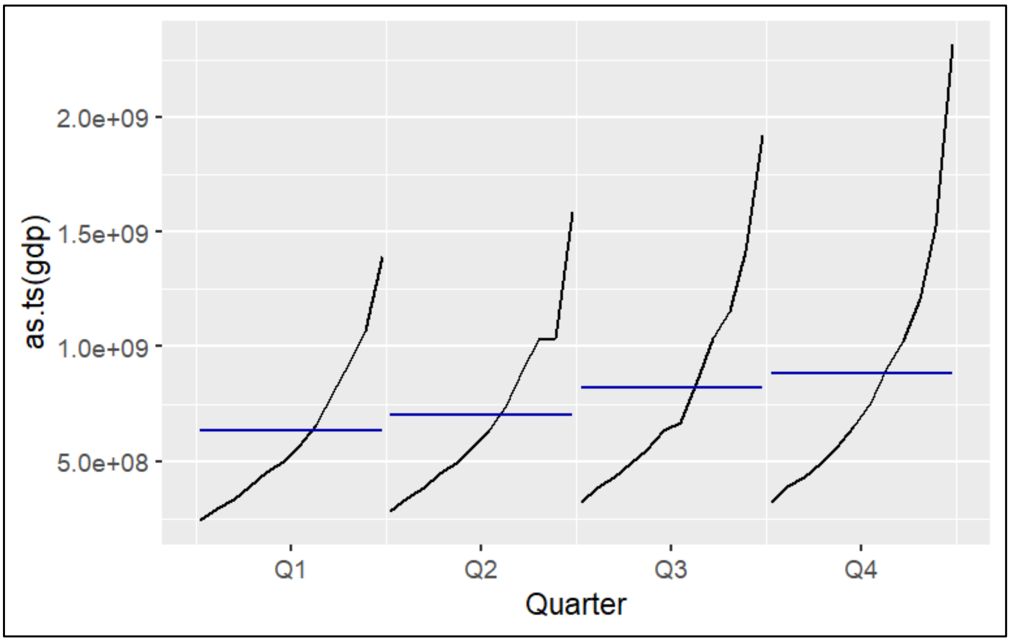

Figure 3. The seasonality in terms of frequencies

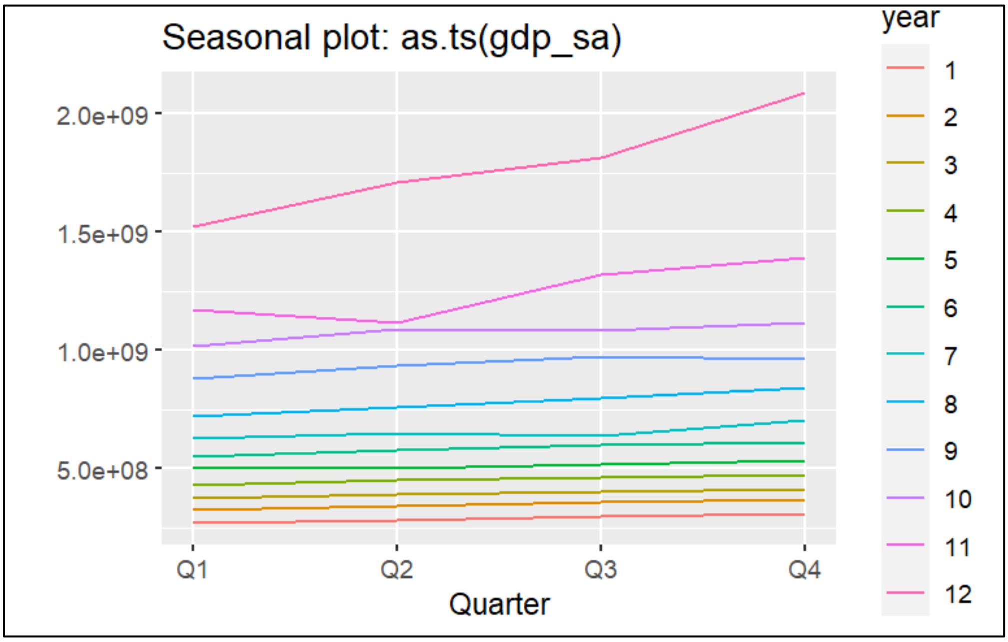

Figure 4. The seasonality by years after data transformation by TramoSeat

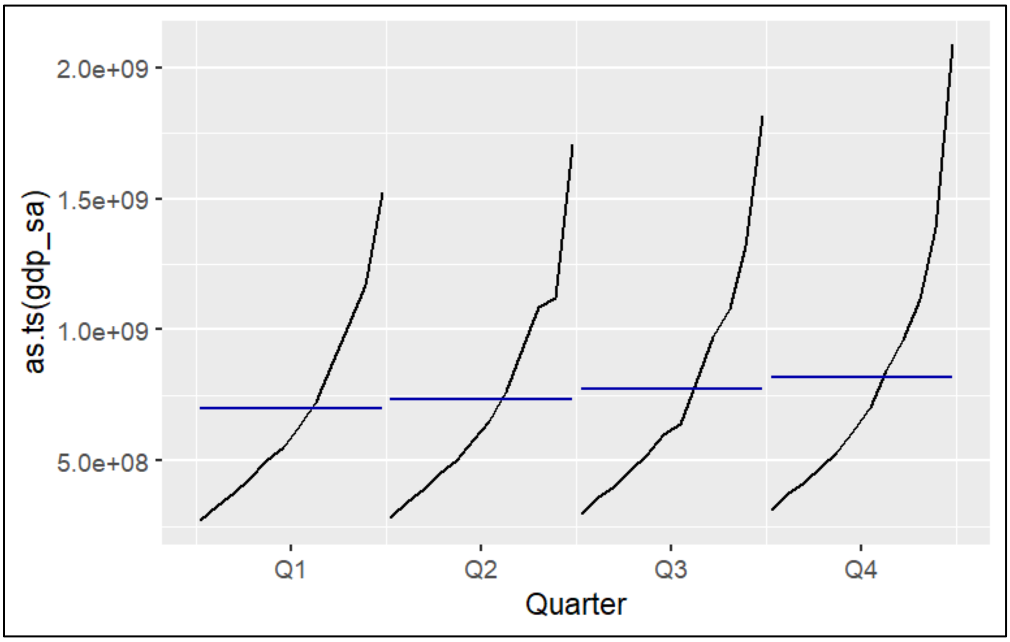

Figure 5. The seasonality in terms of frequencies after data transformation by TramoSeat

After this process, we check whether seasonally adjusted GDP is the stationarity by applying Phillips-Perron Unit Root Test. Since the p-value (0.99) is greater than 0.05, we conclude that there is no enough evidence to reject the null hypothesis, meaning that the time series of the data is nonstationary. For the stationarity, the variance and the mean of seasonally adjusted time series homogenized. For this process, we take log and then first difference of the time series. The p-value (0.01) of the test is smaller than 0.05, we reject the null hypothesis and conclude that the time series is now stationary.

auto.arima code in R gives the best ARIMA model by calculating AIC, AICc or BIC value. In our case, the best model is ARIMA (1,0,0). We make the forecast based on AR (1).

As seen in Table 9, the forecasting exercises were applied at each quarter. As each quarter is announced, the errors are expected to drop but we did not observe a significant decrease.

Table 9. The Statistical Error of ARIMA Model

The Estimation Time	MSE	MAE	RMSE
Q1_20	0.0005	0.0158	0.0213
Q2_20	0.0004	0.0156	0.0211
Q3_20	0.0005	0.0177	0.0232
Q4_20	0.0005	0.0181	0.0227
Q1_21	0.0001	0.0090	0.0119
Q2_21	0.0006	0.0184	0.0246
Q3_21	0.0013	0.0235	0.0357

The autocorrelation function (ACF) of the residuals, the differences between expected and actual GDP is also check to determine whether the residuals have autocorrelation. In a good forecasting method, the residuals must be uncorrelated. Because the residuals are within the dash lines in Figure 6, the residuals does not have autocorrelation.

