SHORT-TERM INDUSTRIAL PRODUCTION FORECASTING FOR TURKEY

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

BY

AHMET DEĞERLİ

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

SEPTEMBER 2012

Approval of the Graduate School of Social Sciences

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ABSTRACT

SHORT-TERM INDUSTRIAL PRODUCTION FORECASTING FOR TURKEY

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September 2012, 45 pages

This thesis aims to produce short-term forecasts for the economic activity in Turkey. As a proxy for the economic activity, industrial production index is used. Univariate autoregressive distributed lag (ADL) models, vector autoregressive (VAR) models and combination forecasts method are utilized in a pseudo out-of-sample forecasting framework to obtain one-month ahead forecasts. To evaluate the models' forecasting performances, the relative root mean square forecast error (RRMSFE) is calculated. Overall, results indicate that combining the VAR models with four endogenous variables yields the most substantial improvement in forecasting performance, relative to benchmark autoregressive (AR) model.

Keywords: Short-term Forecasting, Economic Activity, Industrial Production Index, Vector Autoregressive models, Combination Forecast

ÖZ

TÜRKİYE İÇİN KISA DÖNEMLİ SANAYİ ÜRETİMİ ÖNGÖRÜSÜ

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Tez Yöneticisi: Dr. Dilem Yıldırım

Eylül 2012, 45 sayfa

Bu tez Türkiye için kısa dönemli ekonomik aktivite öngörüsü yapmayı amaçlamaktadır. Ekonomik aktivite için gösterge olarak sanayi üretim endeksi kullanılmaktadır. Bu bağlamda, Tek Değişkenli Gecikmesi Dağıtılmış Ardışık Bağımlı modeller, Vektör Ardışık Bağlanım modelleri ve Birleştirilmiş Öngörü modelleri, örneklem dışı metot çerçevesinde bir ay ileriye yönelik öngörü elde etmede kullanılmaktadır. Modellerin öngörü performansı, göreli ortalama hata karesinin kökü hesaplanarak değerlendirilmektedir. Buna göre, dört değişkenli Vektör Ardışık Bağlanım modelleri kullanılarak elde edilen Birleştirilmiş Öngörü modelleri referans model olan Ardışık Bağlanım modeline kıyasla öngörü performansında en büyük iyileşmeyi sağlamaktadır.

Anahtar Kelimeler: Kısa Dönemli Öngörü, İktisadi Faaliyet, Sanayi Üretim Endeksi, Vektör Ardışık Bağlanım modelleri, Birleştirilmiş Öngörü Modelleri

To My Parents

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my thesis supervisor Dr. Dilem Yıldırım for her guidance and effort throughout this study. I would also like to thank the examining committee members for their valuable comments and critiques.

I owe special thanks to The Scientific and Technological Research Council of Turkey for the financial support they provided throughout my graduate study.

I also want to sincerely thank İhsan Bozok and Selen Başer for their support and helpful suggestions.

TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

CHAPTER I

INTRODUCTION

Before 2001, Turkey adopted an economic program supported by IMF to decrease the high level of public debt and inflation. However, in 2001 Turkey experienced a banking crisis. In the post 2001 crisis period, Turkey started to implement implicit inflation targeting. In this period the Central Bank of the Republic of Turkey (CBRT) had tried to decrease high level of inflation rate. After successful reduction of inflation rate to single digit levels, official inflation targeting regime has been adopted, with the beginning of 2006. Thereafter, official point targets and forecasts for the inflation rate are announced by CBRT, through Inflation Report, periodically[1]. CBRT uses a model based approach in forecasting inflation rate. In the process of forecasting, one of the most important inputs of the model is the output gap. Output gap is crucial for the model, because it is an indicator of inflationary pressure in an economy. It is the gap between potential and actual economic activity. Therefore to calculate output gap, we need to have the level of economic activity. Gross Domestic Product (GDP) and industrial production are two common ways of measuring economic activity.

GDP has a wide use in measuring economic activity in a country. It is the market value of all final goods and services produced within a country in a specific period of time. Despite its wide use, the goodness of GDP as a measure for economic

[1] For a detailed discussion of inflation targeting regime in Turkey, see the booklet of "Inflation Targeting Regime", 2006.
http://www.tcmb.gov.tr/yeni/evds/yayin/kitaplar/EnflasyonHedeflemesiRejimi.pdf

activity is a controversial issue since it does not account for household production, voluntary work and public administration. Furthermore, inclusion of compensation for a previous destruction into GDP is also controversial. In spite of these drawbacks, it is still the most widely used method to evaluate economic activity within a country. The main components of GDP are agricultural sector, services sector and manufacturing industry sector. Manufacturing industry constitutes the one fourth of GDP. Furthermore, most of the businesses in services sector are related to the manufacturing industry sector. Therefore, when we analyze the GDP and industrial production series, we observe that they move together, as expected. In this sense, given the controversial issues related to GDP, the use of the industrial production index as an indicator for economic activity in Turkey can provide several advantages in terms of short-term forecasting exercise. The first advantage is that the industrial production index is issued at the monthly frequency, whereas GDP figures are at the frequency of three months. Secondly, GDP figures are announced with 3 months lag, while industrial production with 2 months lag. Therefore, we use industrial production index as an indicator for economic activity in Turkey.

Given the importance of forecasting economic activity accurately, there are many papers aim to predict economic activity through in-sample or out-of-sample methods. Studies utilizing in-sample forecasting methods are Stock and Watson (1998), Stock and Watson (2003), Chauvet and Morais (2010) and Özatay (1986). Stock and Watson (1998) analyzes the cyclical behavior of U.S. economic activity, using in-sample methods. Stock and Watson (2003) also use in-sample Granger causality test results to forecast inflation and output for seven developed OECD countries. Brazilian and Turkish economy, two emerging countries, are also analyzed through in-sample methods by Chauvet and Morais (2010) and Özatay (1986), respectively. The issue of determining leading indicators is crucial in forecasting exercise. In this sense, Stock and Watson (1998) develop leading indicators for GDP by using cross correlations of series with GDP, while Chauvet and Morais (2010) utilize an autoregressive probit model to specify leading indicators for the Brazilian economy. There are also studies developing indicators for Turkish economic activity (Özatay, 1986; Neftçi and Özmucur, 1991; Atabek, Coşar and Şahinöz, 2005).

