CONSTRUCTION OF AN ECONOMIC ACTIVITY INDICATOR FOR TURKEY

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF SOCIAL SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

AYSU ÇELGİN

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
THE DEPARTMENT OF ECONOMICS

AUGUST 2020

Approval of the thesis:

CONSTRUCTION OF AN ECONOMIC ACTIVITY INDICATOR FOR TURKEY

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ABSTRACT

CONSTRUCTION OF AN ECONOMIC ACTIVITY INDICATOR FOR TURKEY

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August 2020, 75 pages

In this thesis, a monthly economic activity indicator is constructed for the Turkish economy for the period 1988-2020. Dynamic factor modelling framework is utilized in the estimation of the indicator because of being good at synthesizing macroeconomic variables into an indicator. Variables used in the estimation of the indicator are industrial production index, electricity production, total vehicles production, the volume of production over the past 3 months, real sector confidence index, import volume index, non-farm employment, credit stock, CDS and GDP. Data selection is done with the help of the hard-thresholding method. In this context, first of all, the variables are categorized into five types as: activity (hard data), activity (survey-based data or soft data), trade, employment and financial variables. After determining the candidate variables for each category, data selection is finalized by using the hard-thresholding method. The results indicate that our monthly economic activity indicator is successful in detecting the past recessionary periods of the Turkish economy and providing timelier information about the course of economic activity.

Keywords: Economic Activity, Dynamic Factor Model, Hard-Thresholding, Real Time Analysis

ÖZ

TÜRKİYE İÇİN BİR İKTİSADİ FAALİYET GÖSTERGESİ OLUŞTURULMASI

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Ağustos 2020, 75 sayfa

Bu tezde, Türkiye ekonomisi için 1988-2020 dönemini kapsayan bir iktisadi faaliyet göstergesi oluşturulmuştur. Göstergenin oluşturulmasında, makroekonomik değişkenlerin bir göstergeye sentezlenmesinde başarılı olduğu için, dinamik faktör modeli yönteminden faydalanılmıştır. Gösterge hesaplanırken sanayi üretim endeksi, elektrik üretimi, toplam araç üretimi, son 3 aydaki üretim hacmi, reel kesim güven endeksi, ithalat miktar endeksi, tarım-dışı istihdam, kredi stoku, CDS ve GSYİH verileri kullanılmıştır. Veri seçimi, sert-eşikleme yöntemiyle yapılmıştır. Bu kapsamda, öncelikle değişkenler faaliyet (gerçekleşme verileri), faaliyet (anket göstergeleri), ticaret, istihdam ve finansal değişkenler olmak üzere beş gruba ayrılmıştır. Her kategori için aday değişkenler belirlendikten sonra, sert-eşikleme yöntemi kullanılarak veri seçimi tamamlanmıştır. Sonuçlar, aylık iktisadi faaliyet göstergemizin, Türkiye ekonomisinin geçmiş daralma dönemlerini tespit etmede ve ekonomik faaliyetin seyri hakkında zamanlı bilgi sağlamada başarılı olduğunu göstermektedir.

Anahtar Kelimeler: İktisadi Faaliyet, Dinamik Faktör Modeli, Sert-Eşikleme,
Gerçek Zaman Analizi

To My Family

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my supervisor Prof. Dr. Elif AKBOSTANCI for her guidance, advices and encouragement during the research process for this thesis.

I would also like to thank to the examining committee members Assist. Prof. Dr. Pınar DERİN GÜRE and Prof. Dr. Hakkı Ozan ERUYGUR for their invaluable comments and suggestions.

I wish to express my gratitude to my colleagues Çağlar YÜNCÜLER, Mahmut GÜNAY and Çağrı SARIKAYA for their support and suggestions.

Finally, I would like to thank to my mother Ülkü ÇELGİN, my father Ahmet ÇELGİN and my sister Duygu ÇELGİN. Feeling their love is worth everything in this world.

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CHAPTER 1

INTRODUCTION

Economic activity is one of the main indicators to evaluate how a country performs over time. Academicians, business people and decision makers give much importance to the detection of expansion/contraction phases and the real-time cyclical analysis of the economic activity as it is considered crucial for implementing efficient policies, especially in crisis periods. To this end, accurate assessment of the economic activity has an important place in the economic literature.

Gross Domestic Product (GDP) is the most widely known indicator for making deductions about the overall performance of economic activity. However, it has certain drawbacks regarding its timing and content. First of all, it is published with a considerable time lag, e.g. 60 days after the end of the related quarter in Turkey, and is exposed to data revisions after the initial dissemination. Second, GDP itself is not enough to encompass all information about the overall economic activity (Aruoba and Sarikaya, 2013). Tracking the developments in markets other than goods market, e.g. labor market, financial markets, etc., necessitates different data sources and more information than GDP provides. Moreover, utilizing soft data (survey-based data) related with production, consumption, trade and employment may also be useful (Aruoba, Diebold and Scotti, 2009). To sum up, a timelier indicator of economic activity, which encompasses all units of the economy, would be preferable to GDP.

The literature on constructing economic activity indicators is well established, in particular for the US economy. It has progressed over time in terms of data type and estimation methodologies. The pioneering study of Stock and Watson (1989) presents three monthly economic activity indicators for the US economy by using different macroeconomic variables on monthly frequency with the help of dynamic factor modelling framework. They conclude that the indicators are good at detecting recessionary periods in the US economy. Other examples for the US economy that prefer dynamic factor modelling as estimation framework are Mariano and Murasawa (2003), Proietti and Moauro (2006) and Auroba et al. (2009). These papers differ from Stock and Watson (1989) in selecting different frequency variables to their data set. In a later study, Evans (2005) contributes to the literature by estimating the state of the US economy in real-time on a daily basis. Furthermore, Aruoba et al. (2009) construct an indicator on a daily basis for the US economy. Proietti and Moauro (2006) extend their work by constructing economic indicators for Euro Area. In a later paper, Matheson (2011) also extends the country coverage to 32 countries by utilizing dynamic factor modelling approach and monthly variables out of 6 different variable blocks in the construction of economic activity indicator. Darne and Ferrara (2011) construct indicators for both Euro Area and six main countries by using a Markov-Switching VAR model and Markov-Switching factor model. Additionally, Dua and Banerji (2000) and Simone (2001) construct economic activity indicators by using NBER methodology and general to specific approach for Indian economy and Argentina, respectively.

The literature on constructing economic activity indicator for Turkey is scarce. Among them, Aruoba and Sarikaya (2013) construct one by using mixed frequency variables. On the other hand, Çakmaklı and Altuğ (2014) construct a coincident real economic activity indicator for Turkey. Both studies use dynamic factor modelling, while the latter utilize Bayesian semiparametric estimation instead of Kalman filtering algorithm used by the former.

Most of the papers in the literature prefer using dynamic factor modelling framework in the estimation of economic activity indicators, since dynamic factor models allow to summarize the information contained in these variables efficiently (Barhoumi, Darne and Ferrara, 2010). Further, it can be applied to construct economic activity indicators regardless of the sample and data size. While earlier studies use monthly variables, later studies utilize variables with different frequencies, i.e. daily, weekly, monthly, quarterly, as well. The selection of variables is usually done by expert judgement.

In this thesis, we construct a monthly economic activity indicator to detect historical expansion/contraction periods and to evaluate the economic outlook of the Turkish economy so that we provide timely information about the near future of economic conditions in Turkey. Similar to most of the studies in the literature, dynamic factor modelling approach is preferred in constructing economic activity indicator because of being good at synthesizing macroeconomic variables into an indicator (Barhoumi, Darne and Ferrara, 2013). In this method, economic conditions are considered as unobserved variable and tried to be explained by different observed indicators (Aruoba, Diebold and Scotti, 2009). This method also provides flexibility in using data with different frequencies simultaneously (Aruoba and Sarikaya, 2013). Based on this methodology, we construct an economic activity indicator using the industrial production index, electricity production, total vehicles production, volume of production over the past 3 months, real sector confidence index, import volume index, non-farm employment, credit stock and credit default swap (CDS) in the estimation. GDP is also added to the data set since it is the broadest measure of economic activity.

One of the main contributions of this study is that the variables are selected in an analytical and systematic way. First of all, the variables that are used in the analysis are grouped in five different categories which are activity (hard data), activity (survey-based data/soft data), trade, employment and financial variables. In doing this categorization, we follow Evans (2005) and Matheson (2011) and also consider the data availability. After doing the categorization, candidate variables for each category are determined. Although there are some data limitations, such as the beginning of data is belated or data for a specific period is not available, we can find more than one variable for each category. In the construction of our data set for the economic activity indicator, we implement the hard-thresholding method by Bai and Ng (2008). In this method, the relation between the explained variable y_t and the explanatory variables X_{ti} is evaluated for every i-th variable by considering the t-statistics associated with every X_{ti}. In our case, the annual percentage change of GDP is selected as y_t and the candidate variables in each category are considered as X_{ti}. Then, the annual percentage change of GDP is regressed on each candidate variable and t-statistics are compared. We pay attention to select at least one variable from each category, so that t-statistics of the variables are compared within their own groups. By this method, the most parsimonious variables are obtained for estimation of the economic activity indicator from the available data set.

Another contribution of this thesis is that we use a timelier data set compared to other papers about Turkey, i.e. Aruoba and Sarikaya (2013) and Çakmaklı and Altuğ (2014). Variables used in Aruoba and Sarikaya (2013) are GDP, industrial production index, imports of intermediate goods, non-farm employment and electricity production. Except electricity production, other variables are released with a lag of 40 to 60 days. On the other hand, Çakmaklı and Altuğ (2014) use GDP, industrial production index, total employment less agricultural employment, trade and services turnover index, retail sales volume index, final consumption, total export quantity index and total import quantity index. The additional variables compared to Aruoba and Sarikaya (2013) are also announced with a 40 to 50 day lag. Although our data set also contains variables announced with lagged periods- GDP, industrial production index, import volume index, non-farm employment- six of the ten variables are released at the appertaining month or at the beginning of next month. In this respect, we can update our indicator earlier than the other two studies and get timelier signals about the course of economic activity.

The last contribution of our work is that our indicator is better in detecting the past recession periods compared to Aruoba and Sarikaya (2013) and Çakmaklı and Altuğ (2014). While determining the recessionary periods, these two studies apply the same approach. They select the periods in which the indicator has negative values longer than one-month length and both the upper band of the indicator and itself have values lower than zero. Aruoba and Sarikaya (2013) construct their indicator for the period of 1987-2011 and detect three crisis periods for Turkish economy which are 1994, 2001 and 2008-2009. Çakmaklı and Altuğ (2014)'s indicator covers the period of 1989-2014 and signals nearly the same periods as Aruoba and Sarikaya (2013) as recessions: 1994-1995, 2000-2001 and 2008-2009. The monthly economic activity indicator constructed in this thesis covers the period starting from 1988 to February 2020. In our work, we implement the same approach with these two papers when determining the recessionary periods. However, we detect that October 1988-February 1989, April 1994-January 1995, October 1998-March 1999, August 1999-September

1999, February 2001-February 2002, October 2008-September 2009 and August 2018-January 2019 are recessionary periods. This means that our indicator detected three more periods as recessions which are October 1988-February 1989, October 1998-March 1999, August 1999-September 1999 compared to others. The second one overlaps with the Russian crisis that also hits its neighbouring countries including Turkey; and, the last one coincides with the earthquake on August, 17 in Turkey. Additionally, our indicator is successful in detecting the recessionary periods, such as August 1999-September 1999, that have lower durations whereas Aruoba and Sarikaya (2013) and Çakmaklı and Altuğ (2014) only detect prominent crisis.

The results show that the economic activity indicator, calculated by using different macroeconomic variables and GDP, is good at detecting historical recession periods. To evaluate whether the indicator provide timely information about the current state of the economy or not and to show importance of using the timelier variables in the estimation, a real-time application is performed. In this regard, the model is estimated until a certain period and the parameters are fixed; then, the economic activity indicator is calculated at new data announcements for different data releases. It is concluded that with the timelier variables announced more promptly, we would get information about the current decline in economic activity. For this study we are able to assess the decline in economic activity starting from April 2020, even in that month. Thus, including timely variables that captures the current developments is important for providing real-time information about the economic activity.

The paper proceeds as follows. In Chapter 2, we present the literature review about the construction of the economic activity indicators for different country categorizations. Chapter 3 provides the model and methodology, dynamic factor modelling framework and its state-space representation, used in the estimation of the indicator. Chapter 4 introduces the data set and variable selection methodology. Further in this chapter, the variable selection procedure is explained in detail and the robustness check of the variable selection process is presented. Chapter 5 presents the results of the estimation using the two monthly economic activity indicators estimated with the selected variables including and excluding GDP. Additionally, implied recession periods indicated for Turkish economy are compared with other papers on Turkey. Chapter 5, also presents a real-time application for the Turkish economy. Finally, Chapter 6 presents a brief summary of the findings and concludes the thesis.

CHAPTER 2

LITERATURE REVIEW

There has been an extensive literature on constructing economic activity indicators. In this chapter, the most prominent examples of the literature are introduced under different country categorizations in a chronological order. In this recap, the methodology of variable selection and the construction of the indicators are introduced; then, the criteria to evaluate the performance of the constructed indicators are covered in detail.

Stock and Watson (1989) [1], as one of the pioneering works, construct three monthly economic activity indicators for the US for the period 1959-1988: coincident economic indicator (CEI), leading economic indicator (LEI) and recession index (RI). CEI is an indicator which shows the co-movements in different macroeconomic variables by combining in a single variable and informs about the overall state of the US economy. LEI is the forecast of the growth rate of CEI for the next six months, while the RI shows the probability of getting in a recession over the next six months. They use dynamic factor modelling framework in computing CEI, whereas LEI is calculated by modelling the selected leading variables and the unobserved component extracted from the estimation of CEI with the vector autoregressive system. The parameters of CEI are estimated by maximum likelihood (ML) by using the Kalman filter after casting the model in state-space form. Then, LEI is estimated with the help of these estimated parameters. On the other hand, RI is calculated by approximating a negative/positive growth rate of the CEI, which lasts at least six months. In the analysis, only monthly variables are selected, and so mixed frequency data is not used. The variables used in CEI are industrial production, real personal income less transfer

[1] Stock and Watson (1991) is an edited version of their 1989 paper.

payments, real manufacturing and trade sales, and hours of employees in nonagricultural establishments. They argue that the estimated peaks and troughs of CEI usually overlap with the National Bureau of Economic Research (NBER) expansion and contraction periods. Further, they find that the growth of CEI is highly correlated with the growth rate of GNP of US and another activity indicator constructed by US Department of Commerce (DOC). For LEI, they select variables according to their predictive performance of the US DOC index among the most 55 timely indicators under ten different headings: 1) measures of output and capacity utilization, 2) consumption and sales, 3) inventories and orders, 4) money and credit, 5) interest rates and asset prices, 6) exchange rates and foreign trade, 7) employment, earnings, and measures of the labor force, 8) wages and prices, 9) measures of government fiscal activity, 10) other variables. As a result, seven leading variables are selected by using a stepwise regression procedure, in which six-month growth rate of CEI is regressed on both current and past values of each candidate variable. Then, the variables are selected according to the R^2 of the estimations. Moreover, in the LEI, lagged values of some of the variables, the order of which is determined by using the Akaike information criterion are used. The performance of LEI is evaluated by comparing the recession dates it implies with the ones calculated by the true six-month growth rate of CEI. Finally, RI is calculated by using four coincident and seven leading variables. The performance of RI is evaluated by checking whether it leads NBER recession points or not. It is concluded that the index is broadly matched with the NBER-dated recessions. In sum, the said three indicators are capable of matching with the NBER-announced recession points and perform better than US DOC indicators.

Dua and Banerji (2000) constructs two coincident economic activity indexes for Indian economy for the period of January 1957 and June 1999 to analyze the phase of the business cycle and to forecast the probable recessions and expansions. They conclude that the constructed coincident indexes are good at measuring how pronounced, pervasive and persistent the upswings and downswings of the economic activity. Furthermore, the recession and expansion periods implied by the indexes can be confirmed by specific circumstances in India, such as wars, restrictive policies, industrial deceleration, droughts, reforms, deregulations, foreign borrowing etc. Additionally, the duration of slowdowns is longer in the coincident index calculated by growth rates cycle approach compared to the business cycle approach. At the first part of their work, the definitions of business cycle, growth cycle and growth rate cycle are done. Business cycle shows the ups and downs of the economy by considering the levels of variables in the calculation. Growth cycle and growth rate cycle measures the speedups and slowdowns by considering the deviations from long-run trend of growth and growth rate of the variables in the index, respectively. It is concluded that growth cycle is better in historical analysis and the other two are better for real-time analysis. In this respect, coincident indexes for Indian economy are calculated by using the business cycle and growth rate cycle approaches. While calculating the coincident indexes, NBER methodology is used. In this methodology, series are log-transformed and then standardized by dividing them to the standardization factor, which is the standard deviation of the detrended trend-cycle component of the variables. After that, the average of the standardized series are calculated and the trend adjustment is applied to this average by multiplying by a trend factor. In the end, the antilog of this series is calculated. When applying these steps to the growth rates, the log transformation step is not implemented. Since GDP of India is available on annual basis, it is inefficacious in tracking the fluctuations in aggregate economic activity. Moreover, a single measure may be inadequate in representing the whole economic activity and sometimes may give false signal about being or entering in a recession/expansion. In this respect, variables are selected to represent the measures of output, employment, income and trade. Since available data for India is scarce and does not have too long historical series, variable selection becomes a challenging task. To represent output category, two variables are used in the estimation of coincident index: quarterly real GDP at factor cost and monthly index of industrial production. The quarterly variable is simply interpolated by repeating it in all months in the corresponding quarter in order to convert into monthly frequency. As a measure of income, wages in the factory sector is selected. Because of being at annual frequency, it is converted to monthly basis by interpolating it with the help of monthly industrial production in consumer goods data. For the (un)employment category, monthly registered unemployed data is added to the analysis. Because of not finding a suitable variable for trade category, industrial production for consumer goods is used in the estimation. In selection of turning points, authors consider three important criteria: 1) there must be at least fifteen months between peaks and troughs, 2) there must be five months opposite movement, 3) the latest one must be selected if the data is flat for periods.

Simone (2001) constructs three coincident economic activity indicators for Argentina for the period of 1993Q1- 2000Q1 by using general to specific modeling approach and concludes that these three indicators are good at producing significant forecasts of real GDP for one quarter and four-quarters ahead. Because of the data constraints regarding Argentina, variables are scarce and are usually in quarterly frequency. Variables are selected by categorizing them into four groups: real sector, government sector, financial sector and external sector. In this approach, after detecting candidate variables, they are tested by unit root, bivariate Granger causality and bivariate cointegration tests. By applying unit root tests, variables having same order of integration with real GDP- integration order of one (I(1))- are chosen. In the Granger causality testing part, variables that Granger causes real GDP are detected. To the variables having unit roots, cointegration tests are implemented. Later on, variables both having the same order of integration with real GDP and Granger causing real GDP are selected even if they are not cointegrated. At the starting point of the model estimation, autoregressive distributed lag (ARDL) models are constructed, in which the dependent variable (real GDP) is regressed on its lagged values and the current and lagged values of the independent variables. Because of data limitations, two or three lags of the variables are tried. In the second stage, whether the candidate variables can be eliminated without causing remarkable loss on model fit is tested by zero restriction tests; then, the so-called unrestricted models are estimated. Later on, predictions for the real GDP growth is calculated and they are considered as the economic activity indicators. Three of the unrestricted models are selected for the construction of the indicators according to their R^2 values and expert judgement. Variables in these models are listed as: Model 1) M1[2], FIEL's[3] industrial production index and volume of imports of consumption goods index, Model 2) M1 and INDEC's[4] industrial production index, Model 3) Volume of imports and real credit to private sector. M1

[2] M1 is the monetary aggregate consisting of currency in circulation and checking deposits.