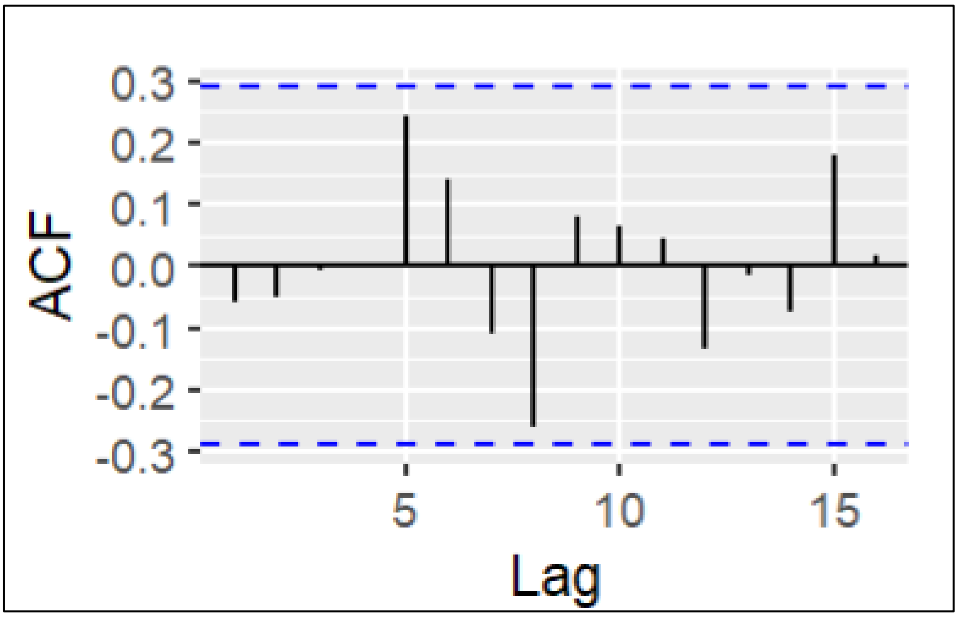

Figure 6. ACF plot for the residuals

CHAPTER 5

CONCLUSIONS

This last chapter holds the conclusions of the thesis. The section 5.1 outlines the nowcasting study and summarizes the main findings of the empirical application of two models, that is, dynamic factor model and ARIMA model. The next section 5.2 points out the limitations of the thesis and present recommendations for future studies.

5.1 Summary and key findings

The focus of the thesis was to nowcast the quarterly GDP growth rate of the Turkish economy for the period 2020-2021 by utilizing dynamic factor model. This model exploits large dataset which can be summarized in a few latent factors. Also, it enable us to use variables with different frequencies. Additionally, it can deal with the problems of the missing values and the jagged edges. We choose this model since our dataset has missing values at the beginning and the end of the sample with mixed frequencies. For the estimation of GDP, we select 24 monthly indicators which categorized into three types as: real, financial and survey data.

To generate the nowcast is rather different from the traditional macroeconomic forecasting exercises since the nowcasting exercises contains the backcasting, the nowcasting and the forecasting scenerios for same quarter and the nowcasting is a model projection not involve any judgmental approaches.

The results show that the accuracy of the dynamic factor model increases month by month. The inclusion of survey data in the dataset did not statistically change the result. The comparison the dynamic factor model with ARIMA model was not made since the estimation period of the ARIMA model is quarterly.

However, the accuracy of the ARIMA model was not improve by the time, unlike dynamic factor model.

As a result, the dynamic factor model is more successful than ARIMA model. If we list the reasons; the accuracy of the model is improving. The model can be developed and adapted to different macroeconomic variables like inflation. The estimation period is more frequent than ARIMA model and can even be applied daily or weekly. It also provides more economic interpretations. Several indicators can be used and so the impact of the data can be observed. Lastly, using timelier indicators gives an idea for policymakers about the current GDP.

5.2 Limitations of the study and recommendations

The selection of indicators relies on the author's opinion which intends to encompass all dimensions of economic outlook. In this way, it was believed that the GDP would be predicted successfully. Although the content of the variables would be reasonable, before applying dynamic factor model, a formal statistical selection procedures can be applied and then the dataset can be constructed. Furthermore, the selected evaluation period was short. Because the year of 2020 is affected by COVID 2019, the performance of the dynamic factor model might have been generalized. Regardless of specific or unprecedented periods, a longer evaluation time-span would be studied for the general performance of the nowcasting.

One of the possible objections is - considering ARIMA model, the benchmark model of the thesis, it is not used in practice by the policy makers. Although we do not know how much the nowcasting has been adopted by policy makers in Turkey, it can be say that it is an insightful and an alternative model to grasp the current state of Turkish economy.

The scope of the study was to observe the accuracy of the nowcasting by using dynamic factor model and the forecasting by using ARIMA. Howover, comparing nowcasting methodologies among themselves might display different results and interpretations. In this sense, the dynamic factor model and MIDAS can be compared based on the nowcasting literature. Also, bank transactions can be used for nowcasting. Finally, the nowcasting study can be extended by using weekly and daily indicators. It can be discovered whether higher frequency data actually succeeds in estimating the GDP. The limitations noted above naturally offer suggestions for future researches.