The other type of the model which is widely used in the literature of inflation and economic activity forecasting is out-of-sample forecasting method. In addition to in-sample forecasting, Stock and Watson (2003) examines the role of asset prices in forecasting output and inflation for seven developed economies by using out-of-sample method. Leigh and Rossi (2002) examines the forecasting power of indicators for inflation and real output growth in Turkey. While Leigh and Rossi (2002) examines the pre-2001 crisis period, Altug and Uluceviz (2011) studies the post-crisis period in Turkey and develop a set of leading indicators of real activity and inflation. Another study which utilizes out-of-sample forecasting method is Akdoğan, Başer, Chadwick, Ertuğ, Hülagü, Kösem, Öğünç, Özmen and Tekatlı (2012). They study the short term inflation forecasting in Turkey using a large number of models, including univariate models, decomposition based models, time varying parameter models, VAR and Bayesian VAR models, and dynamic factor models. They use a wide range of short-term economic models to forecast inflation, compare the models and choose the one with better forecasting performance.

In this paper, we produce short term forecasts for the economic activity in Turkey, using pseudo out-of-sample forecasting method. We estimate univariate models and 31549 vector autoregressive (VAR) models to forecast industrial production index growth. Furthermore, using combination forecast method we combine VAR forecasts to get better point forecasts for the industrial production, following Leigh and Rossi (2002) and Akdoğan et al (2012). To compare and evaluate the models, we calculate root mean square forecast error (RMSFE) of each model. The exhaustive work of constructing 31549 VAR models and combining the information they have using combination forecast method is the first study in the economic activity forecast literature of Turkey.

The plan for the rest of the study is organized as follows. Section 2 goes over the existing literature of forecasting economic activities. In section 3, we explain the methodology used in this study and the data is described in section 4. In section 5, empirical results are discussed. Finally, section 6 presents the concluding remarks.

CHAPTER II

LITERATURE REVIEW

In the literature, there are two types of econometric methods for measuring predictive content: in-sample and out-of-sample methods. In the in-sample technique, the full sample at hand is used in fitting the model. The reliability of the in-sample method is tested by using test statistics, and then the model can be used for forecasting purposes. Standard t-tests, F-tests and Granger-causality tests are all examples of in-sample tests statistics. In-sample methods usually benefit from Granger-causality test statistics observed from all available data. However, the main problem in using granger-causality test statistics is that it is not entirely reliable in terms of forecasting future values. That is, a significant granger causality relationship observed from the full sample may not ensure the model to forecast future values correctly. In-sample statistics may contain little or no information for the future. In other words, the predictability based on in-sample methods may not be supported by out-of sample data.

Unlike in-sample methods, out-of-sample methods are based on sample-splitting and require simulating real-time forecasting. For instance while working with monthly data over the period 2001-2011, the researcher initially splits the sample into two subsamples, say, 2001:1-2005:12 and 2006:1-2011:12. The first and the second subsample are called training sample and pseudo out-of-sample, respectively. Once the model is estimated, the estimated equation is used to produce a pseudo out-of-sample forecast for 2006:1. This exercise is repeated throughout the sample, moving ahead one month at a time until the end of sample period is achieved. In other words, in every step one more data point is included into the training sample. At the end, point forecasts are observed for the whole pseudo out-of-sample period.

There are papers which employ either in-sample or out-of-sample methods to predict economic activity. Stock and Watson (1998), Stock and Watson (2003), Chauvet and Morais (2010) and Özatay (1986) are the studies utilizing in-sample methods to forecast cyclical turning points of economic activity. A comprehensive study by Stock and Watson (1998) analyzes the cyclical behavior of U.S. economic activity over the period 1946-1996. Stock and Watson (2003) also use in-sample Granger causality test results to forecast inflation and output for seven developed OECD countries. They conclude that asset prices have better forecasting performance for inflation than output. Chauvet and Morais (2010) and Özatay (1986), on the other hand, analyze emerging economies, Brazilian and Turkish economy, respectively. Chauvet and Morais (2010) try to construct a model which predicts recessions in Brazil, while Özatay (1986) discusses the theories explaining cyclical movements and analyzes the cyclical movements of Turkish economy.

The most important and challenging issue in both in and out-of sample forecasting is developing appropriate leading indicators. Stock and Watson (1998) investigate 71 economic time series to find leading, lagging and coincident indicators by using cross correlations of series with GDP and regression analysis. Developing leading indicators becomes more difficult for emerging countries due to volatile structure of economic activities and unstable policy regimes. Chauvet and Morais (2010) determine leading indicators for Brazilian economy by using an autoregressive probit model. They analyze the turning points of Brazilian economic activity and compare it with the turning points of candidate leading indicators.

There are also several studies trying to develop indicators for Turkish economic activity. Özatay (1986) analyzes the cyclical movements of Turkish economic activity. 15 variables are investigated to find the most appropriate leading indicator for the economic activity, measured by industrial production, but it is found that only electricity production has a significant forecasting performance for industrial production. Altay, Arıkan, Bakır and Tatar (1991) also investigate a number of possible indicators to forecast industrial production index. They conclude that the use of imports, imports of intermediate goods, total number of insured workers and construction improve forecasts of the production index. Another paper studying the leading indicators for Turkish economic activity is Neftçi and Özmucur (1991), who contribute to the literature in two fields. Firstly, they create an economic conditions index and composite leading indicator. They incorporate monetary and real variables to construct the composite leading indicator. The second contribution of their study is to calculate the probability of turning points in economic activity using sequential probability algorithm. Similar to Neftçi and Özmucur (1991), Mürütoğlu (1999) and Atabek et al. (2005) also provide composite leading indicators for Turkish economic activity. Mürütoğlu (1999) constructs a composite leading indicator by using imports of intermediate goods, currency issued, bank credits, M2, consolidated budget expenditures, and real capital of newly constructed firms as leading indicators. The aim of Atabek et al. (2005) is to construct a composite leading indicator for the economic activity in Turkey. They use the constructed leading indicator to predict the cyclical turning points of economic activity. They determine a set of leading indicators of industrial production using cross-correlations, in-sample Granger causality tests, and peak/trough analysis. They conclude that imports of intermediate goods, discounted Treasury auction interest rates, electricity production and responses to various survey questions from the CBRT Business Survey are the best indicators to construct the composite leading indicator. Çanakçı (1992), Selçuk (1994), Üçer, Rijckeghem and Yolalan (1998), and Küçükçiftçi and Şenesen (1998) are other studies which aim to find leading indicators for Turkish economic activity. However, no matter how appropriate the leading indicator is, the in-sample results may not guarantee the forecast accuracy for the future, as stated before.