[3] Fundacion de Investigaciones Economicas Lationamericanas (FIEL)

[4] Instituto Nacional de Estadisticas y Censos (INDEC)

and real credit to private sector are variables from financial sector, industrial production indexes are from real sector, and volume of imports variables are from external sector. Forecasting accuracy of the indicators are tested by evaluating the ex-ante and ex-post forecasts of them. To this end, normality tests applied to the forecast errors and how many times the indicators predicted significantly signs of one and four quarter ahead growth rates of real GDP are presented. Based on these tests, the forecast errors of one and four quarter ahead are found to have normal distribution. Furthermore, all three models are shown to have significant sign forecasts. For point forecasts of real GDP, the root mean squared forecast errors of one and four quarter ahead estimates are calculated. As a conclusion, all models passed the ex-post forecasting accuracy tests. Additionally, ex-ante forecasts of model 2 and 3 are better than the model 1 and the forecasts of model 1 usually biased downward.

Mariano and Murasawa (2003) criticize coincident economic indicators index of Stock and Watson (1989) in two different grounds. The first one is that exclusion of quarterly indicators prevents utilization of extra information other than monthly indicators. Second, the peaks and troughs of the said index lacks economic interpretation. Accordingly, they extend the work of Stock and Watson (1989) by using mixed frequency data set, which includes quarterly Gross Domestic Product (GDP). The rationalization of incorporating GDP is that it is the most important measure of the overall state of the economy and ought to be used in the evaluation of the economic activity. The variables used in the analysis, except quarterly real GDP, are same four monthly variables in Stock and Watson (1989): employees on nonagricultural payrolls, personal income less transfer payments, industrial production, and manufacturing and trade sales. The analysis covers the period of January 1959 and December 2000 and it is done for the US economy. Similar to Stock and Watson (1989), dynamic factor modelling is preferred in the estimation of activity index. After casting the model in state-space form, Kalman filter is used in the maximum likelihood estimation. Unlike Stock and Watson's (1989) updated estimates, smoothed estimates of the common factor is preferred. The rationalization of selecting smoothed estimates is indicated as it enables to use much more information of the variables and to simplify formulation of the state-space model. Moreover, approximate maximum likelihood estimator is used rather than Stock and Watson's (1989) exact ML estimator. They conclude that in capturing the NBER business cycle reference points, new coincident index outperforms CEI of Stock and Watson (1989), while underperforms against US Conference Board's index. Further they argue that smoothing the estimates rather than updating estimates of common factor as in Stock and Watson (1989) reduces the volatility in the coincident index.

Evans (2005) is the first to introduce real-time estimates of the business conditions and the macroeconomic activity in US on a daily basis. Daily estimation of the GDP growth would help apply timelier monetary policy. To this end, they use available macroeconomic variables on the corresponding day and historical values of the GDP up until the previous four quarters. The model parameters are estimated by using the (quasi) maximum likelihood method and the real-time estimates of GDP growth are obtained by applying the Kalman filtering algorithm. This setup has several advantages. First and foremost the specification of the model allows checking the robustness of real-time estimates through various diagnostic tests. Moreover, the model can be used to calculate real-time estimates of future GDP growth on a daily basis for different horizons. For the estimations, they select 18 macroeconomic variables from six different categories, which are real activity, consumption, investment, government, net exports and forward-looking indicators. These variables consist of six real activity (nonfarm payroll employment, retail sales, industrial production, capacity utilization, personal income, consumer credit), two consumption (personal consumption expenditures and new home sales), four investment (durable goods orders, construction spending, factory orders, business inventories), one government (government budget deficit), one net exports (trade balance) and four forward-looking (consumer confidence index, National Association of Purchasing Managers (NAPM) index, housing starts, and index of leading indicators) variables. Additionally, three different releases of GDP, advanced-preliminary-final, are also taken into account. As a conclusion, they report that as forecast horizon expands, the model estimate provides better forecasting results than predicted by professional money managers even though they have access to all data releases, public and private information. Moreover, with the first -advanced- release of GDP, the conditional variance of the model estimate decreases significantly. The preliminary and final releases of GDP have very negligible effects on the variance. Among monthly variables, non-farm payroll employment, retail sales, industrial production, personal consumption expenditures, factory orders, trade balance, consumer confidence index and housing starts are found to provide the most significant information to changes in real-time estimates of GDP growth.

Proietti and Moauro (2006) use mixed frequency variables (variables in monthly and quarterly frequencies) and dynamic factor modelling as in Mariano and Murasawa (2003), but differ from them in using non-linear filtering instead of approximate filtering in dynamic factor modelling. Similar to Mariano and Murasawa (2003), they criticize Stock and Watson (1989) for not including GDP in the analysis as the main coincident macroeconomic indicator. However, they state that the usage of variables in different frequencies- especially inclusion of quarterly GDP- causes temporal aggregation problem. Since the series in the analysis are log-transformed, the linear state-space form will no longer satisfy the true aggregation, i.e. sum of the monthly values may not be equal to quarterly total. To solve this problem, non-linear state-space model is preferred and the extended Kalman filter and smoother are used in the estimation. As an alternative method, they ignore the non-linearity of the aggregation constraint. In this pseudo-linear model experiment, state-space form enforces the aggregation constraint to be linear additive which is called approximate filtering, which is also used in Mariano and Murasawa (2003). The comparison of non-linear model and pseudo-linear model shows that, the former outperforms the latter by giving lower mean-squared error in particular when the variables are used in logarithmic forms. Moreover, as an application, coincident economic indicators indices for both the US and the Euro area are calculated. The selected variables for the US are same with Mariano and Murasawa (2003): industrial production, number of employees on non-agricultural payrolls, manufactured and trade sales, and personal income less transfer payments as monthly series, and GDP as the quarterly one. On the other hand, for the Euro area, they face some constraints on variable selection. Firstly, variables are available for shorter period of time compared to the US, and some variables are either not available or available at lower frequencies. Accordingly, series used in constructing the coincident economic indicator for the Euro area are industrial production, retail sales index, the civilian employment and GDP. The frequency of the first two series are monthly, while the remaining are quarterly. The estimation period is January 1959- March 2003 for the US and January 1980- June 2003 for the Euro Area.

Similar to Evans (2005), Aruoba et al. (2009) construct an economic activity indicator for the US economy on a daily basis and use dynamic factor modelling framework like Stock and Watson (1989), Mariano and Murasawa (2003), and Proietti and Moauro (2006). Although small-sample data set is selected for the analysis, mixed frequency variables are selected in order to update more frequently and supply high-frequency information about the evolution of economic activity. Based on the considerations on the cyclical characteristics, data variability and usage in previous studies, they choose quarterly GDP, employment on monthly frequency, weekly initial jobless claims and the daily yield curve term premium. The missing data problem arising from using high frequency variables is solved by applying Kalman filter and smoother after writing the model in state-space form. The economic activity indicator obtained by using all four variables is broadly coherent with the NBER recession periods. Even, the indicator detects more recessionary periods than NBER does. Moreover, the indicator is good at detecting the turning points when entering/leaving the recession/expansion periods. The use of higher frequency data is thought to be the main reason for better performance of the indicator. To this end, dropping the high frequency variables, which are yield curve term premium and initial jobless claims, one by one, two more indicators are also extracted. By comparing the full four-variable model with the ones excluding higher frequency variables, weekly initial jobless claims and daily yield curve term premium, it is found that especially weekly variable makes a significant contribution to the indicator while matching with the NBER recession points. Comparison of the true factor with the smoothed factors of both four-variable and two-variable economic activity indicators show that incorporation of high frequency data enhances the precision of the factor and hence the economic activity indicator.

Matheson (2011) constructs monthly economic activity indicators for 32 advanced and emerging countries by using the dynamic factor modelling framework but does not work with high frequency data. Instead, compared to the literature, the contribution of this paper is coming from using a large set of variables. By comparing historical performances and recursive out-of-sample forecast performances of the indicators, it is concluded that indicators are good at detecting the historical business cycle turning points and producing good GDP growth forecasts. The variable selection part is given great importance and the variables are selected by categorizing them as six groups: 1) variables related with activity (hard data), 2) variables related with activity (survey based data), 3) trade, 4) financial conditions, 5) employment and income, 6) prices and costs. This categorization enables the model to cover different sectors and to increase diversification by not focusing on a special part of the economy intensively. In addition, eight key series for the US economy are added to each country's data set, aiming at capturing the global business cycle effects. Due to data limitations for some countries and computational cost of using large number of variables, monthly data sets are compiled. Data limitations also lead to differences in estimation periods and the number of variables used between advanced countries and the others. For advanced countries, estimation starts in 1994; but, for emerging countries, it starts later depending on data availability. To evaluate how well the indicators track the trends of GDP, the number of times the indicators and the real quarterly GDP move together and to what extent the variables account for the variation in real quarterly GDP growth rate are considered. After checking these two aspects, indicators are found to be good at explaining the changes in the growth rates and tracking trends in the GDP growth rates, especially for advanced countries. Since some of the series have short-run volatility, smoothed versions of the indicators (7-month moving averages) are calculated to solve this volatility problem. The smoothed indicators are also successful at providing sizable information about the coincident state of the business cycle. In order to evaluate the real-time performance of the indicators, a simulated real-time forecasting experiment is applied by six different modelling methods: baseline quarterly autoregressive model, pooled bridge equations, pooled bivariate VARs, Bayesian VAR, and two different pooled forecasts. The results show that dynamic factor modelling approach produces the most accurate forecasts for the GDP growth rate for more than half of the countries.

Darne and Ferrara (2011) entitle the peaks and troughs of the growth rate as acceleration cycle; then, model the acceleration cycle of Euro Area and six main countries (Germany, France, Italy, Spain, Belgium, Netherlands) to show past turning points, and construct a new turning point indicator to track the real-time fluctuations in acceleration cycle. In the detection of the historical turning points, the non-parametric dating algorithm is applied to the Euro Area GDP. To make the analysis on a monthly basis, the same algorithm is applied to the Euro Area industrial production index for finding a rule to convert quarterly dates to monthly ones. The analysis covers the period of 1970Q1-2007Q3 for quarterly Euro Area GDP growth and the period of January 1990-September 2007 for monthly growth rates of Euro Area industrial production index. It is found that both the quarterly GDP and monthly industrial production index indicate the same points in time as turning point chronologies. For six main countries, the analysis covers the period of 1994Q1-2007Q3 for their GDP growth and the period of January 1990-September 2007 for monthly growth rates of their industrial production indices. Corresponding to GDP growth rate, turning points detected for Euro Area matches with the ones calculated for these six countries with some exceptions. It is concluded that GDP acceleration cycles spread across countries in the area. As regards industrial production index, turning points for Euro Area coincide with turning points of at least one of these countries. But, there have been some divergences of acceleration/deceleration cycles of countries. Furthermore, turning points of Euro Area and six main countries are compared with the ones announced by economic research institutes and the ones indicated by other papers in the economic literature. Turning points chronology estimated in this paper is found to be closely related with the ones estimated by EuroCoin index published by Bank of Italy. As an exercise, a monthly real time turning point indicator is established by using survey variables released by central banks and economic institutions. It is found that industrial sector survey variables are closely related with the Euro Area turning points indicator in detecting historical turning points. Because of this, data sets are constructed for Euro Area and six main countries by using soft indicators related with the industrial sector. In calculating the real-time turning point indicator, two different methodologies are used: Markow-Switching VAR model and Markow-Switching factor model. In the first one, the model is estimated with two regimes Markow-Switching and VAR(p) model. In the second approach, dynamic factor model is estimated by using maximum likelihood estimation through Kalman filter, and the factor switches between two regimes according to a Markov chain. Two regimes in each specification are high regime (acceleration cycle) and low regime (deceleration cycle); and, the turning point indicator shows the probability of being in one of these regimes. The estimation period for the real time turning point indicators is between January 1992 and September 2007. It is concluded that the turning point indicators calculated by two methodologies produce good results in detecting historical peaks and troughs. Moreover, the industrial sector related variables are shown to be good at signaling the acceleration and deceleration times of the Euro Area and six main countries.

So far, articles summarized are about the construction of economic activity indicators for different countries and regions. From this point on, papers about economic activity indicators for Turkey will be introduced. In one of the attempts, Aruoba and Sarikaya (2013) work with dynamic factor modelling framework in the construction of an economic activity indicator for Turkey by using mixed frequency variables. They use GDP, industrial production, imports of intermediate goods, electricity production and employment data in their estimation. The reason for selecting GDP as a variable in the analysis is because of the fact that it is the broadest measure of economic activity. Industrial production is included since it constitutes nearly one-third of national income back then. Electricity production is added not only because it captures the other sectors of the economic activity but also for being available for a long period of time and being a timely variable. Lastly, the employment data is selected for being a comprehensive macroeconomic variable. Except GDP, other variables are released on a monthly basis and GDP is released on quarterly. Therefore, they estimate the model with the variables in multiple frequencies. Their analysis covers the period of 1987-2011. Although being above/below zero of this indicator implies the expansion/contraction periods, the duration of being in the positive/negative area is also important for the evaluation of the economy. They conclude that starting from April 2009, economic activity showed a strong growth performance until the end of 2010. The comparison of the economic activity indicator for Turkey with those for the US and Japan shows that developed countries have less volatile growth structure than the developing ones. Among the variables, industrial production and intermediate goods imports are the ones having the highest correlation with the extracted factor. Although each of the variables makes statistically significant contribution to the economic activity indicator, using the high-frequency data is an important aspect for having timely information. Thus, economic activity indicators with and without using

GDP are also calculated. The fact that the factor estimated without GDP still gives a good signal about the overall economic activity highlights the importance of using high frequency variables in the analysis. In order to evaluate the resistance of expansion/contraction periods, the confidence interval of the estimated factor and bands of it being above/below zero for more than one period is considered. With the help of this approach, three recession periods are detected: 1994, 2001 and 2008-2009. At these periods, the economic activity indicator takes its lowest values and upper band also stays below zero. 1994 and 2001 are the crisis periods in which there observed a sudden-stop in the economy but 2008-2009 is a global crisis that is spread gradually. Moreover, 1991 and 1999 are detected as the mild contraction periods. To sum up, this indicator is found to be useful in the detection of historical expansion/contraction periods. Lastly, the real-time analysis is done and the importance of using timelier variables are shown.

Çakmaklı and Altuğ (2014) construct a coincident real economic activity indicator for Turkey for the period of 1989-2014. Variables in different frequencies, both monthly and quarterly, are used in the analysis. Dynamic factor modelling framework is used in the analysis; but, Bayesian semiparametric estimation is preferred instead of the most widely used Kalman filter in the literature, since they claim that it is better at capturing emerging economy characteristics such as extreme observations and frequently changing policy regimes. Moreover, in contrast to applying seasonal adjustment to the variables prior to analysis, modelling seasonality of the variables in the estimation part of the indicator is listed as another contribution of this paper. The variables included in the analysis are GDP, industrial production index, total employment less agricultural employment, trade and services turnover index, retail sales volume index, final consumption, total export quantity index and total import quantity index. The coincident economic indicator successfully detects the recessionary periods associated with the financial and banking crises in 1994-1995 and 2000-2001, and the global financial crisis in 2008-2009.

Table 2.1. List of Related Articles

Articles	Methods Used in the Estimation	Frequency of Data	Frequency of Model	Sample Size	Estimation Period	Country
Stock and Watson (1989)	Dynamic Factor Model	Monthly Frequency	Monthly	Small Sample	1959-1988	US
Dua and Banerji (2000)	NBER Methodology	Monthly Frequency	Monthly	Small Sample	January 1957- June 1999	India
Simone (2001)	General to Specific Approach	Quarterly Frequency	Quarterly	Small Sample	1993Q1-2000Q1	Argentina
Mariano and Murasawa (2003)	Dynamic Factor Model	Mixed Frequency	Monthly	Small Sample	1959-2000	US
Evans (2005)	State-Space Form with Kalman Filtering Approach	Mixed Frequency	Daily	Medium Sample	April 11, 1993- June 30, 1999	US
Proietti and Moauro (2006)	Dynamic Factor Model	Mixed Frequency	Monthly	Small Sample	1959-2003 1980-2003	US Euro Area
Auroba et al. (2009)	Dynamic Factor Model	Mixed Frequency	Daily	Small Sample	April 1, 1962- February 20, 2007	US
Matheson (2011)	Dynamic Factor Model	Mixed Frequency	Monthly	Large Sample	Sample begins at 1994 for advanced countries and later for emerging countries	32 Advanced and Emerging Economies
Darne and Ferrara (2011)	Markow-Switching VAR Model and Markow-Switching Factor Model	Monthly Frequency	Monthly	Small Sample	Euro Area: 1970Q1-2007Q3 for GDP and January 1990-September 2007 for Industrial Production Six Main Countries: 1995Q1-2007Q3 for GDP and January 1990-September 2007 for Industrial Production	Euro Area and Six Main Countries (Germany, France, Italy, Spain, Belgium and the Netherlands)
Aruoba and Sarikaya (2013)	Dynamic Factor Model	Mixed Frequency	Monthly	Small Sample	1987-2011	Turkey
Çakmaklı and Altuğ (2014)	Dynamic Factor Model with Bayesian Semiparametric Estimation	Mixed Frequency	Monthly	Small Sample	1989-2014	Turkey

As summarized in Table 2.1, dynamic factor modelling is the most preferred approach in constructing economic activity indicators. Estimated models are written in state-space form, while Kalman filter and Kalman smoother are mostly preferred algorithms for filtering. Earlier studies use variables in monthly frequency and construct indicators for the US economy. Later studies are extended to other developed countries, especially European countries, and to developing ones, which also benefit from mixed frequency variables, usually monthly and quarterly. Finally, the sample size is kept small in most studies; commonly less than 10 variables are included in the analysis.

CHAPTER 3

MODEL AND METHODOLOGY

Geweke (1977) and Sargent and Sims (1977) introduce the dynamic factor modelling (DFM) approach by emphasizing its success in extracting information from a set of variables, but they use frequency domain method which does not allow to estimate the factor directly. In this respect, the literature has been extended by considering time domain method that the factor can be estimated directly. Early works of dynamic factor models, named as parametric models, are developed for small number of variables and use the maximum likelihood estimation to estimate the parameters. The factors are calculated by using Kalman filter and smoother after writing the model in state-space form. Later, the dynamic factor model framework is extended to cover the large set of variables, and the factors are usually estimated by principal components and similar methods. These models are called as nonparametric models. Lastly, as a combination of these two approaches, the parameters of the state-space model in the first approach are specified by using nonparametric factor estimates derived from the second one (Stock and Watson, 2010).

As empirical application, DFM framework has been extensively used in the literature usually for three main objectives: nowcasting and forecasting the main macroeconomic variables, monetary policy analysis and construction of economic activity indicators (Barhoumi et al., 2013). The former is the estimation of macroeconomic variables for the coincident month or quarter, whereas forecasting is the prediction of future conditions of the variables for next quarter or further. Using DFM as a tool for forecasting has several examples in the literature especially for the US economy and Euro Area. Banerjee and Marcellino (2006), Camba-Mendez and Kapetanios (2005) and Eickmeier and Ziegler (2008) are listed among those examples. Compared to forecasting, the application of DFM approach in monetary policy analysis is more recent. It is generally used in the identification of the effects of monetary policy shocks on the economy and the transmission mechanisms of these shocks. For example, Del Negro and Otrok (2007) discuss how monetary easing enabled the housing bubble in the US by using factor-augmented VAR model.

As for the use of DFM framework in the construction of economic activity indicators, Barhoumi et al. (2013) state that it is a useful tool in summarizing the information in a large data set by forming a small number of common factors. In other words, DFM framework is generally opted for its success in utilizing the macroeconomic variables and producing reliable estimates. Stock and Watson (1989) is the pioneering work in the construction of economic activity indicator with the help of DFM approach; while Mariano and Murasawa (2003) and Aruoba et al. (2009) extend Stock and Watson (1989) by incorporating different frequency variables into the estimation. On the other hand, Aruoba and Sarikaya (2013) construct an economic activity indicator for Turkey by utilizing DFM framework on the basis of Aruoba et al. (2009).