APPENDIX A

RESULTS OF 2020 ESTIMATIONS

Table A1. Results of Estimations for the First Quarter of 2020

Q1-2020	Realized	M10F	M11F	M12F	M1N	M2N	M3N	M4B
Growth Rate	0.0513	0.0388	0.0367	0.0366	0.0289	0.0270	0.0262	0.0249
Residuals	-	0.0124	0.0146	0.0147	0.0224	0.0242	0.0251	0.0264
Squared Residuals	-	0.0002	0.0002	0.0002	0.0005	0.0006	0.0006	0.0007
Absolute Error	-	0.0124	0.0146	0.0147	0.0224	0.0242	0.0251	0.0264

Table A2. Results of Estimations for the Second Quarter of 2020

Q2-2020	Realized	M1F	M2F	M3F	M4N	M5N	M6N	M7B
Growth Rate	-0.0445	0.0392	0.0375	0.0377	0.0131	0.0112	0.0214	0.0214
Residuals	-	-0.0837	-0.0820	-0.0822	-0.0576	-0.0557	-0.0659	-0.0659
Squared Residuals	-	0.0070	0.0067	0.0068	0.0033	0.0031	0.0043	0.0043
Absolute Error	-	0.0837	0.0820	0.0822	0.0576	0.0557	0.0659	0.0659

Table A3. Results of Estimations for the Third Quarter of 2020

Q3-2020	Realized	M4F	M5F	M6F	M7N	M8N	M9N	M10B
Growth Rate	0.0181	0.0406	0.0389	0.0506	0.0643	0.0542	0.0642	0.0681
Residuals	-	-0.0225	-0.0208	-0.0325	-0.0462	-0.0361	-0.0461	-0.0500
Squared Residuals	-	0.0005	0.0004	0.0011	0.0021	0.0013	0.0021	0.0025
Absolute Error	-	0.0225	0.0208	0.0325	0.0462	0.0361	0.0461	0.0500

Table A4. Results of Estimations for the Fourth Quarter of 2020

Q4-2020	Realized	M7F	M8F	M9F	M10N	M11N	M12N	M1B
Growth Rate	0.0523	0.0375	0.0346	0.0393	0.0492	0.0375	0.0392	0.0387
Residuals	-	0.0149	0.0178	0.0130	0.0031	0.0148	0.0131	0.0136
Squared Residuals	-	0.0002	0.0003	0.0002	0.0000	0.0002	0.0002	0.0002
Absolute Error	-	0.0149	0.0178	0.0130	0.0031	0.0148	0.0131	0.0136

Not: “Realized” denotes the real quarterly rate of GDP change, “M” and its number indicate the month in which the model was applied. For example, M10 shows that the model was applied in October. “F” represents forecasting, “N” represents nowcasting and finally “B” represents backcasting for the quarter indicated at the top left of the table.

APPENDIX B

RESULTS OF 2021 ESTIMATIONS

Table B1. Results of Estimations for the First Quarter of 2021

Q1-2021	Realized	M10F	M11F	M12F	M1N	M2N	M3N	M4B
Growth Rate	0.0966	0.0357	0.0347	0.0368	0.0289	0.0259	0.0302	0.0339
Residuals	-	0.0609	0.0619	0.0598	0.0678	0.0707	0.0664	0.0628
Squared Residuals	-	0.0037	0.0038	0.0036	0.0046	0.0050	0.0044	0.0039
Absolute Error	-	0.0609	0.0619	0.0598	0.0678	0.0707	0.0664	0.0628

Table B2. Results of Estimations for the Second Quarter of 2021

Q2-2021	Realized	M1F	M2F	M3F	M4N	M5N	M6N	M7B
Growth Rate	0.1199	0.0361	0.0360	0.0398	0.0415	0.0578	0.0603	0.0600
Residuals	-	0.0838	0.0839	0.0801	0.0784	0.0621	0.0596	0.0599
Squared Residuals	-	0.0070	0.0070	0.0064	0.0062	0.0039	0.0036	0.0036
Absolute Error	-	0.0838	0.0839	0.0801	0.0784	0.0621	0.0596	0.0599

Table B3. Results of Estimations for the Third Quarter of 2021

Q3-2021	Realized	M4F	M5F	M6F	M7N	M8N	M9N	M10B
Growth Rate	0.0616	0.0358	0.0352	0.0391	0.0346	0.0539	0.0568	0.0563
Residuals	-	0.0259	0.0264	0.0225	0.0270	0.0077	0.0049	0.0053
Squared Residuals	-	0.0007	0.0007	0.0005	0.0007	0.0001	0.0000	0.0000
Absolute Error	-	0.0259	0.0264	0.0225	0.0270	0.0077	0.0049	0.0053

Table B4. Results of Estimations for the Fourth Quarter of 2021

Q4-2021	Realized	M8F	M9F	M10N	M11N	M12N	M1B	M7F
Growth Rate	0.1505	0.0375	0.0414	0.0440	0.0433	0.0473	0.0571	0.0590
Residuals	-	0.1130	0.1092	0.1065	0.1073	0.1032	0.0934	0.0916
Squared Residuals	-	0.0128	0.0119	0.0114	0.0115	0.0107	0.0087	0.0084
Absolute Error	-	0.1130	0.1092	0.1065	0.1073	0.1032	0.0934	0.0916

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