In this sense, the out-of-sample forecasting is widely used in the literature of inflation forecasting and economic activity forecasting. Some of these studies are Stock and Watson (2003), Leigh and Rossi (2002), Altug and Uluceviz (2011), Akdoğan et al. (2012).

In addition to in-sample forecasting, Stock and Watson (2003) perform out-of-sample forecasting by using quarterly data over 1959-1999 to predict output and inflation for seven developed OECD economies (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States). The study examines the role of asset prices in forecasting output and inflation. Real output is measured by real GDP and by the industrial production index. Inflation is measured by percentage change of the consumer price index (CPI) and of the implicit GDP deflator. The out-of-sample forecasting exercise begins in the first quarter of 1971 and continues through the end of the sample period. The out of sample period is divided into two sub-periods, 1971-84 and 1985-99. The main result of the study is that some asset prices have statistically significant predictive content for output, although the forecasts based on individual indicators are unstable. Forecasting models that beat the AR in the first period may or may not beat the AR in the second period. This situation is consistent with the literature, since the forecasting power of a single variable may deteriorate over the time [2]. Furthermore, the methods for combining the information in the various predictors seem to overcome instability problems. As mentioned before, Stock and Watson (2003) also use in-sample Granger causality test results. They conclude that many of the variables at hand have some predictive content for output and inflation. However, they also conclude that significant Granger causality test results do not indicate that a given indicator has a good out-of-sample forecasting power. Therefore, the study relies on pseudo out-of-sample forecast evaluation, by computing RMSFE of candidate forecasts. The study examines 73 candidate predictors per country for each of the inflation and output growth forecasts.

Leigh and Rossi (2002) examines the forecasting power of indicators for inflation and real output growth in Turkey. They focus on 41 candidate indicators with a monthly frequency to forecast industrial production and consumer price index and 42 candidate indicators with a quarterly frequency to forecast real GDP over the

[2] For instance, a widely used predictor in the literature for economic activity is term spread, the difference between interest rates on long and short maturity government debt. But the forecasting performance of the term spread deteriorates since 1985 in the United States (Haubrich and Dombrosky, 1996; Dotsey, 1998; Ang, Piazzesi and Wei, 2003).

period of 1986 -2002. The out-of sample exercise begins in 1992, and ends in 2002. Although there are few indicators which improve on the autoregressive benchmark in out-of-sample forecasts, combinations of individual forecasts give a forecast that outperforms the AR. Furthermore, a two-stage combination forecast is proposed in the study, by taking the median of only the top five performing individual forecasts. This two-stage combination forecast outperforms both the AR benchmark and the combination forecast based on all candidate variables.

Altug and Uluceviz (2011) studies the period 2001-2010 in Turkey to develop a set of leading indicators of real activity and inflation. Real activity and inflation are measured by the industrial production index and consumer price inflation, respectively. They follow the method implemented by Stock and Watson (2003). Using monthly data they examine 47 real and financial candidate variables in order to forecast industrial production growth and consumer price inflation. The data up to 2005:12 is taken for training sample, and the data between 2006:1 and 2010:12 for forecasting exercise. To identify a leading indicator, the root mean square forecast error of the specification including the lags of dependent variable and candidate variable is compared with the root mean square forecast error of autoregressive specification comprising own lags only. They find that asset prices or interest rates have the greatest forecasting power for the future.

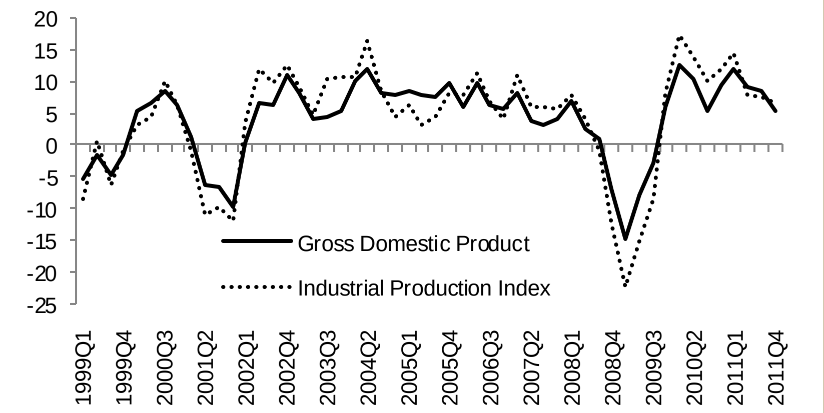
Akdoğan et al. (2012) study the short term inflation forecasting in Turkey using a large number of models, including univariate models, decomposition based models, time varying parameter models, VAR and Bayesian VAR models, and dynamic factor models. They also consider the forecasting performance of combination forecast models, generated by simple average, median and trimming approaches. As an indicator for inflation, the CPI excluding unprocessed food and tobacco is used. They focus the period between 2003:Q1 and 2011:Q2 using quarterly data. The sample period is divided into two parts. All data up to 2009:Q3, the training sample, is used to estimate the forecasting models. The remaining data is the forecasting sample. In the first step of forecasting practice the training sample is used, and the forecast for 2009:Q4 is obtained. Moving one period forward, all the models re-estimated including one more data period. At the end, the forecast performances of the models are evaluated according to the root mean square forecast error (RMSFE).

In this paper, we produce short term forecasts for the economic activity in Turkey, using monthly data over the period 2001-2011. We employ industrial production index as a proxy for economic activity, as in Altug and Uluceviz (2011). Moreover, following the same sample splitting procedure, we use 2001:1-2005:12 subperiod as training sample, and 2006:1-2011-12 as pseudo out-of-sample period. Our study, however, differs from Altug and Uluceviz (2011) in that we utilize 31549 vector autoregressive (VAR) models in addition to standard univariate models to forecast industrial production growth. Furthermore, using combination forecast method we combine VAR forecasts to get better point forecasts for the industrial production. To compare and evaluate the models, we calculate root mean square forecast error (RMSFE) of each model and RMSFE of our benchmark model, AR model. We investigate which and how much the variables yield improvement over and above the AR model.