In the construction of our economic activity indicator, we follow a similar approach to Aruoba and Sarikaya (2013). In this method, economic conditions are considered as unobserved variable and tried to be explained by different observed indicators. Furthermore, variables in different frequencies can be used simultaneously. In order to enhance the real-time property of the economic activity indicator, high-frequency variables are also included in data set. Lastly, with the help of a linear and statistically optimal filter, the economic activity indicator is calculated. To sum up, DFM framework is useful in the calculation of economic activity indicator because it can produce timely and reliable assessment of economic conditions in a statistically optimal manner. Additionally, this method is a useful tool in solving missing observation and multiple frequency problems.

In the first part of this chapter, the model will be introduced by equations. Then, in the next part, the model will be written in the state-space form and the estimation will be wrapped up.

3.1. Dynamic Factor Model at Monthly Frequency

Although economic conditions change at higher frequencies (hourly, daily, etc.), data releases have been less frequent. Most of the indicators are often monthly or quarterly. Therefore, we construct our indicator at monthly frequency. If the data has a higher frequency than monthly frequency, two different approaches are taken depending on the characteristics of the data. If it is a stock variable, end of the month value is taken as the monthly data. If it is a flow variable, then monthly average of the data is calculated.

As mentioned earlier, we adapt the methodology of Aruoba and Sarikaya (2013) while constructing the model. In this framework, the unobserved economic conditions at month t is denoted by y_t and it evolves according to the following transition equation

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t-3} + u_t \tag{1}$$

where u_t~ N (0, σ_n^2) and (a_1, a_2, a_3, σ_n^2) are such that σ_y^2= 1. The units of the factor can be interpreted as standard deviations from the mean.

Then, x_t^i denote the vector of observable variables, which are related to the unobserved factor y_t linearly. Here, i represents the variables. For i-th monthly variable, the measurement equation is written as follows:

$$x_t^i = c^i + d^i y_t + e_t^i \tag{2}$$

In equation 2, c^i is a constant term, $d^i y_t$ is the common component and e_t^i is an idiosyncratic component which is expressed as

$$e_t^i = \beta_1^i e_{t-1}^i + \beta_2^i e_{t-2}^i + \beta_3^i e_{t-3}^i + v_t^i \tag{3}$$

where v_t^i~ N (0, $\sigma_{v^i}^2$). The common component and the idiosyncratic component are assumed to be mutually orthogonal. The common component represents the covariation between the variables related with economic activity and the business conditions represented by the factor. The idiosyncratic component contains the shocks special to each variable. Both in equation 1 and equation 3, it is assumed that the residuals are normally distributed with zero mean and constant variance.

For the monthly variables in the estimation, we use equation 2. However, not all macroeconomic series are published on a monthly frequency. While the frequency of indicators such as industrial production and survey-based variables are monthly, the frequency of GDP is quarterly. Thus, we rewrite the measurement equation for quarterly variables. For stock variables, quarterly data is the average of respective monthly data. Thus, the measurement equation for quarterly stock variables is revised as

$$x_t^i = \begin{cases} \sum_{j=0}^{2} x_{t-j}^i = c^i + \frac{1}{3} d^i \left(y_t + y_{t-1} + y_{t-2}\right) + \frac{1}{3}\left(e_t^i + e_{t-1}^i + e_{t-2}^i\right) & if\ x_t^i\ observed \\ NA & otherwise \end{cases} \tag{4}$$

For flow variables, such as GDP, quarterly data is approximately the sum of monthly data. Accordingly, our measurement equation for quarterly flow data becomes the sum of right-hand side of equation 2 and is expressed as

$$x_t^i = \begin{cases} \sum_{j=0}^{2} x_{t-j}^i = 3c^i + d^i \left(y_t + y_{t-1} + y_{t-2}\right) + \left(e_t^i + e_{t-1}^i + e_{t-2}^i\right) & if\ x_t^i\ observed \\ NA & otherwise \end{cases} \tag{5}$$

3.2. State-Space Representation and Estimation

The state-space representation of the model is in the following form:

$$\begin{gathered} z_{t+1} = Tz_t + R\lambda_t \\ x_t = c + \sigma z_t \end{gathered} \tag{6}$$

Here, z_t represents the state vector containing y_t, e_t and their lagged values. As stated in the first part, x_t represents the vector of observable variables and c is the vector of constant terms. λ_t is the vector of error terms including residuals u_t and v_t in equations

1 and 3, and it is distributed as $\lambda_t \sim (0, Q)$. In other words, it has zero mean and constant variance. Moreover, T, R, σ and Q are constant. The sample size is written as t= 1, 2,...., T, where T is the last observation.

After writing the model in state-space form, Kalman filter is utilized to estimate the model by maximum likelihood estimation and Kalman smoother is used to obtain an estimate of the factor. It should be highlighted that this approach is good at dealing with missing data problem since it puts no weight on the missing values while calculating the common factors (Matheson, 2011). In order to put no weight on the missing observations, the variance of the idiosyncratic component is selected to be extremely large. Barhoumi et al. (2013) also state that in DFM framework, two-step estimation procedure by using Kalman filter solves the end-of-sample missing value problem significantly.

CHAPTER 4

DATA

In this chapter, we list the candidate variables and introduce the selected ones for the estimation of the economic activity indicator. The methodology of selecting the most appropriate variables to construct the economic activity indicator for Turkish economy are elaborated on.

4.1. A Primer on Data Selection

Data selection is probably the most important step of constructing an economic activity indicator. For the best outcome, data would meet the following properties: i) It would be long enough to make a reliable econometric estimation, ii) It would be able to identify the expansion/contraction and crisis periods in the past, iii) It would be easily accessible by the public, iv) It would be released in a timelier manner in order to improve the real-time characteristic of the indicator.

Another important aspect in such analyses is to decide on the number of variables to include in the analysis. Whether inclusion of too many variables improves the model accuracy or not is an important aspect to evaluate the quality of the estimated economic activity indicator. Adding all relevant variables may sound to be the best option to have a more accurate result. However, Watson (2003) claims that increasing the number of variables beyond 50 does not make any substantial contribution to the estimated factors. Boivin and Ng (2006) conclude that if addition of new variables does not make contribution to the estimated factors, there cannot be any improvement in the forecasts made by a larger-sample data. Moreover, Barhoumi et al. (2010) argue that the number of variables need not be extremely high in order to estimate the economic activity precisely and show that widening the dataset causes the forecast accuracy to diminish. Additionally, Barhoumi et al. (2013) claim that addition of a new variable is not preferred if it increases the idiosyncratic noise and does not make any contribution to the performance of the factor. Banerjee and Marcellino (2006), Schumacher (2007), Bai and Ng (2008), Bulligan, Marcellino and Venditti (2015) are other examples in the literature in favor of keeping the dataset narrow to increase the performance of the model estimates.

As a final remark, inclusion of too many variables from a specific sector may lead to biased results as it may increase the weight of that particular sector beyond its true size. In this regard, categorization of variables would improve the diversification among variables and the representation of different sectors in the economy. For example, as introduced earlier in Chapter 3, Evans (2005) categorizes the variables into 6 types as real activity, consumption, investment, government, net exports, forward-looking. Further, he includes at least one variable from each category to the estimation. Matheson (2011) applies another categorization as hard data, survey-based data, trade, financial conditions, employment and income, prices and costs.

4.2. Variables

Before selecting the variables for the analysis, we categorize the candidate variables into five types: activity (hard data), activity (survey-based data or soft data), trade, employment and financial variables. Although our categorization is a mixture of Evans (2005) and Matheson (2011), it does not include some of the headings they consider and it is more similar to what Matheson (2011) does. The reasoning rests on the public availability of the variables and the availability of historical series of the variables. Despite data limitations, we try to form the most extensive categorization for our estimation. Candidate variables for each category are listed as follows:

- **Activity (hard data) –** industrial production index and its components, i.e. intermediate goods, capital goods, durable consumer goods and non-durable consumer goods production indices; electricity production; production and sales of total vehicles and its sub-items, i.e. automobile and commercial vehicles; production and sales of household appliances, etc.
- **Activity (survey-based data or soft data) –** Purchasing Managers' Index (PMI) and its components, i.e. PMI Output and PMI New Orders; capacity

utilization rate; the volume of production over the past 3 months; real sector confidence index, etc.

- **Trade** – import and export volume indices and their sub-items, i.e. intermediate goods, capital goods, durable consumer goods and non-durable consumer goods, etc.
- **Employment** – total employment; non-farm employment; unemployment rate; non-farm unemployment rate, etc.
- **Financial Variables** – credit stock; Credit Default Swap (CDS) and Chicago Board Options Exchange Volatility Index (VIX), etc.

Table 4.1. Candidate Variables and Their Beginning Periods

Activity (Hard Data) Variables	Sample Begins	Activity (Soft Data) Variables	Sample Begins	Trade Variables	Sample Begins
Industrial Production Index (IPI)	1987M01	Purchasing Managers' Index (PMI)	2005M05	Export Volume Index (QX)	1987M01
IPI- Intermediate Goods	1997M01	PMI- Output	2005M05	QX- Intermediate Goods	1994M01
IPI- Capital Goods	1997M01	PMI- New Orders	2005M05	QX- Capital Goods	1994M01
IPI- Durable Consumer Goods	1997M01	Capacity Utilization Rate	1991M02	QX- Durable Consumer Goods	1994M01
IPI- Non-Durable Consumer Goods	1997M01	Volume of Production over the past 3 Months	1988M01	QX- Semi-Durable Consumer Goods	1994M01
Electricity Production	1987M01	Real Sector Confidence Index	1994M06	QX- Non-Durable Consumer Goods	1994M01
Total Vehicles Production	1987M01			Import Volume Index (QM)	1987M01
Commercial Vehicles Production	1987M01			QM- Intermediate Goods	1994M01
Automobile Production	1987M01			QM- Capital Goods	1994M01
Total Vehicles Sales	1993M01			QM- Durable Consumer Goods	1994M01
Commercial Vehicles Sales	1993M01			QM- Semi-Durable Consumer Goods	1994M01
Automobile Sales	1993M01			QM- Non-Durable Consumer Goods	1994M01
Production of Household Appliances	2000M01				
Sales of Household Appliances	2000M10				
Employment Variables	**Sample Begins**	**Financial Variables**	**Sample Begins**		
Total Employment	1989Q01	Credit Stock	1987Q01		
Non-Farm Employment	1989Q01	Credit Default Swap (CDS)	2001M01		
Unemployment Rate	1989Q01	Chicago Board Options Exchange Volatility Index (VIX)	1990M01		
Non-Farm Unemployment Rate	1989Q01				

Note: M denotes month and Q denotes quarter.

For each category, adding more variables could be an option but the availability of historical data becomes a limiting factor in the variable selection phase. In this respect, above-mentioned candidate variables for the estimation and their beginning periods are listed in Table 4.1. From these variables, we select industrial production index, electricity production, total vehicles production, the volume of production over the past 3 months, real sector confidence index, import volume index, non-farm employment, credit stock and Credit Default Swap (CDS) indicators in our analysis. Variable selection method and the rationale for selecting these variables are elaborated in sections 4.3 and 4.4.

Table 4.2. Data Definitions

Variables	Categories	Sample Periods	Frequencies	Sources
Industrial Production Index (IPI)	Activity (hard data)	1988M01-2020M02	Monthly	TURKSTAT
Electricity Production	Activity (hard data)	1988M01-2020M04	Monthly	TETC
Total Vehicles Production	Activity (hard data)	1988M01-2020M03	Monthly	AMA
Volume of Production over the past 3 Months	Activity (soft data)	1988M01-2020M04	Monthly	CBRT
Real Sector Confidence Index	Activity (soft data)	1994M06-2020M04	Monthly	CBRT
Import Volume Index (QM)	Trade	1988M01-2020M02	Monthly	TURKSTAT
Non-Farm Employment	Employment	1990Q1-2020Q1	Quarterly	TURKSTAT
Credit Stock	Financial Variables	1988Q1-2020Q2	Quarterly	BIS and BRSA
Credit Default Swap (CDS)	Financial Variables	2001M01-2020M04	Monthly	Bloomberg

Table 4.2 lists the category, sample period, frequency and source of the variables used in the estimation. First three of the variables are from activity (hard data) category, the next two are from activity (soft data), the sixth and seventh variables are from trade and employment categories, the last two variables are from financial variables. Industrial production index, import volume index and non-farm employment data are published by Turkish Statistical Institute (TURKSTAT). Electricity production and total vehicles production data are taken from Turkish Electricity Transmission Corporation (TETC) and Automotive Manufacturers Association (AMA), respectively. The volume of production over the past 3 months data is a question[5] from

[5] The official question about the volume of production over the past 3 months asked to the manufacturing firms is that “How has your production developed over the past 3 months?”. It is an important indicator about the production of manufacturing firms and positively related with economic activity.

Business Tendency Survey (BTS) Statistics conducted by the Central Bank of the Republic of Turkey (CBRT) to the manufacturing firms, so this data is taken from CBRT database. Real sector confidence index is also taken from the database of CBRT. Credit stock is taken from two different sources, which are Bank for International Settlements (BIS) and Banking Regulation and Supervision Agency (BRSA) for two different periods. The source of CDS data is Bloomberg database.

Estimation of the economic activity indicator starts at the beginning of 1988, but some of our variables do not have data dating back to 1988. Industrial production index, electricity production, total vehicles production and the volume of production over the past 3 months have values since January 1988 on a monthly basis. Even, electricity production is announced on a daily basis, it is included in the analysis on a monthly frequency. However, real sector confidence index and CDS start at June 1994 and January 2001, respectively. For import volume index, the annual percentage changes of 2010-based data is available starting from January 2006. For January 1988-December 1989, annual percentage changes of 1982-based data; for January 1990-December 1997, annual percentage changes of 1989-based data; for January 1998-December 2004, annual percentage changes of 1994-based data; and, for January 2005- December 2005, annual percentage changes of 2003-based data are used. Non-farm employment data is available at three different frequencies. For the period of 1989-1999, it is announced semi-annually; for 2000-2004, it is announced on a quarterly frequency; and, since 2005, it is announced as monthly but calculated as three-months moving average[6]. In order not to make any conflict, it is used in the analysis on a quarterly frequency. Firstly, semi-annual data is transformed to the quarterly frequency by using seasonal factors as in Coşar and Yavuz (2019). Then quarterly annual percentage changes of variables are calculated for non-farm employment data starting from the first quarter of 1990. Credit stock is available on a weekly basis starting from January 2006 in BRSA database. In tracing credit stock back to 1987, we benefit from BIS credit to non-financial sector database. The caveat

[6] Three-months moving average means that February data represents January-February-March period and May data represents April-May-June period. Thus, variables announced at February, May, August and November represent each quarterly variable in that year, respectively.

of BIS data is that it is available on quarterly basis, which forces us to use credit data in this frequency in model estimations.

In the estimation of the economic activity indicator, seasonally adjusted[7] levels of the volume of production over the past 3 months and real sector confidence index, and level of CDS are used. The remaining variables are added to the analysis in the form of annual percentage changes. Table 4.3 summarizes the descriptive statistics of these variables.

Table 4.3. Descriptive Statistics of the Variables

Variables	Mean	Median	Standard Deviation	Maximum	Minimum
Industrial Production Index (IPI)	5.0	5.7	8.6	29.4	-24.0
Electricity Production	6.1	6.7	5.2	19.8	-16.6
Total Vehicles Production	13.3	10.1	44.2	551.3	-75.6
Volume of Production over the past 3 Months	5.9	8.4	13.6	44.3	-49.3
Real Sector Confidence Index	101.1	104.3	10.7	119.0	58.9
Import Volume Index (QM)	8.3	7.5	20.2	65.8	-45.5
Non-Farm Employment	3.2	3.8	3.1	9.9	-5.6
Credit Stock	9.1	9.5	15.5	55.0	-28.6
Credit Default Swap (CDS)	338.4	251.1	241.4	1205.5	119.2

4.3. The Methodology of Variable Selection

One of the main contributions of this study is in the variable selection part. Although some of the previous papers about the construction of the economic activity indicators categorize candidate variables like in our work, most of them decide which ones to include in the analysis by expert judgement. In our work, after deciding on the variables from each category, a large data set is constructed. Then, the variables to include in the estimation are selected by the hard-thresholding method implemented in Bai and Ng (2008). In this method, the relation between the explained variable y_t and the explanatory variables X_{ti} is evaluated for every i-th variable by considering the t-statistics associated with every X_{ti}. The steps of this method are as follows:

[7] Seasonally adjusted data are taken from their official sources, CBRT database.

1. For each i-th variable, perform a regression of y_t on X_t and derive the t-statistics from each regression for every X_t. The t-statistics show the marginal predictive power of each X_t on y_t.
2. Take the absolute values of each t-statistics as $|t_1|, |t_2|, \ldots, |t_i|$ and sort from the largest to the smallest one.
3. Decide a threshold value for t-statistics as t^* and select the variables having larger t-statistics than t^*.

As being the most common measure of economic activity, Gross Domestic Product (GDP) is selected as the dependent variable y_t and the variables in the data set are treated as X_{ti}. Then, the annual percentage change of GDP is regressed on each variable sequentially. When comparing the statistical significance, t-statistics of the variables in the five categories are compared within their own groups in order to select at least one variable from each category. For deciding the threshold value for t-statistics, there are two different applications. In the variable selection part of the forecasting GDP in New Zealand, Eickmeier and Ng (2011) apply hard-thresholding method and sets the threshold value for t-statistics as 1.65, and select variables having larger values than 1.65. On the other hand, Çakmaklı and Dijk (2016) select 0.10 and 0.15 as significance levels and set their corresponding t-statistics as threshold values. In our paper, the significance level is chosen as 0.05 and the corresponding t-statistics value 1.96 is determined as the threshold value. After regressing GDP on the possible variables from each category, variables having larger t-statistics than the threshold value of 1.96 are listed as potential variables for the analysis. Then, the variables are eliminated with respect to their beginning periods and their representativeness of the economy.

4.4. Variable Selection

The candidate variables that GDP is regressed on are listed in Table 4.1. Since GDP is published on a quarterly basis, monthly data are converted to the quarterly frequency by taking averages of the related months and quarterly annual percentage changes are calculated accordingly. Later, quarterly annual percentage change of GDP is regressed on them sequentially. For all of the survey-based activity variables and some of the financial variables such as CDS and VIX, the levels instead of quarterly changes are used in these regressions. The reason behind this is that the survey variables themselves represent the change in periods and the financial variables like CDS and VIX represent the spread. Since GDP is available from 1987Q1, the annual percentage change of GDP is available from 1988Q1, which determines the sample period for the regressions as 1988Q1-2019Q4. Since historical availability of the variables alters, variable selection is made in two different ways. Firstly, GDP is regressed on the variables available since 1988 and the selection is made by considering their t-statistics. Then, in order to evaluate variables starting later than 1988, regression is done by separating the estimation period into 3 sub-periods and variable selection is repeated for each period[8].

Table 4.4. Variables used in the Whole Sample 1988-2019 and Their t-Statistics from Regression with GDP

Activity (Hard Data) Variables	t-statistics	Activity (Soft Data) Variables	t-statistics	Trade Variables	t-statistics
Industrial Production Index (IPI)	19.28	***Volume of Production over the past 3 Months***	13.63	Export Volume Index (QX)	0.32
Electricity Production	4.57			***Import Volume Index (QM)***	8.03
Total Vehicles Production	7.05				
Commercial Vehicles Production	5.79				
Automobile Production	5.81				
Financial Variables	**t-statistics**				
Credit Stock	4.70				

As seen from Table 4.1 and Table 4.4, there are not many variables dating back to 1988. Even there is no variable in the employment category starting at 1988. Based on the t-statistics in Table 4.4, selected variables for the estimation of the economic activity indicator are industrial production index, electricity production, total vehicles production, the volume of production over the past 3 months, import volume index and credit stock. Although commercial vehicles production and automobile production have t-statistics higher than the threshold value, they are not included in the analysis because they are represented by total vehicles production. Since export volume index has lower t-statistics than the threshold value, it is not included in the analysis.

[8] For both of the variable selection exercises, t-statistics are listed in tables and the selected variables are written in ***bold*** and ***italic*** format.

As stated above, in order to evaluate the variables having beginning period later than 1988, same regression is done by dividing the estimation period into three sub-periods, having almost equal durations, as 1988-1997, 1998-2007 and 2008-2019. For the period of 1988-1997, variables are the same as those selected for the whole sample. As depicted in Table 4.5, these variables are: industrial production index, electricity production, total vehicles production, the volume of production over the past 3 months, import volume index and credit stock. Commercial vehicles production and automobile production are not included in the analysis because of the same reason as in the whole sample case. Although, t-statistics of the export volume index increased compared to the whole sample case, it is still lower than the threshold value and not included in the analysis.

Table 4.5. Variables used in Period 1988-1997 and Their t-Statistics from Regression with GDP

Activity (Hard Data) Variables	**t-statistics**	**Activity (Soft Data) Variables**	**t-statistics**	**Trade Variables**	**t-statistics**
Industrial Production Index (IPI)	14.17	***Volume of Production over the past 3 Months***	11.57	Export Volume Index (QX)	1.44
Electricity Production	4.76			***Import Volume Index (QM)***	6.92
Total Vehicles Production	6.60				
Commercial Vehicles Production	4.30				
Automobile Production	3.87				
Financial Variables	**t-statistics**				
Credit Stock	3.30				

Compared to the 1988-1997 period, the data set is enlarged for 1998-2007 period. For the activity (hard data) category, the sub-items of industrial production index, sales of total vehicles and its sub-items, i.e. commercial vehicles and automobile, are included in data set. For activity (soft data) category, capacity utilization rate[9] and real sector confidence index; for trade category, the sub-items of export and import volume indices, and for the financial variables category, VIX are added to the data set.

[9] The capacity utilization rate is a question from BTS conducted by CBRT to the manufacturing firms and the official question is that “At what capacity is your company currently operating (as a percentage of full capacity)”. It is a kind of productivity measurement of firms and positively related with economic activity.

Compared to the whole sample period case and 1988-1997 period, variables representing employment category are also used in the variable selection regression.

Table 4.6. Variables used in Period 1998-2007 and Their t-Statistics from Regression with GDP

Activity (Hard Data) Variables	t-statistics	Activity (Soft Data) Variables	t-statistics	Trade Variables	t-statistics
Industrial Production Index (IPI)	19.39	Capacity Utilization Rate	6.55	Export Volume Index (QX)	0.08
IPI- Intermediate Goods	10.60	***Volume of Production over the past 3 Months***	5.85	QX- Intermediate Goods	0.32
IPI- Capital Goods	8.54	***Real Sector Confidence Index***	5.32	QX- Capital Goods	0.08
IPI- Durable Consumer Goods	0.92			QX- Durable Consumer Goods	0.80
IPI- Non-Durable Consumer Goods	3.79			QX- Semi-Durable Consumer Goods	0.10
Electricity Production	4.05			QX- Non-Durable Consumer Goods	2.08
Total Vehicles Production	4.90			***Import Volume Index (QM)***	5.31
Commercial Vehicles Production	3.93			QM- Intermediate Goods	3.86
Automobile Production	4.46			QM- Capital Goods	6.51
Total Vehicles Sales	2.91			QM- Durable Consumer Goods	7.20
Commercial Vehicles Sales	3.62			QM- Semi-Durable Consumer Goods	2.94
Automobile Sales	2.60			QM- Non-Durable Consumer Goods	1.86
Employment Variables	**t-statistics**	**Financial Variables**	**t-statistics**		
Total Employment	0.61	***Credit Stock***	2.69		
Non-Farm Employment	2.50	Chicago Board Options Exchange Volatility Index (VIX)	1.97		
Unemployment Rate	1.64				
Non-Farm Unemployment Rate	0.28				

The variables used in the regression for the period of 1998-2007 and their t-statistics are listed in Table 4.6. Selected variables for the estimation of the economic activity indicator are industrial production index, electricity production, total vehicles production, the volume of production over the past 3 months, import volume index, credit supply, real sector confidence index and non-farm employment. The last two variables are newly selected and added to the analysis, and the first six variables are already selected in the first period. Because of having lower t-statistics than the industrial production index, its sub-items are not included in the analysis. Although sales of total vehicles and its sub-items have t-statistics larger than the threshold value, they are not included in the analysis because production values, which start earlier than them, of these variables are included. For the survey-based variables, capacity utilization rate might be selected but its monthly data starts later than data of the volume of production over the past 3 months. Since both of the variables have t-statistics larger than the threshold value, the volume of production of manufacturing firms over the past 3 months is not replaced with capacity utilization rate data. Real sector confidence index is added to the analysis in order to have at least one variable from confidence indexes. Although some sub-items of import volume index have larger t-statistics, import volume index is kept in the analysis because of being the main item. Export volume index and its sub-items have t-statistics lower than the threshold value, so they are not included in the data set. For the employment variables category, non-farm employment data is selected because it has the largest significant t-statistics in its category. For the financial variables category, VIX is not selected because its t-statistics is nearly equal to the threshold value.

For the third period containing 2008-2019, there are again additions to the data set. Production and sales of household appliances from activity (hard data) category, PMI and its sub-items from activity (soft data) category and CDS from financial variables category are included in the regression with GDP. The t-statistics from the regression of GDP with all variables are listed in Table 4.7 for 2008-2019 period. Industrial production index, electricity production, total vehicles production, the volume of production over the past 3 months, import volume index, credit stock, real sector confidence index, non-farm employment and CDS are selected for the estimation of economic activity indicator. Except CDS, other variables are the same with the previous period. For industrial production index and total vehicles production, the reason for selecting is because of having largest t-statistics among their sub-items. Production and sales of household appliances are not included because their t-statistics are not that much high. Among PMI and BTS variables, the volume of production over the past 3 months data from BTS has the highest t-statistics so it is kept in the analysis. Export volume index and its sub-items, except capital goods, have t-statistics lower than the threshold value, so they are not added to the data set used in the estimation. Although intermediate goods imports have the largest t-statistics in its category, import volume index is kept in the analysis since its t-statistics is approximately the same with its sub-item, intermediate goods. As having the largest t-statistics in employment category, non-farm employment is kept in the analysis. For the financial variables category, credit supply is kept and CDS is added to the analysis.

Table 4.7. Variables used in Period 2008-2019 and Their t-Statistics from Regression with GDP

Activity (Hard Data) Variables	t-statistics	Activity (Soft Data) Variables	t-statistics	Trade Variables	t-statistics
Industrial Production Index (IPI)	18.14	Purchasing Managers' Index (PMI)	12.61	Export Volume Index (QX)	1.78
IPI- Intermediate Goods	8.86	PMI- Output	8.27	QX- Intermediate Goods	0.58
IPI- Capital Goods	11.34	PMI- New Orders	9.04	QX- Capital Goods	4.45
IPI- Durable Consumer Goods	4.58	Capacity Utilization Rate	3.51	QX- Durable Consumer Goods	1.67
IPI- Non-Durable Consumer Goods	7.52	***Volume of Production over the past 3 Months***	15.45	QX- Semi-Durable Consumer Goods	1.68
Electricity Production	3.08	***Real Sector Confidence Index***	7.54	QX- Non-Durable Consumer Goods	1.53
Total Vehicles Production	2.74			***Import Volume Index (QM)***	5.75
Commercial Vehicles Production	2.26			QM- Intermediate Goods	5.88
Automobile Production	2.47			QM- Capital Goods	3.80
Total Vehicles Sales	4.29			QM- Durable Consumer Goods	2.51
Commercial Vehicles Sales	3.34			QM- Semi-Durable Consumer Goods	3.72
Automobile Sales	4.15			QM- Non-Durable Consumer Goods	3.06
Production of Household Appliances	2.01				
Sales of Household Appliances	2.65				
Employment Variables	**t-statistics**	**Financial Variables**	**t-statistics**		
Total Employment	4.45	***Credit Stock***	4.62		
Non-Farm Employment	4.47	***Credit Default Swap (CDS)***	4.97		
Unemployment Rate	3.53	Chicago Board Options Exchange Volatility Index (VIX)	2.42		
Non-Farm Unemployment Rate	3.61				

At Table 4.8, the correlation of GDP with the selected nine variables are shared to show how strongly they are related with GDP. It is concluded that variables related with production have higher correlation than employment and financial variables. Furthermore, from Figure 4.1 to 4.7, nine variables used in the estimation are sketched with the quarterly annual percentage changes of GDP to show the strong relations between the variables and the most common measure of economic activity, GDP.

Table 4.8. Correlation of GDP with Variables used in the Estimation of Economic Activity Indicator

Variables	Correlation	Variables	Correlation
Industrial Production Index (IPI)	0.91	Import Volume Index (QM)	0.76
Electricity Production	0.56	Non-Farm Employment	0.36
Total Vehicles Production	0.72	Credit Stock	0.45
Volume of Production over the past 3 Months	0.79	Credit Default Swap (CDS)	-0.34
Real Sector Confidence Index	0.76		

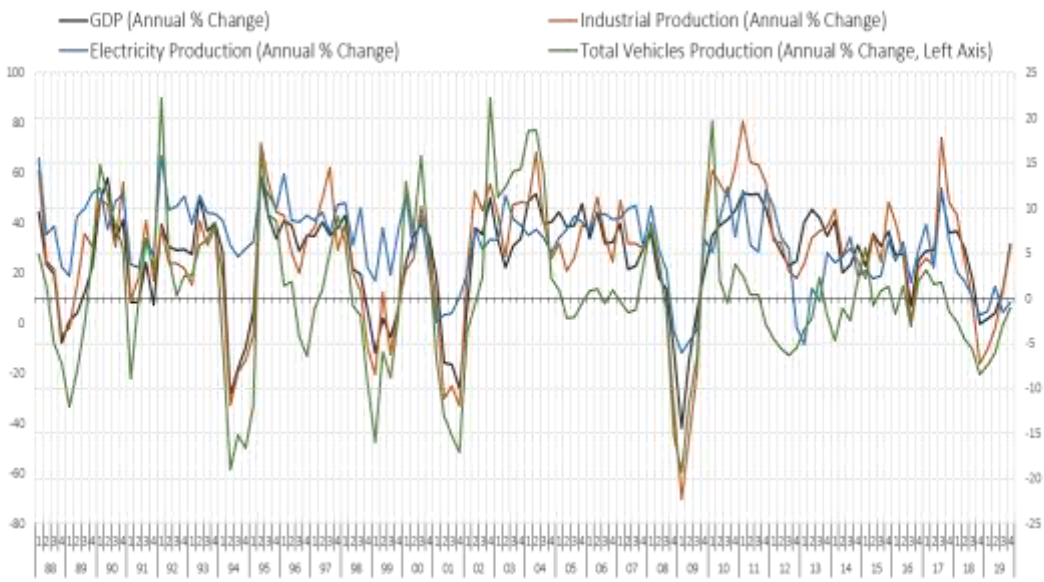


Figure 4.1. GDP and Variables from Activity (Hard Data) Category

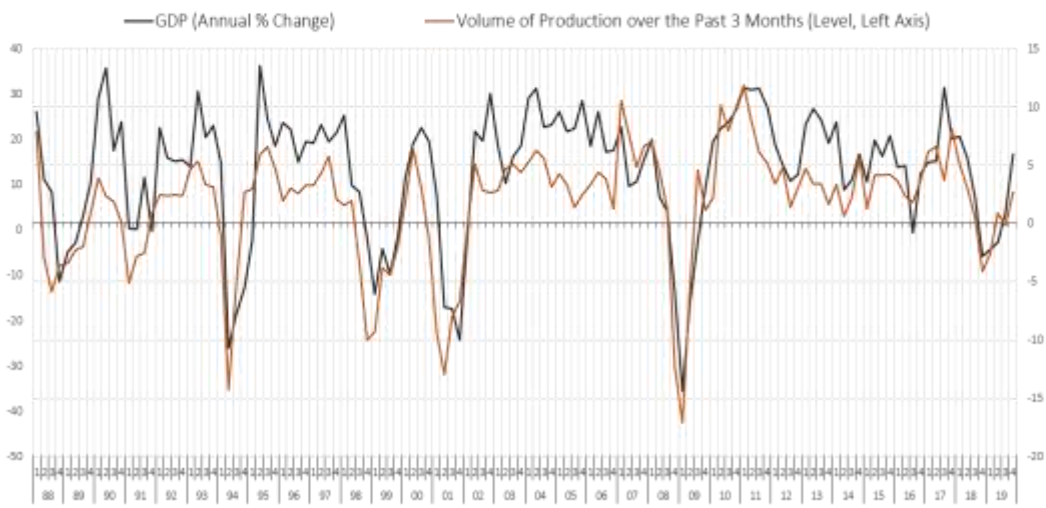


Figure 4.2. GDP and the Volume of Production over the Past 3 Months from Activity (Soft Data or Survey Based Data) Category

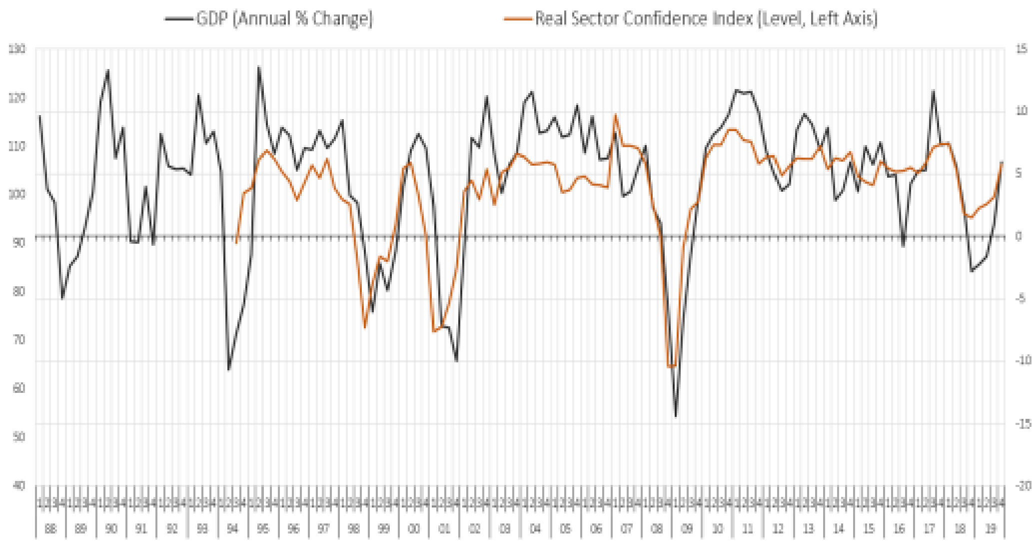


Figure 4.3. GDP and Real Sector Confidence Index from Activity (Soft Data or Survey Based Data) Category

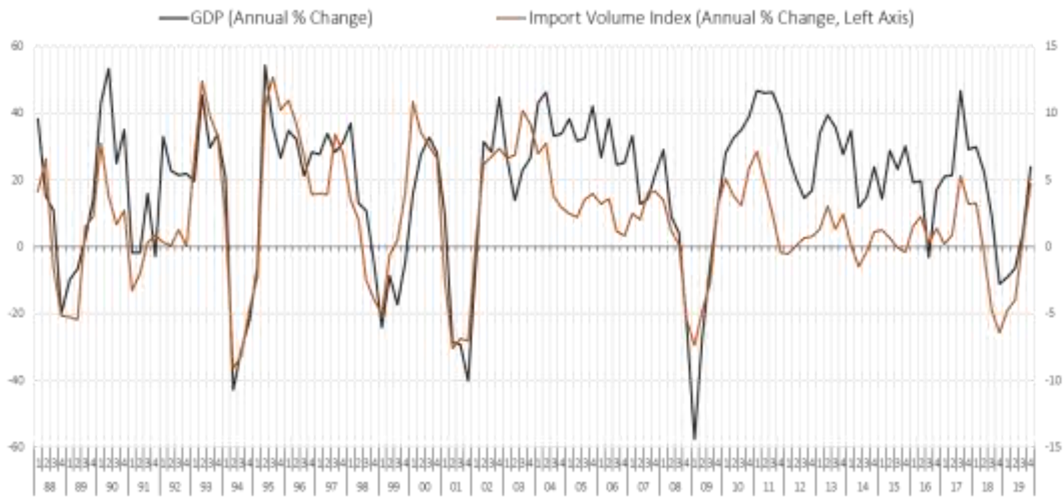


Figure 4.4. GDP and Import Volume Index from Trade Category

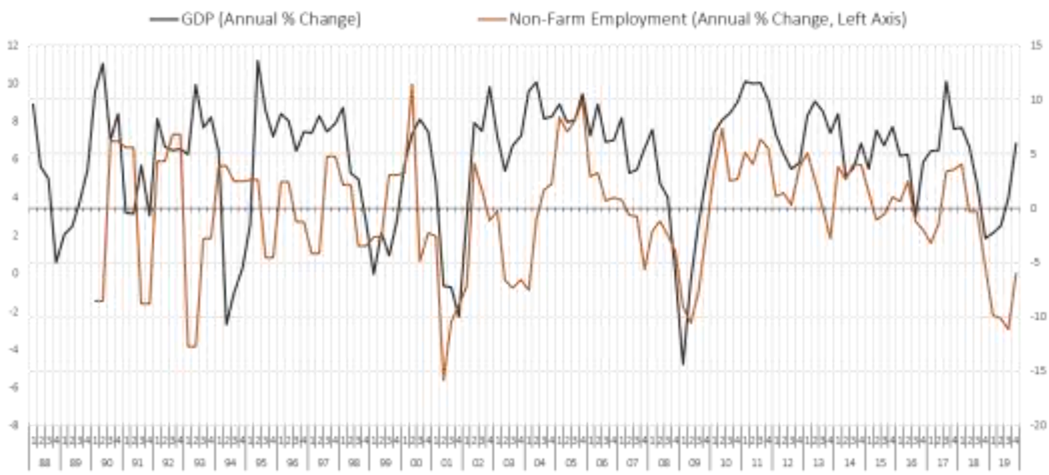


Figure 4.5. GDP and Non-Farm Employment from Employment Category

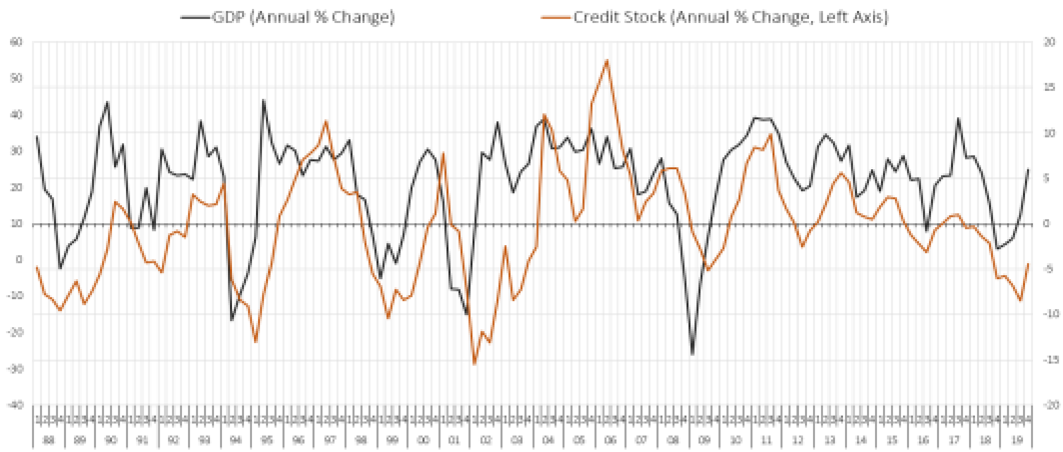
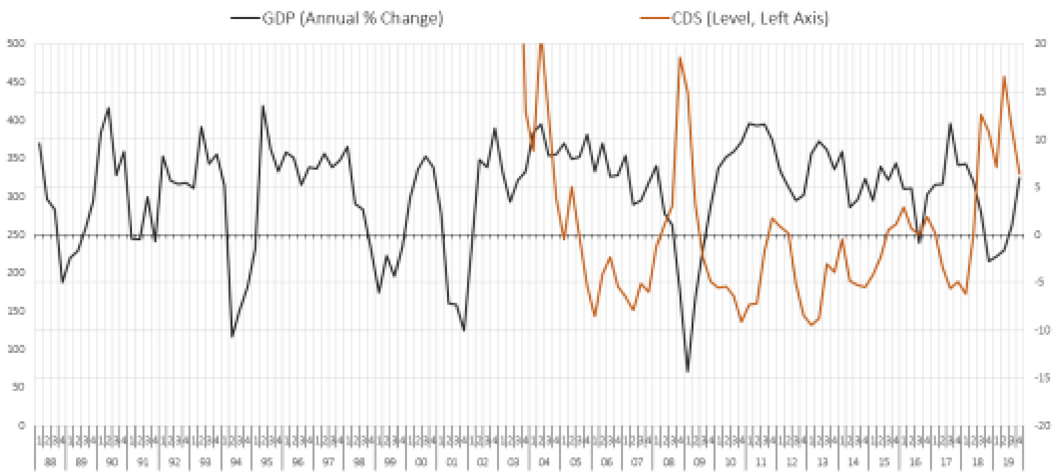


Figure 4.6. GDP and Credit Stock from Financial Variables Category



Note: Although CDS exceeds 500 and reaches to nearly 1200 in 2002Q3, its y-axis is drawn between 0 and 500 to show the relation between CDS and GDP after 2003.