CHAPTER III

DATA

Although GDP is widely used as a measure of economic activity within a country, we prefer to utilize the industrial production index to assess Turkish economic activity. GDP is the market value of final goods and services produced within a country in a specific period. Its main components are agricultural sector, services sector and manufacturing industry sector. The largest share belongs to the services sector in Turkey. Manufacturing industry has a share of approximately 24 percentages. Given this, it is plausible to ask such a question: What is the logic behind using industrial production index to draw some conclusions about economic activity? Although the lion's share does belong to the services sector, many businesses in the services sector are related to the manufacturing industry sector. Therefore, we expect GDP and industrial production index to move together. Illustrating the close link between industrial production index and the GDP, Figure 3.1 supports our expectation. The use of industrial production index instead of the GDP has the advantage of being at the monthly frequency. Furthermore, GDP figures are announced with 3 months lag, whereas industrial production index with 2 months lag. For instance, the GDP figure for the first quarter of 2011 is announced in June, while the industrial production index for the last month of the first quarter is announced in May. As a result, we use the industrial production index as an indicator for economic activity in this study.



Source: CBRT.

Figure 3.1: Indicators of Economic Activity in Turkey
(Annual Percentage Change)

We collect 48 data series, including industrial production index, for Turkey from the beginning of 2001 to the end of 2011 at monthly frequency. Data were mainly collected from six sources: Central Bank of the Republic of Turkey (CBRT), International Monetary Fund (IMF), Turkish Statistical Institute (Turkstat), Istanbul Stock Exchange (ISE), Automotive Manufacturers' Association (AMA), Undersecretariat of Treasury (Treasury).

We allocate candidate variables to forecast industrial production index into six categories. The categories are real activity measures, financial indicators, monetary aggregates, commodity prices, exchange rates and interest rates:

Real Activity Measures: Capacity utilization rate, electricity production, production of agricultural machines, production of buses, production of automobiles, production of truck, production of van, production of midibus, exports, imports, unit value of export, unit value of import, intermediate goods imports, capital goods imports, consumer price index, producer price index, US consumer price index, VAT revenue.

Financial Indicators: Credit Default Swaps (CDS), JP Morgan EMBI Global Index for Turkey, JP Morgan EMBI+ Index for Turkey, ISE 100 Index, Gross International Reserves, Central Bank's Gross FX Reserves, International Gold Reserves, S&P 500 Index, VIX Index, European VIX Index.

Monetary Aggregates: M1, M2, M2Y, M3, Total Credit

Commodity Prices: Brent Oil Price, West Texas Intermediate (WTI) Oil Price, Gold Price

Exchange Rates: US $/TL Nominal Exchange Rate, Euro/TL Nominal Exchange Rate, Real Effective Exchange Rate.

Interest Rates: Central Bank Policy Rate, Benchmark Interest Rate (interest rate with approximately 2-year maturity), Overnight Interest Rate, US Interest Rate with different maturities.

Additional series, such as real asset and real interest rate series are constructed from the series above by using CPI. By using New Keynesian model with nominal rigidities, Gali (1999) concludes that nominal variables could have an effect over and above the effect of real variables. Therefore we use both real and nominal versions of some variables.

For all variables, we use year-on-year growth rate of the series and therefore there is no need for seasonal correction. Furthermore, in order to ensure stationarity of the variables included in univariate and VAR models, we employ the standard Augmented Dickey-Fuller (ADF) test[3]. Then, the level form is used for the variables found to be stationary, and the first differenced form for the variables including a unit root. Moreover, for some variables such as interest rates, it is not clear whether to use their level or difference form in the literature. For instance, Stock & Watson (2003), Altug and Uluceviz (2011) and Leigh and Rossi (2002) use both level and difference form of interest rate. In those cases, we include both forms of such variables.

Hence, taking all these variables and transformations into account, we come up with 73 candidate variables in order to use in univariate and VAR models to forecast industrial production index.

[3] See the Appendix for the Augmented Dickey-Fuller test results for all variables.

CHAPTER IV

METHODOLOGY

This chapter describes three approaches that we apply to produce short term forecasts for the industrial production index in Turkey. To do that, we utilize the methods suggested by Stock and Watson (2003) and Akdoğan et al. (2012). Following these studies, we first determine the set of potential leading indicators for forecasting the industrial production index, which is used as a measure for the economic activity. According to economic intuition and related literature, we select the level or difference form of candidate variables and decide whether to use their nominal or real values. Once candidate variables are determined, univariate and vector autoregressive models are constructed, in order to estimate and forecast the industrial production index. By using pseudo out-of-sample forecasts and actual data, the root mean square forecast error (RMSFE) of each model is calculated and then the models are compared and evaluated according to RMSFE criterion. Lastly, we use combination forecast method to check whether it provides an improvement in forecasting industrial production index.

4.1. Univariate Models

The type of the univariate autoregressive distributed lag (ADL) model we use is as follows:

$$y_t = \beta_0 + \beta_1 \;\; L \;\; y_t + \beta_2 \;\; L \;\; x_t + \varepsilon_t \tag{4.1}$$

$\beta_1(L)$ and $\beta_2(L)$ are lag polynomials, y_t is the industrial production index, x_t refers to candidate variables, and ε_t is the standard White Noise disturbance term. Our benchmark model is autoregressive (AR) model, which includes only the lags of the dependent variable, industrial production index:

$$y_t = \beta_0 + \beta_1(L)y_t + \varepsilon_t \tag{4.2}$$

Of course, the range of potential indicators for economic activity is very large. Asset prices, monetary variables, real activity variables and interest rate variables are all possible indicators for the industrial production index. We select indicators according to economic intuition, related literature and availability of the data at the monthly frequency with sufficient sample length. Furthermore, the indicators at hand are divided into six categories; real activity measures, financial indicators, monetary aggregates, commodity prices, exchange rates and interest rates[4].