Figure 4.7. GDP and CDS from Financial Variables Category

4.5. Robustness of Variable Selection

Table 4.9. Variables used in Period 2006-2019 and Their t-Statistics from Regression with GDP

Activity (Hard Data) Variables	t-statistics	Activity (Soft Data) Variables	t-statistics	Trade Variables	t-statistics
Industrial Production Index (IPI)	18.96	Purchasing Managers' Index (PMI)	12.78	Export Volume Index (QX)	1.85
IPI- Intermediate Goods	9.28	PMI- Output	8.35	QX- Intermediate Goods	0.70
IPI- Capital Goods	11.34	PMI- New Orders	9.83	QX- Capital Goods	3.15
IPI- Durable Consumer Goods	4.70	Capacity Utilization Rate	2.62	QX- Durable Consumer Goods	1.62
IPI- Non-Durable Consumer Goods	6.64	***Volume of Production over the past 3 Months***	11.76	QX- Semi-Durable Consumer Goods	1.48
Electricity Production	2.87	***Real Sector Confidence Index***	8.28	QX- Non-Durable Consumer Goods	1.45
Total Vehicles Production	2.77			***Import Volume Index (QM)***	5.46
Commercial Vehicles Production	2.22			QM- Intermediate Goods	5.71
Automobile Production	2.55			QM- Capital Goods	3.79
Total Vehicles Sales	3.96			QM- Durable Consumer Goods	2.27
Commercial Vehicles Sales	3.23			QM- Semi-Durable Consumer Goods	3.50
Automobile Sales	3.37			QM- Non-Durable Consumer Goods	2.68
Production Household Appliances	2.28				
Sales of Household Appliances	2.69				
Employment Variables	**t-statistics**	**Financial Variables**	**t-statistics**		
Total Employment	4.20	***Credit Stock***	3.48		
Non-Farm Employment	4.50	***Credit Default Swap (CDS)***	4.71		
Unemployment Rate	3.56	Chicago Board Options Exchange Volatility Index (VIX)	2.48		
Non-Farm Unemployment Rate	3.60				

Whether variables selected for the estimation have strong relationship with GDP or not except crisis periods, such as 2001 and 2009, is an important question to evaluate. In order to answer this, variable selection exercise is repeated by taking values of the variables for the period of 2006-2019, excluding 2001 crisis from the sample. By looking at Table 4.9, it can be concluded that all variables selected for the estimation still have significant t-statistics and some of them have the largest values in their categories. Furthermore, the correlation of GDP with these nine variables are given in Table 4.10 for 2006-2019 period. Compared to the correlation of GDP with these nine variables for whole sample period written in Table 4.8, correlation of GDP with these variables, except total vehicles production, increases in 2006-2019 period.

Table 4.10. Correlation of GDP with Variables used in the Estimation of Economic Activity Indicator for 2006-2019 Period

Variables	Correlation	Variables	Correlation
Industrial Production Index (IPI)	0.95	Import Volume Index (QM)	0.80
Electricity Production	0.63	Non-Farm Employment	0.75
Total Vehicles Production	0.62	Credit Stock	0.48
Volume of Production over the past 3 Months	0.83	Credit Default Swap (CDS)	-0.69
Real Sector Confidence Index	0.83		

Table 4.11. Variables used in Period 2010-2019 and Their t-Statistics from Regression with GDP

Activity (Hard Data) Variables	t-statistics	Activity (Soft Data) Variables	t-statistics	Trade Variables	t-statistics
Industrial Production Index (IPI)	11.94	Purchasing Managers' Index (PMI)	7.00	Export Volume Index (QX)	0.15
IPI- Intermediate Goods	8.97	PMI- Output	6.50	QX- Intermediate Goods	1.40
IPI- Capital Goods	4.94	PMI- New Orders	6.76	QX- Capital Goods	2.34
IPI- Durable Consumer Goods	6.67	Capacity Utilization Rate	1.02	QX- Durable Consumer Goods	0.20
IPI- Non-Durable Consumer Goods	5.57	***Volume of Production over the past 3 Months***	5.44	QX- Semi-Durable Consumer Goods	1.06
Electricity Production	2.23	***Real Sector Confidence Index***	8.82	QX- Non-Durable Consumer Goods	0.14
Total Vehicles Production	1.67			***Import Volume Index (QM)***	9.49
Commercial Vehicles Production	1.65			QM- Intermediate Goods	6.44
Automobile Production	1.22			QM- Capital Goods	4.50
Total Vehicles Sales	3.43			QM- Durable Consumer Goods	2.25
Commercial Vehicles Sales	2.68			QM- Semi-Durable Consumer Goods	3.58
Automobile Sales	3.43			QM- Non-Durable Consumer Goods	3.05
Production of Household Appliances	1.68				
Sales of Household Appliances	2.21				
Employment Variables	**t-statistics**	**Financial Variables**	**t-statistics**		
Total Employment	5.17	***Credit Stock***	7.60		
Non-Farm Employment	5.49	***Credit Default Swap (CDS)***	5.46		
Unemployment Rate	2.99	Chicago Board Options Exchange Volatility Index (VIX)	1.69		
Non-Farm Unemployment Rate	2.71				

In order to exclude 2009 crisis, variable selection exercise is repeated by taking values of the variables for the period of 2010-2019. By looking at Table 4.11, it can be concluded that all variables selected for the estimation still have significant t-statistics, except total vehicles production, and some of them have the largest values in their categories. Furthermore, the correlation of GDP with these nine variables are given in Table 4.12 for 2010-2019 period. Variables having high correlations with GDP for whole sample period and 2006-2019 period still have high values, except total vehicles production. But, it still has correlation equal to 0.40, which is not that much low and still credible for selecting it. Moreover, it can be concluded that correlation of GDP with non-farm employment, CDS and especially with credit supply increase in recent years. It shows that the significance of credit stock has improved since 2010.

Table 4.12. Correlation of GDP with Variables used in the Estimation of Economic Activity Indicator for 2010-2019 Period

Variables	Correlation	Variables	Correlation
Industrial Production Index (IPI)	0.91	Import Volume Index (QM)	0.76
Electricity Production	0.52	Non-Farm Employment	0.72
Total Vehicles Production	0.40	Credit Stock	0.80
Volume of Production over the past 3 Months	0.76	Credit Default Swap (CDS)	-0.66
Real Sector Confidence Index	0.81		

To sum up, variables selected for the estimation of economic activity indicator have significant t-statistics derived from the regression of GDP on each variable and have high correlations with GDP for different periods. Moreover, at least one variable from five different categories are selected in order to enhance diversification among variables. They are also publicly and quickly available from the websites of sources; and, announced with a timely manner. Usually, survey-based data and financial variables are announced in a timelier manner such as at the end of the related month or one month later. However, hard data, data related with employment and trade are released with some lags changing between 40 to 45 days. In this respect, among all selected nine variables, the latest updated one is industrial production index, which is published 45 days later after the end of related month.

CHAPTER 5

ESTIMATION RESULTS

In this chapter, we present the comprehensive estimation results of our economic activity indicator. In the first part, two monthly economic activity indicators estimated with and without GDP are introduced. Then, we compare our indicator, estimated with GDP, with the indicators presented in other studies about Turkey. Then, we evaluate the historical performance of our economic activity indicator. In the last part, we conduct a real time application of our economic activity indicator.

5.1. Monthly Economic Activity Indicators

The monthly economic activity indicator constructed with the aforementioned nine variables in Chapter 4 and GDP is illustrated in Figure 5.1. The black line shows the economic activity indicator and the red dotted-lines show its upper and lower bands (95 percent confidence interval). The values below/above zero imply that the economy is in contraction/expansion period. Furthermore, absolute values of the indicator in the related periods show the rate of contraction/expansion. In this regard, we should consider the duration of the indicator being below/above zero in deciding the course of economic activity. The grey shaded areas shown in Figure 5.1 point out the periods when both the indicator and its upper bands are lower than zero. Accordingly, there are seven detected recession periods: October 1988-February 1989, April 1994-January 1995, October 1998-March 1999, August 1999-September 1999, February 2001-February 2002, October 2008-September 2009 and August 2018-January 2019. When determining the recessions, we select the periods that indicator has negative values longer than one-month length and both the upper band of the indicator and itself have values lower than zero. Simple correlations of the variables with the indicator are demonstrated in Table 5.1. It can be concluded that industrial production index has the highest correlation with the estimated factor (indicator). Import volume index, GDP and electricity production are also highly correlated with the indicator. Among all variables, credit stock and CDS have the lowest correlations with the estimated factor and make limited contributions to it.

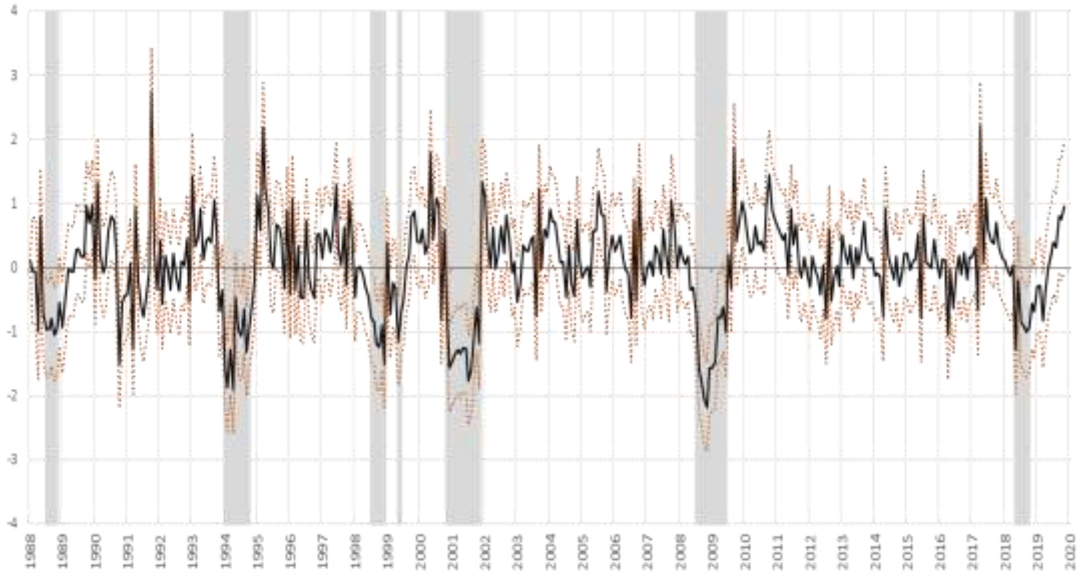


Figure 5.2. Economic Activity Indicator including GDP for Turkey

Table 5.1. Correlation of the Economic Activity Indicator with Variables used in the Estimation

Variables	Correlation	Variables	Correlation
Industrial Production Index (IPI)	0.95	Import Volume Index (QM)	0.86
Electricity Production	0.75	Non-Farm Employment	0.52
Total Vehicles Production	0.62	Credit Stock	0.27
Volume of Production over the past 3 Months	0.72	Credit Default Swap (CDS)	-0.26
Real Sector Confidence Index	0.65	Gross Domestic Product (GDP)	0.80

Although GDP is the most common measure of economic activity, it is announced on a quarterly basis with some lags (especially 60 days later than the appertaining quarter). In order to get a timelier indicator, the factor is reestimated with nine variables and excluding GDP. Figure 5.2 demonstrates this indicator drawn with blue line and its confidence intervals with red-dotted lines. Similar to Figure 5.1, the grey shaded areas show the periods when the indicator and its upper bands are lower than zero. The periods selected by this indicator as recessions are October 1988-February 1989, April 1994-February 1995, November 1998-March 1999, March 2001-February

2002, November 2008-September 2009 and August 2018-January 2019. Therefore, the two estimated economic activity indicators detect nearly the same periods as recession. In Table 5.2, the correlations between the indicator and the variables used in its estimation are shown. Still, variables related with the activity, both hard data and survey-based data, have the highest correlations whereas financial variables have the lowest correlations with the indicator. The small declines in the correlations are negligible.

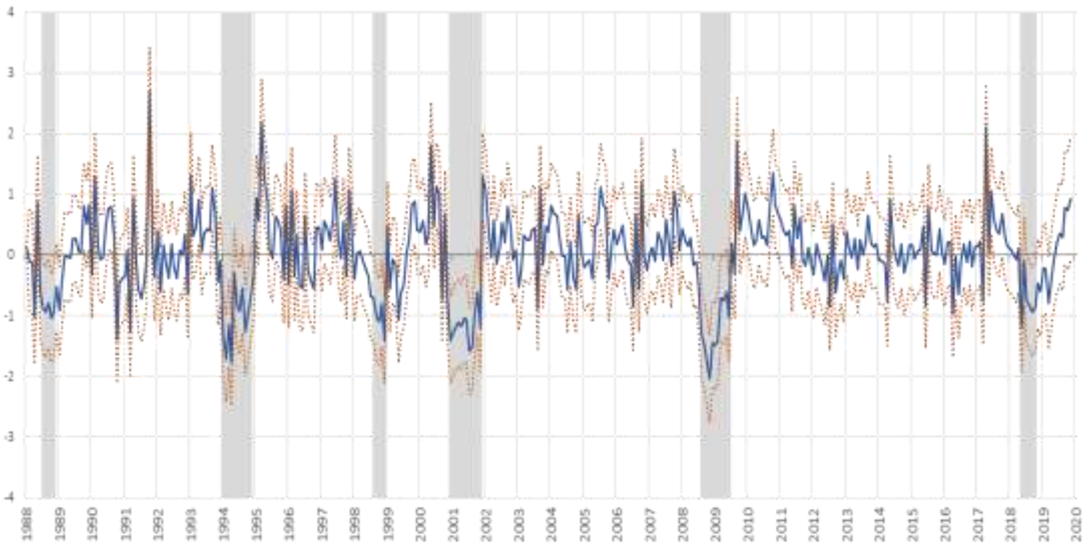


Figure 5.2. Economic Activity Indicator excluding GDP for Turkey

Table 5.2. Correlation of the Economic Activity Indicator Estimated Excluding GDP with Variables used in the Estimation

Variables	Correlation	Variables	Correlation
Industrial Production Index (IPI)	0.94	Import Volume Index (QM)	0.84
Electricity Production	0.73	Non-Farm Employment	0.47
Total Vehicles Production	0.60	Credit Stock	0.25
Volume of Production over the past 3 Months	0.68	Credit Default Swap (CDS)	-0.24
Real Sector Confidence Index	0.61		

After calculating both monthly indicators, their simple averages are calculated to convert them to quarterly basis and compared with the annual percentage change of GDP in Figure 5.3. Both indicators are usually successful in tracking the growth rate of national income, especially in terms of its direction. Compared to the expansion periods, the relationship between the indicators and GDP strengthens in the recessions.

In Table 5.3, annual percentage changes of GDP for 1988Q1-2019Q4 are listed and the quarters when both GDP has negative annual growth rates and recessions indicated by two indicators are shaded grey. It seems that almost in all quarters when GDP has contracted largely, both indicators signal them as recession periods. These periods are usually quarters where both indicators we derive and other studies have determined as recessions.

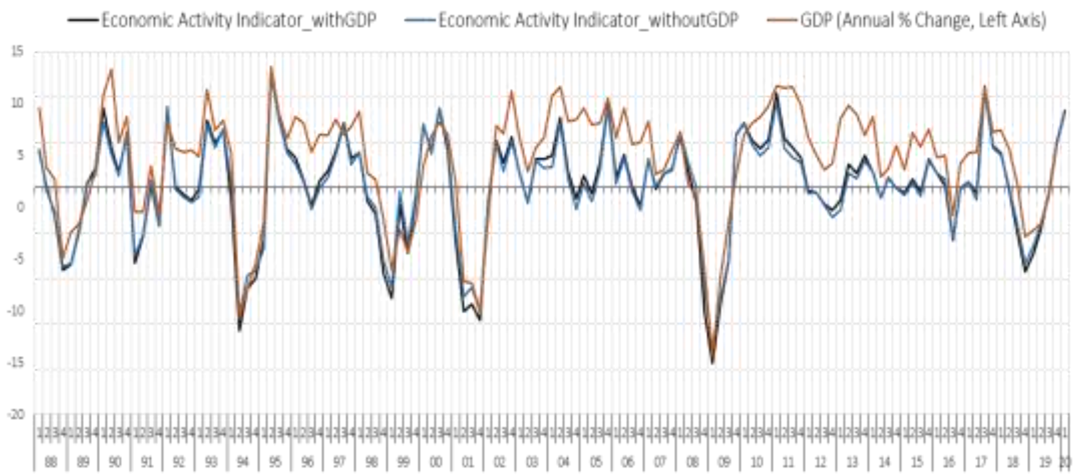


Figure 5.3. Economic Activity Indicators with and without GDP for Turkey and GDP (Annual % Change)

Table 5.3. GDP Growth Rates

1988Q1-1991Q4	1992Q1-1995Q4	1996Q1-1999Q4	2000Q1-2003Q4	2004Q1-2007Q4	2008Q1-2011Q4	2012Q1-2015Q4	2016Q1-2019Q4
9.6	8.2	8.7	4.0	10.8	7.2	6.8	4.8
3.8	5.7	8.1	6.9	11.6	2.3	5.0	4.9
2.7	5.4	5.3	8.2	8.3	1.0	3.6	-0.8
-5.0	5.5	7.0	7.0	8.5	-5.9	4.2	4.2
-2.4	4.9	6.9	2.4	9.6	-14.4	8.5	5.3
-1.7	11.3	8.5	-7.2	7.9	-6.7	9.8	5.3
0.6	7.4	7.0	-7.3	8.1	-1.5	8.9	11.6
3.5	8.4	7.8	-10.0	10.5	3.1	6.9	7.3
10.8	5.2	9.2	-1.1	6.7	7.0	8.7	7.4
13.3	-10.7	3.3	7.9	9.6	8.1	2.9	5.6
6.2	-7.8	2.7	7.1	6.1	8.7	3.7	2.3
8.7	-5.5	-1.2	11.2	6.3	9.7	5.9	-2.8
-0.4	-1.5	-6.1	6.6	8.3	11.7	3.6	-2.3
-0.5	13.5	-2.2	3.4	3.2	11.5	7.2	-1.6
3.9	9.0	-4.3	5.8	3.6	11.6	5.8	1.0
-0.7	6.6	-1.2	6.6	5.5	9.9	7.5	6.0

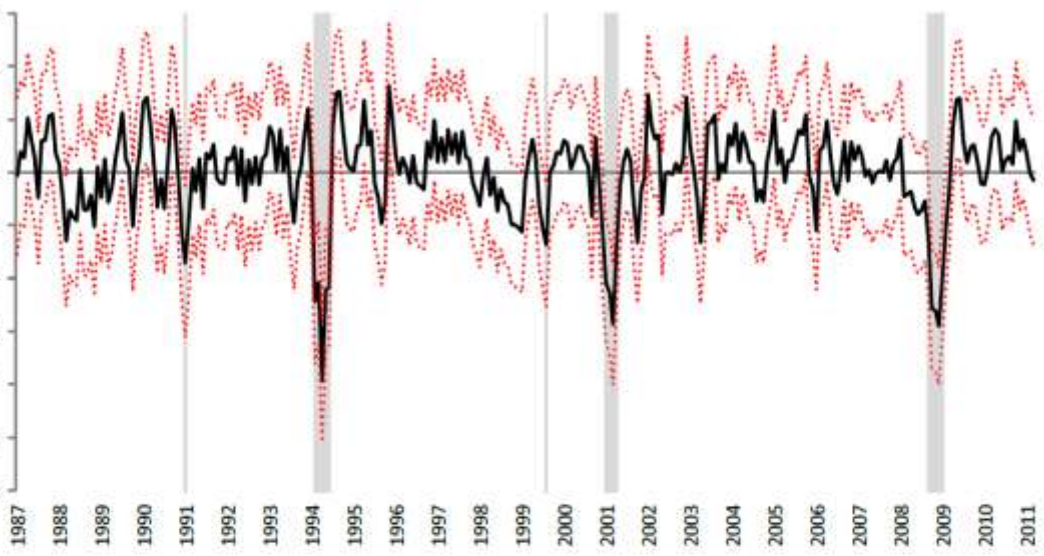
Note: Shaded periods show both GDP has negative annual growth rates and recessions indicated by both economic activity indicators.

In the following sections, we continue with the indicator including GDP. The comparison of our indicator with other indicators for Turkey will be made and the recession periods stated by it will be explained in detail. Then, a real time application of our economic activity indicator will be conducted.

5.2. Comparison of the Economic Activity Indicator with Others' Indicators for Turkey

In Chapter 2, we introduce two different papers, Aruoba and Sarikaya (2013) and Çakmaklı and Altuğ (2014), which construct economic activity indicators for Turkey. We utilize the same methodology with Aruoba and Sarikaya (2013) in our estimation. Here, the recession periods detected by our indicator with the ones detected by these two works are compared. Since the estimation periods for these two studies are 1987-2001 and 1989-2014, respectively, the comparison is done for overlapping periods.

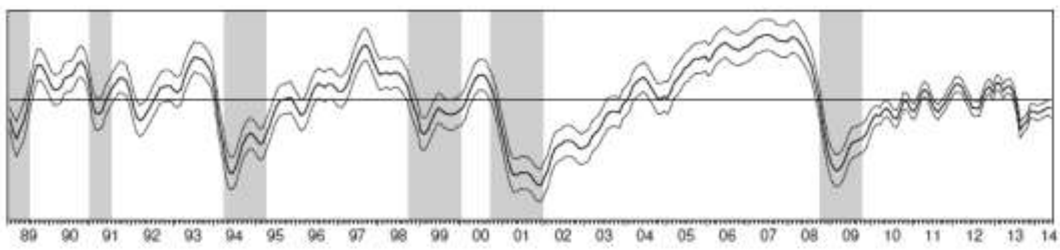
Aruoba and Sarikaya (2013) estimate an economic activity indicator with four variables and GDP. They also construct the indicator excluding national income data and compare both indicators with quarterly growth rate. Figure 5.4 shows economic activity indicator of Aruoba and Sarikaya (2013) with its 95 percent confidence intervals. They also put grey shaded areas to the periods when both the indicator and its upper bands are lower than zero. They call grey shaded areas as turbulence when they have one-month length and as recession when they have more than one-month length. In this respect, they identify 1991 and 1999 as turbulence, while 1994, 2001 and 2008-2009 as recession periods. These three recession periods are the same with the ones we detect by considering our economic activity indicator with some differences in their lengths. Additionally, our indicator detects four more periods as recession: October 1988-February 1989, October 1998-March 1999, August 1999-September 1999 and August 2018-January 2019.



Source: Aruoba and Sarikaya (2013).

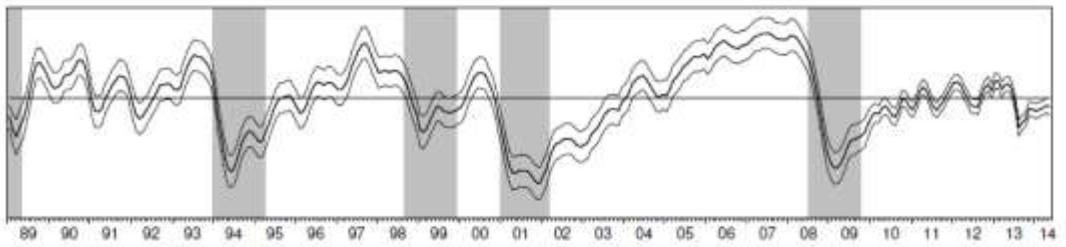
Figure 5.4. Economic Activity Indicator of Aruoba and Sarikaya (2013) for Turkey

Çakmaklı and Altuğ (2014) calculate coincident economic indicators based on GDP and industrial production index, shown in Figure 5.5 and Figure 5.6. Like our work as well as Aruoba and Sarikaya (2013), they select the crisis periods by considering both the indicators and their upper bands are lower than zero at the same time. Although there are several months when their indicators imply negative growth rates, the recession periods detected are 1994-1995, 2000-2001 and 2008-2009. Like in the case of Aruoba and Sarikaya (2013), our indicator detects the recessions better compared to Çakmaklı and Altuğ (2014).



Source: Çakmaklı and Altuğ (2014).

Figure 5.5. Coincident Economic Indicator and GDP based Recession Periods of Çakmaklı and Altuğ (2014) for Turkey



Source: Çakmaklı and Altuğ (2014).

Figure 5.6. Coincident Economic Indicator and Industrial Production based Recession Periods of Çakmaklı and Altuğ (2014) for Turkey

5.3. Historical Evaluation of Recession Periods

In the first part, the recession periods indicated by our monthly economic activity indicator are shown in Figure 5.1 by grey shaded areas. As mentioned, they are determined by considering both the indicator and its upper bands being below zero. These recession periods are shown closely in Figure 5.7-5.12. Three periods which are April 1994-January 1995, February 2001-February 2002 and October 2008-September 2009 last longer than the other three periods.

By considering the values of the indicator in October 1988-February 1989 recession period, we can say that this is a kind of sudden-stop because the indicator falls below zero two months before the recession period. However, it does not jump above zero so quickly after the end of recession.

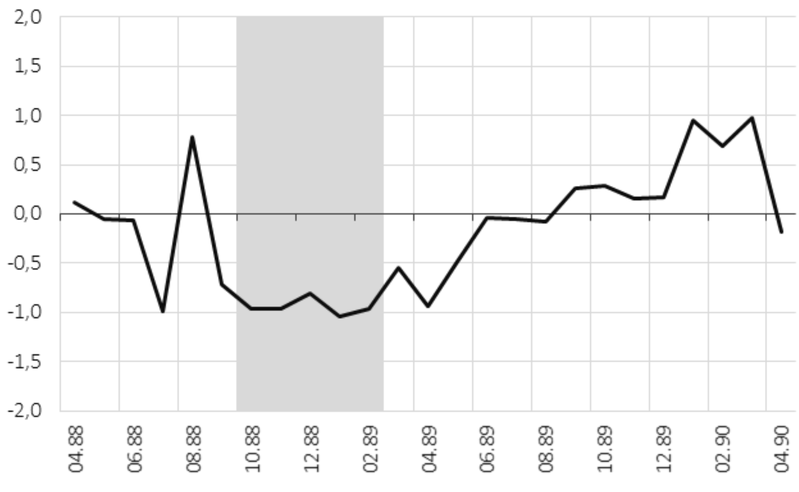


Figure 5.7. October 1988-February 1989 Recession

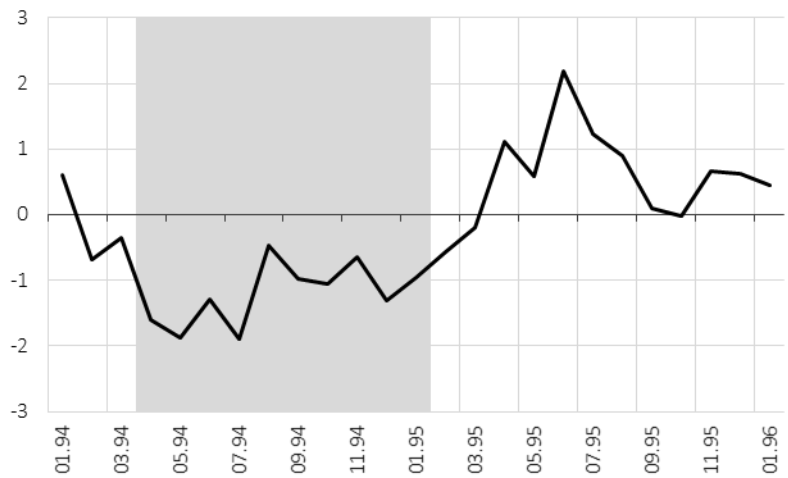


Figure 5.8. April 1994-January 1995 Recession

April 1994-January 1995 can be considered as a sudden-stop period because economic activity indicator falls below zero starting one or two months before the detected recession periods. This is one of the important financial crises that Turkish economy went through. In this crisis, government used the Central Bank reserves to finance public debt instead of foreign borrowing and this caused both huge reserve and foreign exchange losses. As a result, the exchange rate (value of Turkish Lira against US dollar) plummeted and the overnight interest rate ascended to historically peak levels. Additionally, the inflation rate rose to three-digit levels. Although a stand-by agreement with IMF was signed in April 1994, the terms of the agreement were not implemented properly.

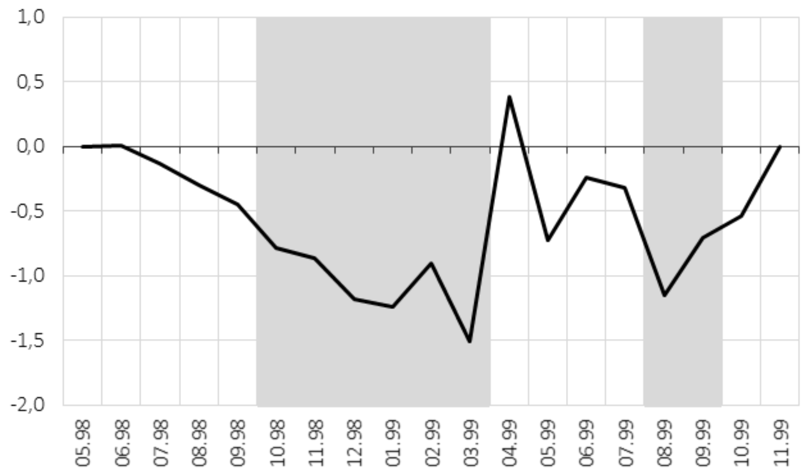


Figure 5.9. October 1998-March 1999 and August 1999-September 1999 Recessions

Although the indicator gradually worsens starting earlier than the beginning of October 1998-March 1999 recession, it jumps above zero very quickly. Then, it falls below zero after two months but upper band of it does not fall below zero. So, this period cannot be classified as recession. However, for August 1999-September 1999 period, the indicator and the upper bands again fall below zero indicating recession. The first recession period overlap with the Russian crisis. Although the crisis hit Russia on July 1998 and continued for shorter period, it had serious effects both on Russia and its many neighbouring countries including Turkey. It seriously caused the foreign investors to lose their confidence and affected the capital inflows to countries including Turkey. Loss in capital inflows affected the economic activity negatively by slowing it down. The second recession period is a shorter one compared to others and is thought to be caused by earthquake happened in August 17, 1999.

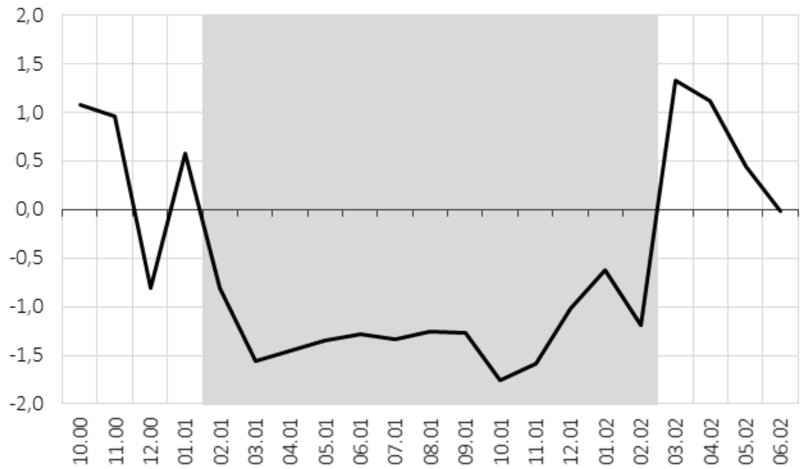


Figure 5.10. February 2001-February 2002 Recession

February 2001-February 2002 is another example to the country-specific financial crises. It can also be considered as sudden-stop because of the indicator falling below zero at the very beginning of the grey shaded area. 2001 crisis is a serious banking sector crisis that Turkish economy experienced. Interest rate reached its peak and the prices of treasury bills crashed causing deterioration in banks' balance sheets. Furthermore, political instability caused foreign investors to withdraw their fundings from Turkey. In order to keep the devaluation of Turkish Lira under control, Central

Bank lost considerable amount of its reserves. To cure the devastating effects of the crisis, different reforms were implemented together with IMF assistance.

October 2008-September 2009 is a part of the global financial crisis period. In contrast to 1994-1995 and 2001-2002 sudden-stop domestic recessions, our economic activity indicator gradually worsens starting earlier than the beginning of October 2008-September 2009 recession. Moreover, this period is a global crisis initiated by the US economy. It is considered as the worst one after the Great Depression in 1929. Although it emerged in the US economy, its effects spread to all countries rapidly. Turkish economy was also affected seriously from the global crisis. Firstly, financial flows came to a standstill causing the amount of foreign exchange available to decline. Moreover, the exports of Turkey declined sharply especially to European countries which are the major trading partners of Turkey. Decline in exports further aggravated the foreign exchange supply which caused the imports of Turkey to decline. The deficiency of imported intermediate goods and the private sector indebtedness led to disruption in production chain and economic activity.

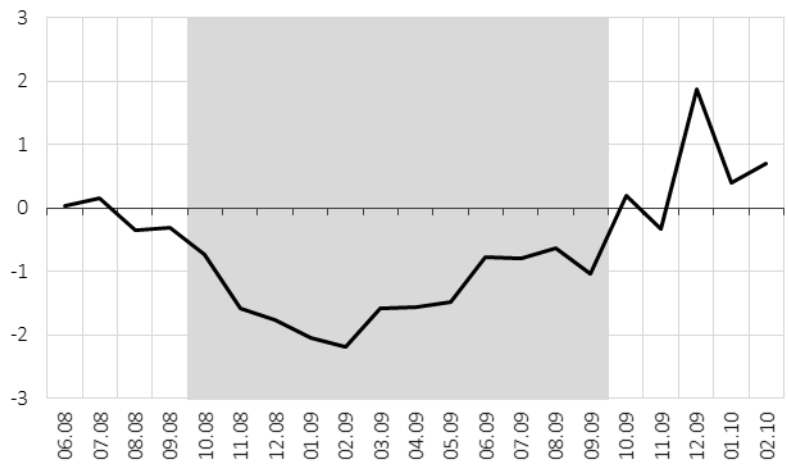


Figure 5.11. October 2008-September 2009 Recession

Figure 5.12. August 2018-January 2019 Recession

August 2018-January 2019 is a recession period in which the economic activity indicator and its upper band suddenly fall below zero together but they do not jump above zero simultaneously. The indicator recovers very slowly until the end of 2019 even its upper bands turn back to positive earlier. Following the exchange rate shock hitting the Turkish economy at August 2018, Central Bank implemented a tight monetary policy by raising the interest rate. In this period, inflation rate reached high levels. Domestic demand led contraction in economic activity because of the volatile financial conditions and the descending credit demand. Although monetary tightening of advanced economies led to declines in financial flows to Turkey, depreciation of exchange rate and strong tourism revenues backed up net exports.

Table 5.4. Recession Periods Detected by Economic Activity Indicator with Their Durations

Recession Periods	Duration of Recessions	Corresponding Crisis
October 1988-February 1989	3 Months	…
April 1994-January 1995	10 Months	1994 Financial Crisis
October 1998-March 1999	6 Months	1998 Russian Financial Crisis
August 1999-September 1999	2 Months	August, 17 Earthquake
February 2001-February 2002	13 Months	2001 Banking Crisis
October 2008-September 2009	12 Months	Global Financial Crisis
August 2018-January 2019	6 Months	Exchange Rate Shock in August 2018

The recession periods detected by our economic activity indicator with their durations and the corresponding crisis to these periods are listed in Table 5.4. To sum up, our economic activity indicator, calculated by using different macroeconomic variables and GDP, is good at detecting historical recession periods, better than other papers about Turkey, and giving signals about very near-term realizations.

5.4. Real Time Application

Like historical performance of the economic activity indicator in detecting past well-known recession periods, timely information of it about the current state of the economy is crucial for policy makers. With new data arrivals, estimation of the indicator may change because of both new observations and revisions to previous observations. Therefore, the real-time characteristics of the variables are given great importance in constructing the economic activity indicators.

In the first part, we estimate the indicator for the period of 1988M01 and 2020M02 because the data of the latest announced variables are available for February 2020. As given in the third column of Table 5.5, some of the variables used in the indicator have data available for later months when that estimation is done. Thus, variables used in the estimation are announced at different times during a month and the most recent observations of them can be different. Aruoba and Sarikaya (2013) estimate the model until a certain period and get fixed parameters; then, calculate their economic activity indicator with these fixed parameters at each new data announcements to make a real-time evaluation of the economic activity. Similar to their real-time analysis, we estimate the model for the period of 1988M01-2019M03 and take the fixed parameters. Then, we calculate our economic activity indicator up to February 2020 and April 2020 with available variables when the first estimation is done (at the end of April 2020). Then, with new data arrivals, the indicators are recalculated at May 22, 2020 up to May 2020.

Table 5.5. Latest Available Observation of Variables When the Estimation is Done

Variables	Categories	Last Observation at First Estimation[10]	Last Observation at May 22, 2020[11]
Industrial Production Index (IPI)	Activity (hard data)	2020M02	2020M03
Electricity Production	Activity (hard data)	2020M04	2020M05
Total Vehicles Production	Activity (hard data)	2020M03	2020M04
Volume of Production over the past 3 Months	Activity (soft data)	2020M04	2020M04
Real Sector Confidence Index	Activity (soft data)	2020M04	2020M04
Import Volume Index (QM)	Trade	2020M02	2020M03
Non-Farm Employment	Employment	2020Q1	2020Q1
Credit Stock	Financial Variables	2020Q2	2020Q2
Credit Default Swap (CDS)	Financial Variables	2020M04	2020M05
Gross Domestic Product (GDP)	Activity (hard data)	2019Q4	2019Q4

Figure 5.13 demonstrates the economic activity indicators estimated at the end of April until February and April 2020, and at 22nd of May until May 2020 due to the disclosure of data at different times. The indicator named as "Economic Activity Indicator_2019M03" belongs to the estimation that is done for the period of 1988M01 and 2019M03 to get fixed parameters. Other indicators named as "Economic Activity Indicator_2020M02", "Economic Activity Indicator_2020M04" and "Economic Activity Indicator_2020M05_May22" show the indicators estimated until February, April and May, respectively. The red-dotted lines are the confidence bands of the indicator calculated on 22nd of May, 2020.

When the model estimation is first made at the end of April, half of the variables contain information about the activity in April. The economic activity indicator and its upper bands fall below zero at April 2020 indicating that month as a starting of a recession period. If we do not have these timely variables and the most recent variable could have been available for February, we would not have timely information on the decline in economic activity in April or we would get informed about it with two months lagged. In the analysis made on 22nd of May, again we have data for April for six of the all ten variables and for May for three of the all ten variables, so we can

[10] Although non-farm employment and credit stock is used in quarterly frequency because of the reasons explained in Data part, their latest data is January 2020 period for non-farm employment and April 2020 for credit stock.