Methodologically, we follow the pseudo out-of-sample forecasting method proposed by Stock and Watson (2003). In the pseudo out-of-sample forecasting method, the first step is splitting the sample into two subsamples and then simulating real-time forecasting. Similar to Altug and Uluceviz (2011), we split the whole sample into two as 2001(1)-2005(12) being the first subsample and 2006(1)-2011(12) as the second. The sample period has some noteworthy characteristics. Turkey adopted institutional reforms after the banking crisis in 2001, such as banking regulations and supervision and central bank independence. Furthermore, Turkey started to implement implicit inflation targeting in the post 2001 crisis period. The year of 2006 is also important in terms of inflation

[4] See the Appendix for the complete list of variables and their sources.

targeting regime in Turkey. Official inflation targeting regime was adopted with the beginning of 2006. Hence, different dynamics are allowed to occur in the second subsample, which strengthens the convenience of the selected out-of-sample approach.

Once the first sample is labeled as the training sample and the second one as the pseudo out-of-sample, we estimate each univariate ADL model by standard Ordinary Least Squares (OLS) estimation procedure using the training sample. With the parameters of estimated equation, we produce a pseudo out-of-sample forecast for 2006:1. At the next step, one more data point, the data of 2006:1, is included to the training sample. We use this new training sample to estimate the model, again and then use this estimated model to forecast 2006:2. This exercise is repeated throughout the sample, moving ahead one month at a time until all observations are covered.

One issue in constructing univariate AR and ADL models to estimate and forecast industrial production index is the specification of the appropriate lag length. In this sense, we use the general to specific approach, which is preferred due to its dependence on the theory of reduction[5]. In this type of modeling, empirical analysis begins with a general model. Then, the general model is simplified by eliminating statistically insignificant variables. The validity of this elimination process is checked at every stage. We apply the general to specific approach at the 10% significance level with a maximum autoregressive order of twelve due to using monthly data. At the end, we come up with an AR model and 73 univariate

[5] See Campos, Ericsson & Hendry (2005) for a detailed discussion of general-to-specific modeling and the theory of reduction.

autoregressive distributed lag (ADL) models to estimate and forecast the industrial production index. By using each model, we obtain pseudo out-of-sample forecasts; and compare these forecasts with the actual realized data to compute root mean square forecast error (RMSFE):

$$RMSFE_i = \sqrt{\frac{1}{n}\sum \left(y_{i,t}^{f} - y_t\right)^2} \qquad i = 0,1,2,...,73 \tag{4.3}$$

$y_{i,t}^{f}$: i^th candidate pseudo out-of-sample forecasts for industrial production index

y_t : actual value for industrial production index

n : the pseudo out-of-sample size

where $RMSFE_0$ represents the root mean square forecast error of the benchmark model, AR model. To evaluate the candidate variable, we need to compare the RMSFE's of each univariate ADL model with the RMSFE of AR model. Therefore, calculate relative root mean square forecast error (RRMSFE) of all 73 models:

$$RRMSFE_i = \frac{RMSFE_i}{RMSFE_0} \qquad i = 1,2,3,...,73 \tag{4.4}$$

If the RRMSFE of the model is less than 1 (one), then the ADL model with the candidate variable has a better forecasting performance than the AR model.

4.2. Vector Autoregressive (VAR) Models

In addition to univariate modeling, following Akdoğan et al. (2012), multivariate vector autoregressive (VAR) models are also utilized to forecast industrial production index. In VAR models, we define a set of endogenous variables as a function of their lagged values. A VAR (p) with p lags is defined as:

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \tag{4.5}$$

where $y_t = \left[y_{1,t}, y_{2,t}, ..., y_{k,t} \right]'$ is the vector of endogenous variables, and ε_t is the standard White Noise disturbance term.

A_0 : kx1 vector of constants
A_i : kxk matrix of coefficients of y_{t-i}

As discussed in Chapter 3, we divide 73 candidate variables into six different categories to cover all dynamics of the economy. The variable of interest, industrial production index, is included in all VAR models. VAR models are constructed in three different ways according to the number of endogenous variables included. VAR models may include two, three or four endogenous variables. At this point, we come up to the problem of determining the variables of the VAR model. How to combine 73 variables from six categories in a VAR model? We follow the procedure used by Akdoğan et al. (2012). Each VAR model draws its variables from these six categories in a way that more than one variable from a category never exists in the VAR model at the same time. In other words, at most one candidate variable from a given category may exist in a VAR model. This procedure results in 73 VAR models with 2 endogenous variables, 2077 VAR models with 3 endogenous variables and 29399 VAR models with 4 endogenous variables. Therefore, by combining industrial production index with 73 variables in six different categories in such a way that at most one variable from a given category may exist in a VAR model, we generate 31549 VAR models in total[6].

Another issue to tackle with is the choice of the lag length in VAR estimation. We have to choose an appropriate lag length to grasp the dynamics between endogenous variables. The decision is a kind of trade-off: using a high lag order or low lag order. With the increasing number of parameters in a VAR model, degrees of freedom decreases, resulting less precise coefficients. Conversely, with too short lag length, autocorrelation of error terms could not be removed. So, we cannot get the true dynamics between variables and may come up with inefficient coefficients. Information criteria are designed to consider this trade-off. They try to minimize error terms on the one hand, and have a penalty term for the number of lags on the other hand. Ivanov and Kilian (2001) analyze six different lag length selection criteria. Based on their simulation studies, they conclude that for monthly VAR models, the Akaike Information Criterion (AIC) tends to produce most accurate results. Therefore, at each recursive estimation for each VAR model, we choose the lag length of the model by using AIC.

Once we have determined the variables and appropriate lag lengths of VAR models, estimation is carried out by OLS and, the aforementioned method of pseudo out-of-sample forecasting is followed to calculate RRMSFE, given in equation (4.4).

[6] All VAR models are estimated by using Eviews programming codes. We benefit from the work of Akdoğan et al. (2012) with some modifications and revisions in order to construct 31549 VAR models in our case.

4.3. Combination Forecast Method

Once we have univariate and VAR models at hand, the last method that we utilize is the combination forecast method. By combining the information we get from VAR models, we question whether we have an improvement over and above the benchmark model and VAR models. The rationale behind combining forecasts of individual models is that combined forecast benefit from a pooled and larger information set (Bates and Granger, 1969; Clemen 1989). In this study, VAR models are evaluated in four different ways using combination forecast. According to the number of variables included, we have three types of VAR models. Initially, we analyze these three types of VAR models separately and then we pool all VAR models and analyze them altogether. Within each category, VAR models are ranked from the lowest to the highest with respect to RRMSFE. According to the ranked RRMSFE, average of the forecasts of 1 to 1000 best performing models is computed. Then, we investigate where the lowest RRMSFE has occurred.