[11] For electricity production, the latest data is for May 21, 2020 but the available 21-days variables are rescaled into monthly data. For credit stock, the up-to-date data belongs to the second week of May 2020. For CDS, the latest data is available for May 21, 2020.

obtain information about the course of economic activity. As given in Table 5.3, GDP contracted by 2.8 percent in the third quarter of 2018. Figure 5.13 demonstrates that the indicator estimated on 22nd of May takes the value between -2 and -1 in August 2018 and the averages of July-August-September 2018 take the value of nearly -1 that corresponding to the third quarter of 2018. When considering the value of nearly -4 in May 2020, it can be inferred that the GDP may contract between 6 and 11 percent in annual terms in the second quarter of 2020. However, because of having limited variables for April and May, it is better to make prudent inferences. Widening of the confidence interval at the end of the sample, especially at April and May, are also due to the data uncertainty.

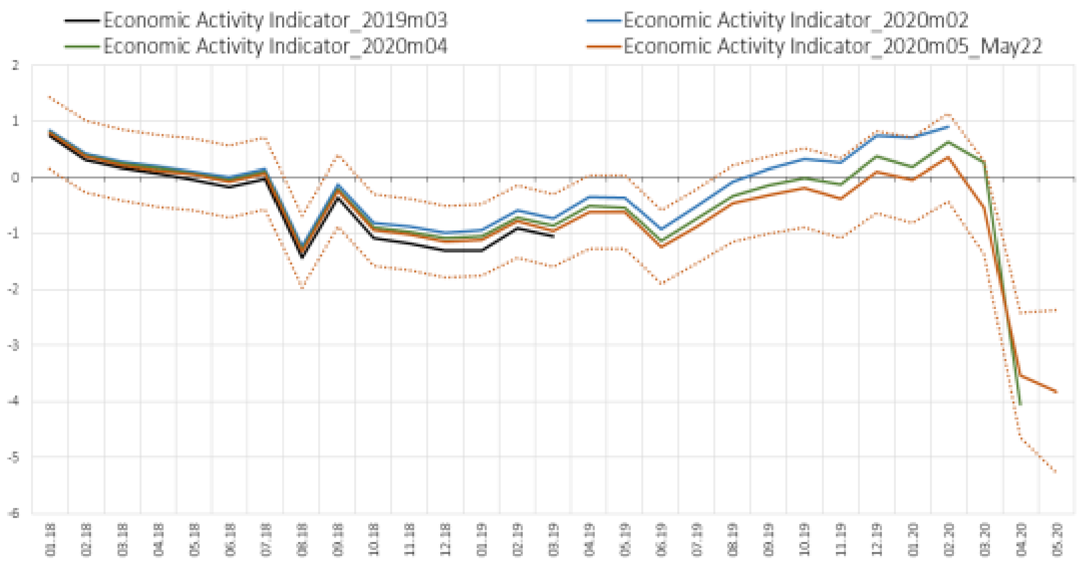


Figure 5.13. Real-Time Application to the Economic Activity Indicator

In sum, having timely variables are important for providing real-time information about the economic activity. However, lags in data announcements and revisions in recently announced variables obstruct evaluation of the economic activity in real-time.

CHAPTER 6

CONCLUSION

In this thesis, we construct an economic activity indicator for the Turkish economy for the period 1988-2020. Dynamic factor modelling framework is utilized in the estimation of the indicator. In this approach, economic conditions are considered unobserved, while the variables used in the estimation are considered observed. After writing the model in state-space form, we use Kalman filter to estimate the model and Kalman smother to obtain the factor, i.e. economic activity indicator. One of the advantages of this framework is that it enables us to use variables with different frequencies simultaneously. Additionally, it is good at solving the missing values problem by giving no weight to them in the calculation of the factor.

We select industrial production index, electricity production, total vehicles production, the volume of production over the past 3 months, real sector confidence index, import volume index, non-farm employment, credit stock and CDS for the estimation of the economic activity indicator. As being the broadest measure of economic activity, GDP is also added to the data set. Data selection is done with the help of the hard-thresholding method. In this context, first of all, the variables are categorized into five types as: activity (hard data), activity (survey-based data or soft data), trade, employment and financial variables. For each category, the candidate variables that date back to earlier periods are preferred to be selected. Then by using the hard-thresholding method, variable selection is finalized.

The results indicate that our monthly economic activity indicator is successful in detecting the past recessionary periods of the Turkish economy. The recessions detected by our economic activity indicator are October 1988-February 1989, April 1994-January 1995, October 1998-March 1999, August 1999-September 1999, February 2001-February 2002, October 2008-September 2009 and August 2018-January 2019. Almost all of these periods correspond to the crisis periods that are commonly accepted in the literature. For instance; April 1994-January 1995 corresponds to a significant financial crisis in the Turkish economy. As a result of using the Central Bank reserves to finance public debt, huge reserve and foreign exchange losses are observed in this crisis. Moreover, October 1998-March 1999 overlap with the period of Russian sovereign debt crisis that had serious contagion effects for the neighbouring countries. Compared to the others, August 1999-September 1999 is a shorter recession that can be attributed to the aftermath of the devastating earthquake that hit one of the most industrial regions of Turkey in August 17. February 2001-February 2002 corresponds to a typical emerging market twin crisis in which interest rates reached the peak values and the prices of the treasury bills crashed simultaneously with the currency crisis causing the deterioration in banks' balance sheets. October 2008-September 2009 is the well-known global financial crisis period initiated in the US economy and spread to the world rapidly. Finally, August 2018-January 2019 is a recession caused by the exchange rate shock that hits the Turkish economy at August 2018. While determining the recessionary periods, we implement the same methodology with Aruoba and Sarikaya (2013) and Çakmaklı and Altuğ (2014) which also use Turkish data. They select the periods in which the indicator has negative values longer than one-month length and both the upper band of the indicator and itself have values lower than zero. Comparing with these two papers considering the same time period, our indicator detects recessions better than their indicators.

Using timely variables gives an advantage to our indicator; so that it provides real-time information about the current state of the economy. Data sets in the other studies consist of variables announced with a lag of 40 to 60 days. Whereas six of the ten variables in our data set are released at the appertaining month or at the beginning of next month. In this respect, our indicator can be updated earlier than the indicators estimated in these two studies. Additionally, for the purpose of showing the importance of timelier variables, a real-time application is performed. We estimate the model until a certain period and fixed the model parameters. Then, we calculate our economic activity indicator at new data announcements for different data releases.

With the help of the timelier variables, we can get information about the decline in economic activity which enables to implement timelier and stronger policies.

All in all, our economic activity indicator is good at detecting historical recession periods and providing timelier information about the course of economic activity. This research can be developed in two different ways. First of all, the economic activity indicator in this paper is constructed with a monthly frequency. Evans (2005) and Aruoba et al. (2009) construct economic activity indicators for the US economy on a daily basis. Thus, our work can be developed by constructing an economic activity indicator on weekly or daily basis. Secondly, although we utilize timelier variables in the estimation of our economic activity indicator compared to other papers about Turkey, we still have variables announced with some lags. In this respect, an indicator can be constructed by using a data set that consists of variables only released at the concurrent month. However, it is hard to find variables that are announced so early and at the same time available for a long period of time. For this reason, such an indicator will not be able to represent past developments.

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APPENDICES

A. TURKISH SUMMARY / TÜRKÇE ÖZET

İktisadi faaliyet, bir ülkenin zaman içinde nasıl bir performans sergilediğini değerlendirmek için ele alınan ana göstergelerden biridir. Akademisyenler, iş insanları ve politika yapıcılar genişleme/daralma dönemlerinin tespit edilmesine ve iktisadi faaliyetin gerçek zamanlı konjonktürel analizine, özellikle kriz dönemlerinde etkili politikaların uygulanması için, önem vermektedir. Bu amaçla, ekonomik aktivitenin doğru değerlendirilmesi iktisat literatüründe önemli bir yere sahiptir.

İktisadi faaliyetin seyrine ilişkin takip edilen en yaygın gösterge Gayri Safi Yurt İçi Hâsıla (GSYİH) olmakla birlikte bu göstergenin zamanlaması ve içeriği ile ilgili bazı dezavantajları bulunmaktadır. İlk olarak, GSYİH önemli bir gecikme ile yayımlanmakta (ilgili çeyrek bittikten yaklaşık 60 gün sonra) ve ilk açıklandıktan sonraki veri akışında geriye dönük revizyonlara maruz kalmaktadır. Ayrıca, GSYİH verisi, genel ekonomik faaliyet hakkındaki tüm bilgileri kapsamak için yeterli olmayabilmektedir. İşgücü piyasası, finansal piyasalar vb. gibi mal piyasası haricindeki gelişmeleri takip edebilmek için GSYİH haricindeki farklı veri kaynaklarına da ihtiyaç duyulmaktadır. Bununla birlikte, üretim, tüketim, ticaret ve işgücü ile ilgili anket göstergeleri de faaliyetin seyrine ilişkin bilgi verme hususunda faydalı olabilmektedir. Özetle, ekonominin tüm birimlerini kapsayan zamanlı bir göstergenin türetilmesi iktisadi faaliyetin seyrine ilişkin çıkarım yapmakta daha faydalı olabilecektir.

İktisadi faaliyet göstergesi oluşturulması konusunda özellikle ABD ekonomisi için kapsamlı bir yazın bulunmaktadır. Stock ve Watson (1989) öncü çalışmasında dinamik faktör modelleme yönteminden faydalanarak ve aylık frekansta açıklanan farklı makroekonomik değişkenler kullanarak ABD ekonomisi için üç farklı iktisadi faaliyet göstergesi türetmiştir. Analizde sadece aylık frekansta değişkenlere yer verilip farklı frekansta açıklanan veriler birlikte kullanılmamıştır. Türetilen endekslerin NBER tarafından ABD ekonomisi için belirtilen daralma dönemleriyle büyük ölçüde uyumlu olduğu ve ABD Ticaret Bakanlığı tarafından oluşturulan göstergeden daha iyi performans sergiledikleri bulgulanmıştır. Mariano ve Murasawa (2003) çalışmasında ise Stock ve Watson'ın (1989) çeyreklik verilere yer vermemesini eleştirmiş ve aylık göstergeler haricindeki değişkenlerden gelebilecek ek bilgiden faydalanılamadığının altını çizmiştir. Bu sebeple, Stock ve Watson (1989) çalışmasını çeyreklik frekanstaki GSYİH verisini dâhil ederek güncellemiştir. Stock ve Watson'a (1989) benzer şekilde, iktisadi faaliyet endeksinin tahmininde dinamik faktör modellemesi tercih edilmiştir. Model, durum-uzay biçiminde yazıldıktan sonra, maksimum olabilirlik tahmininde Kalman filtresi kullanılmıştır. Sonuç olarak, Stock ve Watson (1989) çalışmasına kıyasla oluşturulan göstergenin NBER tarafından belirtilen daralma dönemlerini yakalamada daha başarılı olduğu gözlenmiştir.

Evans (2005), GSYİH büyümesinin günlük frekansta tahmininin zamanlı para politikası uygulanmasında önemli olabileceğine dikkat çekmiş ve ABD'deki iş koşulları ve ekonomik faaliyeti günlük frekansta modellemiştir. Bu amaçla, söz konusu günde mevcut makroekonomik değişkenleri ve GSYİH'nin önceki dört çeyreğine kadar olan tarihsel değerlerini kullanmıştır. Model parametreleri (yarı) maksimum olabilirlik yöntemiyle tahmin edildikten sonra GSYİH büyümesinin gerçek zamanlı tahminleri Kalman filtresi kullanılarak elde edilmiştir. Model tahminleri için veriler öncelikle reel aktivite, tüketim, yatırım, kamu, net ihracat ve ileriye dönük göstergeler olmak üzere 6 farklı kategoriye ayrılmış; sonrasında, her bir kategoriden toplamda 18 farklı değişken seçilmiştir. Veri seçiminde her kategoriden en az bir değişkene yer vermeye dikkat edilmiştir. Ayrıca, GSYİH'nin gelişmiş-ön-final olmak üzere üç farklı açıklanan değerlerine de yer verilmiştir. Model tahminleri elde edildikten sonra profesyonel iş insanlarının ABD ekonomisi için verdiği tahminler ile kıyaslanmıştır. Sonuç olarak, tahmin ufku genişledikçe, model tahminlerinin profesyonel iş insanlarının tahminlerinden daha iyi sonuçlar verdiği tespit edilmiştir. Ayrıca, kullanılan değişkenler arasından sanayi üretimi, tarım dışı istihdam, perakende satış gibi reel aktiviteye ilişkin göstergelerin model tahminlerine en yüksek bilgiyi sağladıkları bulgulanmıştır.

Proietti ve Moauro (2006), Mariano ve Murasawa (2003) çalışmasına benzer şekilde farklı frekanslı değişkenleri veri setine dâhil etmiş ve gösterge oluşturulmasında dinamik faktör modelleme yöntemini kullanmıştır. Ancak, dinamik faktör modellemesinde Mariano ve Murasawa'nın (2003) aksine doğrusal olmayan filtreleme tercih etmiş; alternatif olarak, karşılaştırma yapabilmek için, doğrusal filtreleme içeren bir sözde model tahmini almıştır. Doğrusal olmayan model ile sözde doğrusal modelin karşılaştırılması, ilkinin özellikle değişkenler logaritmik formlarda kullanıldığında daha düşük hata kareleri ortalaması vererek ikincisinden daha iyi performans sergilediğini göstermektedir. Ayrıca, bu çalışmada hem ABD ekonomisi hem de Euro bölgesi için iktisadi faaliyet göstergeleri türetilmiştir. ABD ekonomisi için seçilen değişkenler Mariano ve Murasawa (2003) ile aynı olup Euro bölgesi için değişken seçiminde benzer tanımlı değişkenlere yer verilmeye çalışılmıştır. Ancak, ABD ekonomisine kıyasla değişkenlerin daha kısa bir süre için mevcut olması, benzer değişkenlerin olmaması ya da daha düşük frekanslarda yayımlanması gibi veri kısıtlarından ötürü tahmin dönemi Euro bilgesi için daha geç bir tarihten başlatılmıştır.

Evans'a (2005) benzer şekilde, Aruoba ve diğ. (2009) de ABD ekonomisi için günlük frekansta takip edilebilen bir iktisadi faaliyet göstergesi oluşturmuştur. Bu çalışmada, Stock ve Watson (1989), Mariano ve Murasawa (2003) ve Proietti ve Moauro (2006) çalışmalarına benzer şekilde dinamik faktör modelleme yönteminden faydalanılmış ve farklı frekansta takip edilebilen değişkenleri içeren bir veri seti oluşturulmuştur. Veri çeşitliliğine dikkat edilmesinin yanı sıra, önceki çalışmalardaki kullanımları ve döngüsel özellikleri göz önünde bulundurularak çeyreklik GSYİH, aylık istihdam, haftalık işsizlik haklarından yararlanma başvuruları ve günlük getiri eğrisi primi verileri göstergenin oluşturulmasında kullanılmıştır. Sonuç olarak, elde edilen iktisadi faaliyet göstergesinin NBER tarafından belirtilen daralma dönemleri ile büyük ölçüde uyumlu olduğu gözlenmiştir. Ayrıca, göstergenin daralma ve genişleme dönemlerine girerken ve çıkarken gözlenen dönüm noktalarını tespit etmede iyi bir performans sergilediği tespit edilmiştir. Yüksek frekanslı verilerin kullanılmasının göstergenin performansını olumlu etkileyip etkilemediğini araştırmak için günlük ve haftalık veriler sırayla modelden çıkartılarak yeniden iktisadi faaliyet göstergeleri oluşturulmuştur. Dört değişkenli ana gösterge ile günlük ve haftalık verilerin modelden çıkartıldığı göstergeler kıyaslandığında, haftalık frekanstaki işsizlik haklarından yararlanma başvuruları değişkeninin göstergeye önemli bir katkı yaptığı ve modelden çıkartılmasının performansı olumsuz etkilediği gözlenmiştir.

Matheson (2011) çalışmasında gelişmiş ve gelişmekte olan 32 ülke için dinamik faktör modelleme yöntemini kullanarak aylık frekansta iktisadi faaliyet göstergeleri türetmiştir. Model tahminlerinde diğer çalışmalara kıyasla daha geniş veri setleri kullanılması çalışmanın en büyük katkısı olarak belirtilmiştir. Değişken seçiminde veriler şu şekilde altı gruba ayrılmıştır: 1) aktivite (gerçekleşme verileri), 2) aktivite (anket göstergeleri), 3) ticaret, 4) finansal koşullar, 5) istihdam ve gelir, 6) fiyatlar ve maliyetler. Bu sınıflandırma, veri setinin farklı sektörleri kapsamasını ve ekonominin özel bir kısmına yoğun bir şekilde odaklanmadan çeşitliliği artırmasını sağlamaktadır. Ayrıca, küresel etkileri temsil edebileceği düşünülerek, her ülkenin veri setine ABD ekonomisi için oluşturulan verilerden seçilen sekiz temel seri eklenmiştir. Veri kısıtlamaları ve çok sayıda değişken kullanmanın hesaplama maliyeti nedeniyle aylık veri setleri derlenmiştir. Tarihsel performansları ve özyinelemeli örneklem dışı tahmin performansları karşılaştırıldığında, göstergelerin dönüm noktalarını tespit etmede ve GSYİH büyüme tahminleri türetmede başarılı oldukları sonucuna varılmıştır. Ayrıca, göstergelerin gerçek zamanlı performansını değerlendirmek için altı farklı modelleme yöntemiyle gerçek zamanlı tahminler elde edilmiş ve dinamik faktör modelleme yaklaşımıyla elde edilen tahminlerin ülkelerin yarısından fazlasında GSYİH büyüme oranı için en doğru tahminleri verdiği gözlenmiştir.

Literatürde dinamik faktör model yaklaşımı haricinde de yöntemler kullanılarak iktisadi faaliyet göstergesi türeten çalışmalar bulunmaktadır. Örneğin; Darne ve Ferrara (2011), Euro Bölgesi ve altı ana ülkenin (Almanya, Fransa, İtalya, İspanya, Belçika, Hollanda) geçmiş dönüm noktalarını göstermek ve gerçek zamanlı dalgalanmaları izlemek için dönüm noktası göstergeleri türetmiştir. Dönüm noktası göstergeleri hesaplarken iki farklı yöntem kullanmıştır: Markow-Switching VAR modeli ve Markow-Switching faktör modeli. İlkinde, model iki rejimli Markow-Switching ve VAR (p) modeli ile tahmin edilmektedir. İkinci yaklaşımda ise Kalman filtresi yardımıyla maksimum olabilirlik modeli kullanılarak elde edilen faktör, hızlanma ve yavaşlama dönemi olarak belirlenen iki rejim arasında geçiş yapmaktadır. Özetle, iki yöntem ile hesaplanan dönüm noktası göstergelerinin tarihsel tepe ve dip noktalarını tespit etmede iyi sonuçlar verdiği sonucuna varılmıştır. Ayrıca, sanayi sektörü ile ilgili değişkenlerin Euro Bölgesi ve altı ana ülkenin hızlanma ve yavaşlama dönemlerini tespit etmede daha etkili oldukları gözlenmiştir.