CHAPTER V

EMPIRICAL RESULTS

This chapter discusses the results of the application of three approaches, explained in Chapter 4, to produce short-term one-month ahead forecasts of the industrial production index. According to RRMSFE criterion, the forecast results of each model are compared with respect to our benchmark model, AR model[7]. After evaluating univariate, AR and VAR models, forecasts of VAR models are combined in order to check whether an improvement is observed by pooling VAR forecasts through the combination forecast method.

5.1. The Results of Univariate Modeling

Initially, we analyze and evaluate the results of univariate ADL models given in equation (4.1). Figure 5.1 shows the results of some selected univariate models[8]. As an illustration, we select the candidate variables of the equation (4.1) which show the best and the worst forecasting performance relative to AR model in equation (4.2) and graph the relative root mean square forecast error with respect to AR model. In the Figure, on the left side of the AR model, we can see the candidate variables of univariate ADL models which have an RRMSFE of less than one.

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[7] In the literature, the two commonly used statistics evaluating forecasts are the average absolute error (AAE), the root-mean-squared error (RMSE), with the latter being used more widely. In this study, all models are compared according to the average absolute error as well and nearly identical findings point to the robustness of the analysis to the forecast evaluation criterion.

[8] See the Appendix for the complete list of variables with corresponding RRMSFEs.

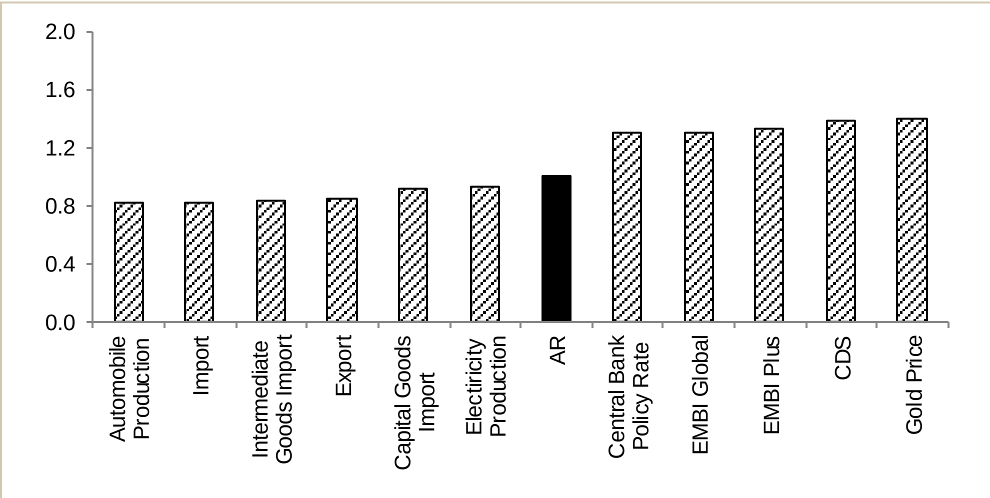

Figure 5.1: RRMSFE of Univariate Models
(relative to AR model)

Among those candidate variables, automobile production has the best forecasting performance, with an RRMSFE of 0.82. At first glance, it would be a bit surprising to see that automobile production is superior to other variables in forecasting industrial production index. However, automobile production constitutes an important portion of manufacturing industry. The share of automobile production in the manufacturing industry is 9.8 percentages[9]. As we discussed before, since the manufacturing industry is much related to industrial production, automobile production seems to forecast industrial production well. Furthermore, automobile production is also related to the other sectors of economy. Throughout the automobile production process, the usage of rubber, dyes, metals are intensive. Because of this high integration of automobile industry with other sectors, Turkish government takes precautionary measures by tax reductions in automobile industry and thereby gives incentive to economic

[9] Turkish Statistical Institute (Turkstat).

activity in order to prevent economic contraction and recession after the 2008 financial turmoil. Similarly, Altug and Uluceviz (2011) analyze the production of tractors and production of buses as candidate variables and conclude that the model with the production of tractors has a better forecasting performance relative to AR model.

The role of imports, intermediate goods imports and capital goods imports in determining the economic activity of Turkey is also important. To a great extent, the manufacturing industry in Turkey is dependent on the imports of intermediate goods. As discussed before, one of the variables used to construct composite leading indicator in Atabek et al. (2005) is intermediate imports. Altay et al. (1991) and Mürütoğlu (1999) also use imports of intermediate goods as a leading indicator. As a result imports, imports of intermediate goods and capital goods imports, having RRMSFE of 0.82, 0.83 and 0.92 respectively, show good forecasting performance for the economic activity in Turkey.

Another candidate variable having better forecasting performance than AR model is exports, which has an RRMSFE of 0.84. Exports is related to the economic activity of Turkey’s trade partners. Given export is related to the economic activity of Turkey’s trade partners, this finding implies that the economic activity of Turkey is closely related to economic activity of its trade partners. Another important predictor of industrial production index is electricity production, with an RRMSFE of 0.94. As an important industrial input, Özatay (1986) and Atabek et al. (2005) both conclude that electricity production has a high forecasting performance for economic activity.

5.2. The Results of VAR Modeling

As come to VAR models, we analyze them in three categories: VAR models with two endogenous variables, VAR models with three endogenous variables and VAR models with four endogenous variables. Industrial production index is included in all VAR models, for sure.

Figure 5.2 displays the RRMSFE of VAR models with two variables given in (4.5). As an illustration, we show only the candidate variables of the top five performing models.