Türkiye için iktisadi faaliyet göstergesi oluşturulması ile ilgili literatür görece daha sınırlıdır. Aruoba ve Sarikaya (2013) çalışmasında, farklı frekanstaki verileri bir arada kullanarak dinamik faktör modeli yardımıyla Türkiye ekonomisi için 1987-2011 dönemini kapsayacak şekilde bir iktisadi faaliyet göstergesi türetmiştir. Aruoba ve Sarikaya (2013) modelini oluştururken, Aruoba ve diğ. (2009) çalışmasında oluşturulan dinamik faktör modelleme çerçevesini temel almıştır. Veri setinde çeyreklik frekansta GSYİH verisi ile aylık frekanstaki sanayi üretimi, ara malı ithalatı, elektrik üretimi ve tarım-dışı istihdam değişkenlerine yer vermiştir. Daralma dönemlerini tespit etmek için, elde edilen faktörün hem kendisinin hem de üst bandının bir dönemden daha fazla sıfırın altında olduğu tarihler dikkate alınmıştır. Bu çerçevede, Türkiye ekonomisi için 1994, 2000-2001 ve 2008-2009 olmak üzere üç kriz dönemi tespit edilmiştir. Türkiye ekonomisi için oluşturdukları göstergeyi Amerika ve Japonya için oluşturulan göstergelerle karşılaştırdıklarında, gelişmiş ülkelerin gelişmekte olanlardan daha az oynak bir büyüme yapısına sahip olduğunu göstermişlerdir. Ayrıca, kullanılan değişkenler arasında sanayi üretimi ve ara malı ithalatı verileri elde edilen iktisadi faaliyet göstergesi ile en yüksek korelasyona sahip olan değişkenler olarak tespit edilmiştir. Daha sonra, zamanlı açıklanan verilerin önemine dikkat çekmek için gerçek zamanlı bir analize yer verilmiştir. Çakmaklı ve Altuğ (2014) çalışmasında, 1989-2014 dönemi için Türkiye ekonomisi için bir reel iktisadi faaliyet göstergesi oluşturmuştur. Göstergenin türetilmesinde dinamik faktör modeli çerçevesi esas alınmış; ancak, literatürde en çok kullanılan Kalman filtresi yerine Bayesçi yarı-parametrik yöntem tercih edilmiştir. Gösterge hesaplanırken, GSYİH, sanayi üretim endeksi, tarım-dışı istihdam, ticaret ve hizmet ciro endeksi, perakende satış hacim endeksi, nihai tüketim, toplam ihracat miktar endeksi ve toplam ithalat miktar endeksi gibi farklı frekansta açıklanan değişkenler kullanılmıştır. Oluşturulan gösterge, Aruoba ve Sarikaya (2013) çalışmasına benzer şekilde 1994-

1995, 2000-2001 ve 2008-2009 dönemlerini Türkiye ekonomisi için daralma dönemleri olarak tespit etmektedir.

Bu tezde, geçmiş genişleme ve daralma dönemlerini tespit etmek ve iktisadi faaliyetin seyrine ilişkin zamanlı bilgi elde etmek amacıyla Türkiye ekonomisi için aylık frekansta takip edilebilen bir iktisadi faaliyet göstergesi türetilmektedir. Göstergenin oluşturulmasında, makroekonomik değişkenlerin bir göstergeye sentezlenmesinde başarılı olduğu için, dinamik faktör modeli yönteminden faydalanılmaktadır. Dinamik faktör modellemesi yaklaşımı, iktisadi faaliyet göstergelerinin oluşturulmasında en çok tercih edilen yöntemdir. Barhoumi ve diğ. (2013), bu yöntemin, az sayıda ortak faktör oluşturarak geniş bir veri setindeki bilgileri derlemede başarılı bir yöntem olduğunu belirtmektedir. Bu sebeple, iktisadi faaliyet göstergesinin modellenmesinde Aruoba ve Sarikaya (2013) yaklaşımı benimsenmiştir. Bu yöntemde, ekonomik koşullar gözlemlenmeyen değişken olarak belirlendikten sonra gözlemlenen farklı değişkenlerle açıklanmaya çalışılmaktadır. Ayrıca, farklı frekanslardaki değişkenler modelde aynı anda yer alabilmektedir. Model oluşturulurken öncelikle durum-uzay formunda yazılmakta, daha sonra Kalman filtresi ve düzgünleştiricisi kullanılarak iktisadi faaliyet göstergesi olan faktör elde edilmektedir.

Gösterge hesaplanırken sanayi üretim endeksi, elektrik üretimi, toplam araç üretimi, son 3 aydaki üretim hacmi, reel kesim güven endeksi, ithalat miktar endeksi, tarım-dışı istihdam, kredi stoku, CDS ve GSYİH verileri kullanılmıştır. Değişken seçiminde öncelikle Evans (2005) ve Matheson (2011) çalışmalarına benzer şekilde aktivite (gerçekleşme verileri), aktivite (anket göstergeleri), ticaret, istihdam ve finansal göstergeler olmak üzere beş farklı grup oluşturulmuştur. Veri kısıtlarına rağmen, her bir kategori için en kapsamlı şekilde aday değişkenler belirlendikten sonra Bai ve Ng (2008) çalışmasında kullanılan sert-eşikleme yöntemi ile veri seçimi yapılmıştır. Bu yöntemde, açıklanan y_t değişkeni ve açıklayıcı X_{ti} değişkenleri arasındaki ilişki, her X_{ti} ile y_t arasındaki regresyondan elde edilen t-istatistikleri dikkate alınarak değerlendirilmektedir. Bu çalışmada, y_t açıklanan değişkeni, iktisadi faaliyetin en yaygın ölçütü olarak kabul edilmesinden dolayı, GSYİH'nin yıllık yüzde değişimi (yıllık büyümesi) olarak seçilmiştir. Her bir gruptaki aday değişkenler ise açıklayıcı değişkenler olarak belirlenmiştir. GSYİH'nin yıllık büyümesi ile aday değişkenler arasında regresyonlar yapıldıktan sonra her bir değişken için t-istatistikleri elde edilmiş ve 1,96'dan daha büyük t istatistiklerine sahip değişkenler, analiz için potansiyel değişkenler olarak listelenmiştir. T-istatistiklerini karşılaştırırken, beş kategorideki değişkenlerin t-istatistikleri, her kategoriden en az bir değişkene veri setinde yer verebilmek için, kendi grupları içinde değerlendirilmiştir. Daha sonra, değişkenlerin başlangıç dönemleri ve iktisadi faaliyeti temsil edebilmeleri göz önünde bulundurularak nihai veri seti oluşturulmuştur. GSYİH verileri çeyreklik frekansta yayımlandığından, aylık frekanstaki açıklayıcı değişkenler ilgili ayların ortalaması alınarak çeyreklik frekansa dönüştürüldükten sonra yıllık yüzde değişimleri hesaplanmıştır. Anket göstergelerinin tümü ve CDS ve VIX gibi bazı finansal değişkenler, modellerde seviye olarak kullanılmıştır. Bunun nedeni, anket göstergelerinin kendilerinin ait oldukları dönemlerdeki değişimi temsil etmeleri ve ilgili finansal değişkenlerin yayılımı göstermeleridir. GSYİH serisi 1987 yılının ilk çeyreğinden itibaren mevcut olduğundan, GSYİH'nin yıllık yüzde değişimi 1988'in ilk çeyreğinden itibaren hesaplanabilmektedir. Bu sebeple regresyonlar için örneklem dönemi 1988Ç1-2019Ç4 olarak belirlenmiştir. Değişkenlerin tarihsel serilerinin başlangıç yıllarının farklılaşmasından ötürü, değişken seçimi iki farklı şekilde yapılmıştır. İlk olarak, GSYİH 1988'den beri mevcut olan değişkenler üzerine koşturulmuş ve veri seçimi t-istatistikleri dikkate alınarak yapılmıştır. Daha sonra, 1988'den sonra başlayan değişkenleri değerlendirmek için, tahmin dönemi 1988-1997, 1998-2007 ve 2008-2019 olmak üzere üç alt döneme ayrılarak modeller koşturulmuş ve her dönemde değişken seçimi tekrarlanmıştır. Tüm örneklem dönemi için yapılan regresyon sonuçlarına göre sanayi üretim endeksi, elektrik üretimi, toplam araç üretimi, son 3 aydaki üretim hacmi, ithalat miktar endeksi ve kredi stoku değişkenleri seçilmiştir. Üç döneme ayrılan veri seçim analizinde ise sanayi üretim endeksi, elektrik üretimi, toplam araç üretimi, son 3 aydaki üretim hacmi, reel kesim güven endeksi, ithalat miktar endeksi, tarım-dışı istihdam, kredi stoku ve CDS değişkenleri seçilmiştir. İktisadi faaliyet göstergesi oluşturmak için seçilen değişkenlerin 2001 ve 2009 gibi kriz dönemleri dışında da GSYİH ile güçlü bir ilişkisi olup olmadığını değerlendirmek amacıyla veri seçim egzersizi sırasıyla 2006-2019 dönemi ve 2010-2019 dönemi için tekrarlanmıştır. Özetle, iktisadi faaliyet göstergesinin tahmini için seçilen değişkenlerin GSYİH'nin yıllık büyümesi ile regresyonları sonucu elde edilen t-istatistikleri farklı dönemler için anlamlı bulunmuştur. Ayrıca, seçilen değişkenlerin her birinin GSYİH'nin yıllık büyümesi ile korelasyonları hesaplanmış ve farklı dönemler için korelasyonların yüksek olduğu gözlenmiştir. İktisadi faaliyet göstergesi oluşturmak için seçilen değişkenlerin üçü aktivite-gerçekleşme verileri (sanayi üretim endeksi, elektrik üretimi, toplam araç üretimi), ikisi aktivite-anket göstergeleri (son 3 aydaki üretim hacmi, reel kesim güven endeksi), biri ticaret (ithalat miktar endeksi), biri istihdam (tarım-dışı istihdam) ve ikisi finansal göstergeler (kredi stoku, CDS) kategorisinde yer almaktadır.

İktisadi faaliyet göstergesi oluşturulurken öncelikle seçilen dokuz değişkene ek olarak GSYİH verisi de, aktivitenin en yaygın takip edilen göstergesi olması sebebiyle, analize dâhil edilmiştir. Bu sebeple, Türkiye ekonomisi için 1988-2020 dönemini kapsayacak şekilde GSYİH verisini içeren ve içermeyen olmak üzere iki farklı iktisadi faaliyet göstergesi türetilmiştir. Göstergenin sıfırın altında/üstünde aldığı değerler faaliyetin daralma/genişleme döneminde olduğuna işaret etmektedir. Ayrıca, göstergenin mutlak değerce ne kadar düşük/yüksek olduğu da daralma ve genişlemenin boyutu hakkında bilgi vermektedir. Daralma dönemleri belirlenirken, Aruoba ve Sarıkaya (2011) ile Çakmaklı ve Altuğ (2014) çalışmalarına benzer şekilde göstergenin bir aydan daha uzun süre negatif değerler aldığı ve hem göstergenin üst bandının hem de kendisinin sıfırdan daha düşük değerlere sahip olduğu dönemler dikkate alınmaktadır. Bu doğrultuda, GSYİH verisini de kapsayan veri seti ile oluşturulan iktisadi faaliyet göstergesi Türkiye ekonomisi için Ekim 1988-Şubat 1989, Nisan 1994-Ocak 1995, Ekim 1998-Mart 1999, Ağustos 1999-Eylül 1999, Şubat 2001-Şubat 2002, Ekim 2008-Eylül 2009 ve Ağustos 2018-Ocak 2019 olmak üzere yedi tane daralma dönemi olduğuna işaret etmektedir. GSYİH verisi dışlanarak oluşturulan gösterge de başlangıç ve bitiş aylarında birkaç farklılıklar olsa da benzer dönemleri Türkiye ekonomisi için daralma dönemleri olarak belirtmektedir. Göstergenin hesaplanmasında kullanılan değişkenler ile gösterge arasındaki korelasyonlara bakıldığında, sanayi üretim endeksi ve elektrik üretimi gibi aktivite-gerçekleşme verileri grubundaki göstergeler ile ticaret kategorisindeki ithalat miktar endeksi verisinin en yüksek korelasyonlara sahip olduğu gözlenmektedir. Ancak, toplam araç üretimi, son 3 aydaki üretim hacmi ve reel kesim güven endeksi gibi daha zamanlı açıklanan değişkenlerin korelasyonları da azımsanmayacak derecede yüksektir.

Aylık frekansta oluşturulan iktisadi faaliyet göstergelerinin üç aylık ortalamaları alınarak çeyreklik frekansa çevrildikten sonra GSYİH'nin yıllık yüzde değişimi ile karşılaştırılması yapılmıştır. Her iki iktisadi faaliyet göstergesi de, özellikle yön bakımından, GSYİH'nin yıllık büyümesinin takibinde genellikle başarılı olmaktadır. Genişleme dönemlerine kıyasla, oluşturulan göstergeler ile GSYİH'nin yıllık büyümesi arasındaki ilişki daralma dönemlerinde daha güçlenmektedir. 1988Ç1-2019Ç4 dönemi için GSYİH'nin yıllık yüzde değişiminin negatif olduğu tüm dönemler ile göstergelerin sıfırın altında değer aldığı dönemler karşılaştırıldığında, GSYİH'nin yıllık bazda daraldığı tüm dönemlerde her iki gösterge de daralma dönemleri olduğuna işaret etmektedir.

Türkiye için iktisadi faaliyet göstergesi oluşturan Aruoba ve Sarikaya (2013) ile Çakmaklı ve Altuğ (2014) çalışmalarında ima edilen daralma dönemleri ile GSYİH verisini dâhil ederek oluşturulan iktisadi faaliyet göstergesinin işaret ettiği daralma dönemleri kıyaslandığında, diğer iki çalışmada tespit edilen 1994, 2001 ve 2008-2009 yıllarına ek olarak dört daralma dönemi daha tespit edilmiştir. Bu durum, oluşturulan iktisadi faaliyet göstergesinin, önceki çalışmalarda oluşturulan göstergelere kıyasla, Türkiye ekonomisindeki daralma dönemlerinin tespitinde daha başarılı olduğuna işaret etmektedir.

Oluşturulan iktisadi faaliyet göstergesinin ima ettiği daralma dönemleri daha yakından incelendiğinde, büyük çoğunun geçmişteki önemli kriz yıllarına denk geldiği görülmektedir. Örneğin; Nisan 1994-Ocak 1995 dönemi Türkiye ekonomisinin karşılaştığı önemli finansal krizlerden birisidir. Bu krizde hükümet Merkez Bankası rezervlerini, dış borçlanma yerine, kamu borcunu finanse etmek için kullanmış ve bu durum hem büyük bir rezerv erimesine hem de yüklü miktarda döviz kayıplarına neden olmuştur. Sonuç olarak, döviz kuru (Türk Lirası'nın Amerikan doları karşısında değeri) sert bir şekilde düşerken gecelik faiz oranı ise tarihsel olarak en yüksek seviyelerine yükselmiştir. Ayrıca, bu dönemde enflasyon oranı da üç basamaklı seviyelere yükselmiştir. 1994 yılının Nisan ayında IMF ile bir stand-by anlaşması imzalanmış olmasına rağmen, anlaşmanın şartları düzgün bir şekilde yerine getirilmemiştir. Gösterge tarafından tespit edilen Ekim 1998-Mart 1999 ile Ağustos

1999-Eylül 1999 daralma dönemlerinden ilki Rusya krizinin olduğu yıllara denk gelmektedir. Kriz, Temmuz 1998'te Rusya'da başlayıp kısa bir süre devam etmesine rağmen, hem Rusya ekonomisini hem de Türkiye gibi komşu ülke ekonomilerini ciddi şekilde etkilemiştir. Kriz döneminde yabancı yatırımcılar güvenlerini kaybederken, Türkiye dâhil birçok ülkeye sermaye girişleri olumsuz etkilenmiştir. Sermaye girişlerindeki kayıp ise ekonomik aktiviteyi yavaşlatarak faaliyetin olumsuz etkilenmesine sebep olmuştur. Gösterge tarafından tespit edilen ikinci dönem ise diğerlerine göre daha kısa olup 17 Ağustos 1999'da Türkiye'nin en çok sanayileşmiş bölgelerinden birinde meydana gelen deprem sonucunda ortaya çıkan yıkıcı etkilerden kaynaklandığı düşünülmektedir. Şubat 2001-Şubat 2002 olarak tespit edilen daralma dönemi, Türkiye ekonomisinin yaşadığı ciddi bir bankacılık sektörü krizi dönemine denk gelmektedir. Bu dönemde, faiz oranları tarihi yüksek seviyelerine ulaşırken hazine bonosu fiyatları bankaların bilançolarında bozulmalara neden olacak şekilde dip seviyelere düşmüştür. Bunlara ek olarak, gözlenen siyasi istikrarsızlık, yabancı yatırımcıların fonlarını Türkiye'den çekmelerine neden olmuştur. Türk Lirası'nda gözlenen değer kaybını kontrol altında tutmak amacıyla Merkez Bankası ciddi oranda bir rezerv kaybı ile karşı karşıya kalmıştır. Krizin yıkıcı etkilerini iyileştirmek için IMF yardımı ile birlikte farklı reformlar uygulamaya konulmuştur. Gösterge tarafından daralma dönemi olarak belirtilen Ekim 2008-Eylül 2009 dönemi, Amerika ekonominde ortaya çıkan ve hızla tüm dünyayı etkisi altına alan küresel finans krizine denk gelmektedir. 1929 yılındaki Büyük Buhran'dan sonra en kötüsü olarak kabul edilen küresel kriz, Türkiye ekonomisini de ciddi şekilde etkilemiştir. Öncelikle, sermaye akımları durma noktasına geldiği için kullanılabilir döviz miktarı düşüş kaydetmiştir. Ayrıca, Türkiye'nin ihracatı, özellikle başlıca ticaret ortakları olan Avrupa ülkelerine olmak üzere, sert bir düşüş kaydetmiştir. İhracattaki bu düşüş döviz arzını daha da olumsuz etkileyerek ithalatın azalmasına neden olmuştur. İthal ara mallarının eksikliği ve özel sektör borçluluğu üretim ve iktisadi faaliyette aksamalara neden olmuştur. Son olarak, Ağustos 2018-Ocak 2019 dönemi, Ağustos 2018'de Türkiye'de gözlenen kur şokunun etkilerinin hissedildiği bir daralma dönemidir. Ağustos 2018'te döviz kurunda gözlenen kuvvetli değer kaybının akabinde Merkez Bankası faiz oranını yükselterek sıkı bir para politikası uygulamıştır. Bu dönemde, enflasyon oranı çift haneli seviyelere ulaşırken; iç talep, değişken finansal koşullar ve azalan kredi talebi nedeniyle ekonomik aktivitede daralmaya neden olmuştur.

Gelişmiş ekonomilerin parasal sıkılaştırma uygulamalarının, Türkiye'ye gelen sermaye akımlarında düşüşe yol açmasına rağmen, döviz kurundaki değer kaybı ve güçlü turizm gelirleri net ihracatı desteklemiştir.

İktisadi faaliyet göstergesinin geçmişte bilinen daralma dönemlerini tespit etmedeki tarihsel performansı gibi, ekonominin mevcut durumu hakkında zamanlı bilgi alınmasındaki başarısı da politika yapıcılar için çok önemlidir. Yeni veri akışlarında, hem yeni gözlemler hem de önceki gözlemlerde yapılan revizyonlar nedeniyle göstergelerin tahmini değişebilmektedir. Bu nedenle iktisadi faaliyet göstergelerinin oluşturulmasında değişkenlerin daha zamanlı açıklanmalarına büyük önem verilmektedir. Bu amaçla, çalışmanın son bölümünde gerçek zamanlı bir uygulama yapılmıştır. Gösterge oluşturulurken kullanılan model Ocak 1988- Mart 2019 dönemi için tahmin edilmiş ve model parametreleri sabitlenmiştir. Daha sonra, yeni veri akışı için model tahminleri yeniden alınarak oluşturulan iktisadi faaliyet göstergesi sabit katsayılarla güncellenmiştir. Sonuç olarak, zamanlı açıklanan değişkenler sayesinde iktisadi faaliyette son dönemde gözlenen düşüş hakkında gerçek zamanlı bilgi alınabileceği gözlenmiştir.

Sonuç olarak, bu çalışmada oluşturulan iktisadi faaliyet göstergesinin Türkiye ekonomisinin geçmiş daralma dönemlerini tespit etmede ve ekonomik faaliyetin seyri hakkında zamanlı bilgi sağlamada başarılı olduğu görülmektedir.

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