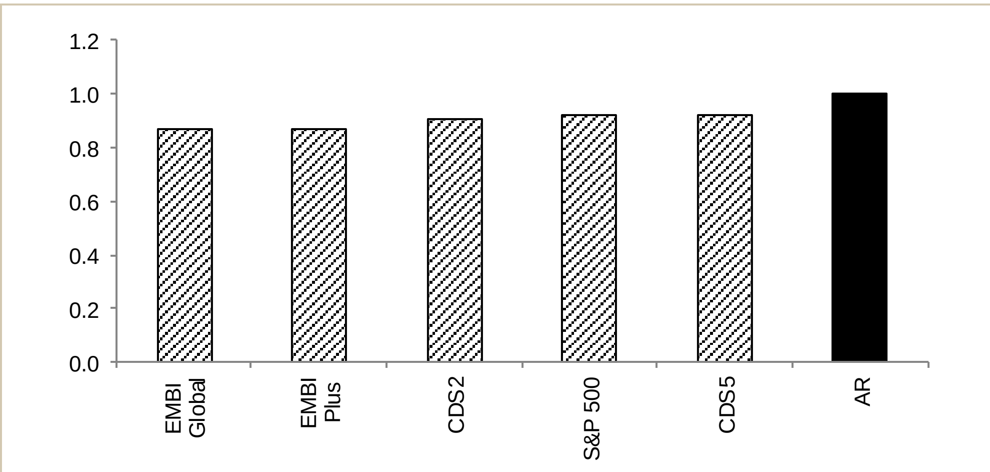

Figure 5.2: RRMSFE of VAR Models with two endogenous variables
(relative to AR model)

EMBI Global and EMBI Plus are issued by J.P. Morgan Securities Inc. and they are comprehensive US-dollar emerging markets debt benchmarks. They track total returns for actively traded external debt instruments of emerging countries and differ with respect to instrument selection processes. Given the low saving ratio of the Turkish economy, Turkish economic activity is largely dependent on external funding and capital inflows in stimulating economic activity is very crucial[10]. Since EMBI indices are calculated from returns of foreign debt instruments, they can be used as indicators for the riskiness of Turkish economy. Another indicator of riskiness of a country is Credit Default Swap (CDS). It is a swap agreement in which the seller compensate the buyer in case of a credit default. Both EMBI indices and CDS are widely used by reporting agencies to evaluate country riskiness. With this information, it is not surprising to see that EMBI indices and CDS have high forecasting power for the industrial production index with RRMSFEs of 0.87, 0.87 and 0.91, respectively.

Another indicator which improves forecast of the industrial production is Standard & Poor 500 Index (S&P 500). It delivers an RRMSFE of 0.92. S&P index is a weighted index of stock prices of 500 American companies, and widely used as representative indicator for U.S. economy. Although Turkey and U.S. do not have much close linkage in terms of trade, U.S. economy is like an engine which stimulates all world economy. Therefore the economic activity of U.S. economy has the capacity to affect all economies.

In Figure 5.3, we show the candidate variables of the top five performing VAR models with three variables. As distinct from the VAR models with two variables, these VARs include capacity utilization rate, TL / U.S. $ Nominal Exchange Rate, VAT and U.S. interest rate as important variables.

[10] Saving ratio is estimated as 13 % in 2011 (State Planning Organization).

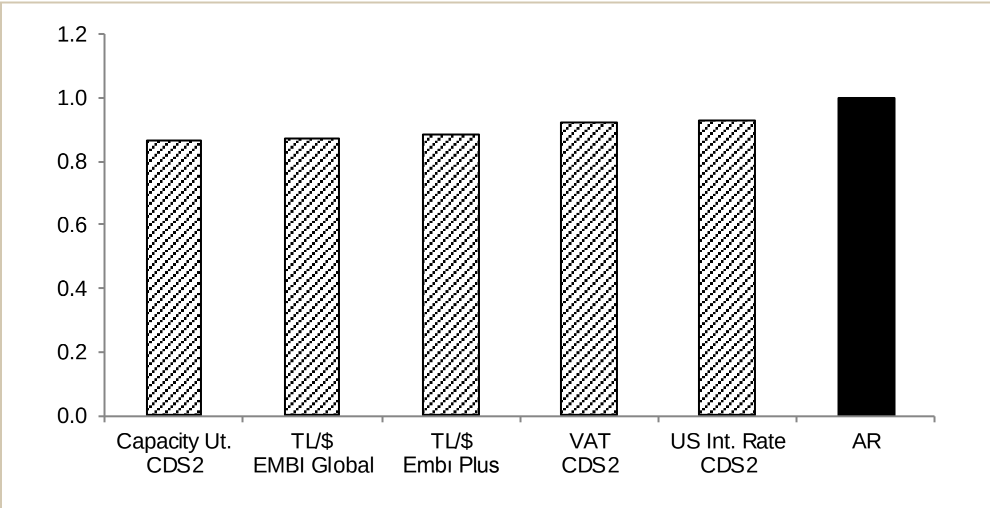

Figure 5.3: RRMSFE of VAR Models with three endogenous variables
(relative to AR model)

Capacity utilization rate is calculated based on the responses of firms operating in the manufacturing industry and included in the Business Tendency Survey of CBRT. Capacity utilization rate is the ratio of realized and utilized capacity of firms to their potential physical capacities. With the capacity utilization rate, it is aimed to grasp some information about the current business environment. It is not an accounting calculation, but the perceptions and assessments of firms' managers. Capacity utilization rate is announced prior to the announcement of industrial production index and therefore closely monitored by policy makers and public as an indicator for industrial production. Among the VAR models with three variables, the one which includes capacity utilization rate and CDS yields the most improvement relative to AR model, an improvement of 0.13.

Another indicator which improves the forecast of industrial production is Value Added Tax (VAT) revenue. VAT is a kind of consumption tax. That is the seller pays a certain amount of tax based on the purchase price of inputs used to produce the final goods, while the buyer pays tax on the purchase price. As a result, the amount of tax paid by seller to the government is the difference between these two amounts. In other words, the VAT is a tax on the value added to a product. Therefore, when we think of the economy as a whole, VAT is a tax on the total value added in an economy. It is a tax taken based on the overall economic activity.

U.S. interest rate is also an important indicator because of its influence on U.S. economic activity and its further influence on other countries' interest rates. As discussed before, U.S. economic activity has the potential to affect all world economy. As a result, it is plausible to expect that U.S. interest rate is significant for other countries' interest rates and economic activities.

In the VAR models with four endogenous variables, real and nominal monetary aggregates, ISE 100 Index and U.S. interest rate appear to perform well relative to AR model (Figure 5.4).

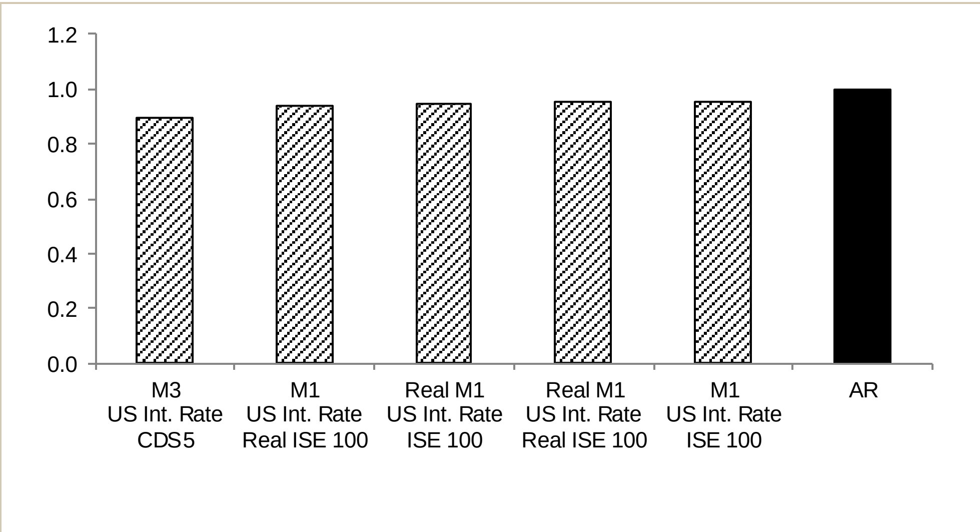

Figure 5.4: RRMSFE of VAR Models with four endogenous variables
(relative to AR model)

However, when we compare the univariate models with VAR models, we observe that forecasting performance based on RRMSFE criterion is poorer under VAR based forecasting. As seen in Table 5.1, while the best performing model among the univariate models yields 0.82 RRMSFE, best VAR models with two, three and four endogenous variables yield 0.87, 0.87 and 0.89 RRMSFE, respectively. VAR based models do not provide an improvement relative to univariate models. In other words, using more variables in a model does not provide us more information, hence better forecasting performance. In VAR based models, we use more variables, suggesting a larger information set. However, having larger information set does not give us better forecasts. The out-of-sample period in our analysis covers the period of global financial crisis of post-2008 period. In this kind of economic environment, the relationship between macroeconomic variables may change and the variables may show different unexpected dynamics. Therefore, results obtained from a single VAR model might suffer from bias and instability during crisis period. To handle this problem and to benefit from larger information set of VAR models, we can utilize combination forecast method, following the literature. Combination forecasts might overcome bias problem even if the individual forecasts give biased forecasts (Granger and Ramanathan, 1984). Lack (2006) shows that combining different VAR models improves the forecasting performance. Akdoğan et al. (2012) also concludes that combination forecast has better forecasts than single VAR models.

Table 5.1: RRMSFE of Top Models within a given type of Model

Type of Model	Variable(s) used	RRMSFE
Univariate Model	Automobile Production	0.82
VAR model with two variables	EMBI Global	0.87
VAR model with three variables	Capacity Utilization Rate, CDS	0.87
VAR model with four variables	M3, US Interest Rate, CDS	0.89

5.3. The Results of Combination Forecast Method

We evaluate VAR models in four different ways using combination forecast. We have three types of VAR models according to the number of variables included. We analyze these three types of models first separately and then pool all VAR models and analyze them altogether.

Within each category, VAR models are ranked from the lowest to the highest with respect to observed RRMSFE values. According to the ranked RRMSFEs, average of the forecasts of top 1 to top 73 best performing models is computed for the case of VAR models with two variables, and average of the forecasts of top 1 to top 1000 best performing models is computed for other VAR models[11]. In other words, our first combined forecast is the best VAR model itself, the second combined forecast is the average of top 2 best performing models, the third combined forecast is the average of top 3 best performing models, and the thousandth (1000^{th}) combined forecast is the average of top 1000 best performing

[11] For the case of VAR models with two variables, total number of models is 73. Therefore, average of the forecasts of 1 to 73 best performing models is computed.

models. This procedure gives us 1000 combined forecasts for each category. For 1000 combined forecasts, we calculate 1000 RRMSFEs for each category.

For two-variable VAR models, the lowest RRMSFE occurred when forecasts of the top 4 models are combined. But the gain from combination is not very much. RRMSFE has decreased from 0.87 to 0.86 and is not less than the RRMSFE of the best univariate model, which is 0.82 (Figure 5.5). The improvement in three-variable VAR models is more prominent. The lowest RRMSFE occurred when forecasts of the top 70 models are combined. The resulting RRMSFE is 0.79, which is less than the RRMSFE of best univariate model (Figure 5.6).

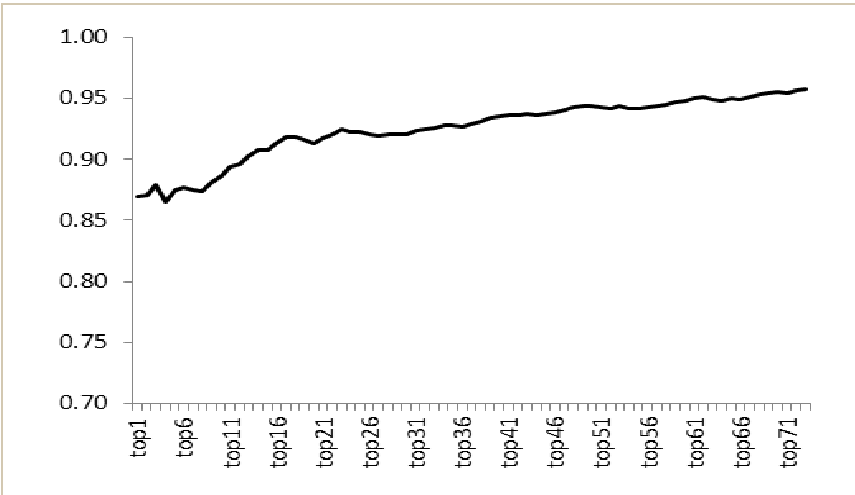

Figure 5.5: Combination of VAR models with two variables

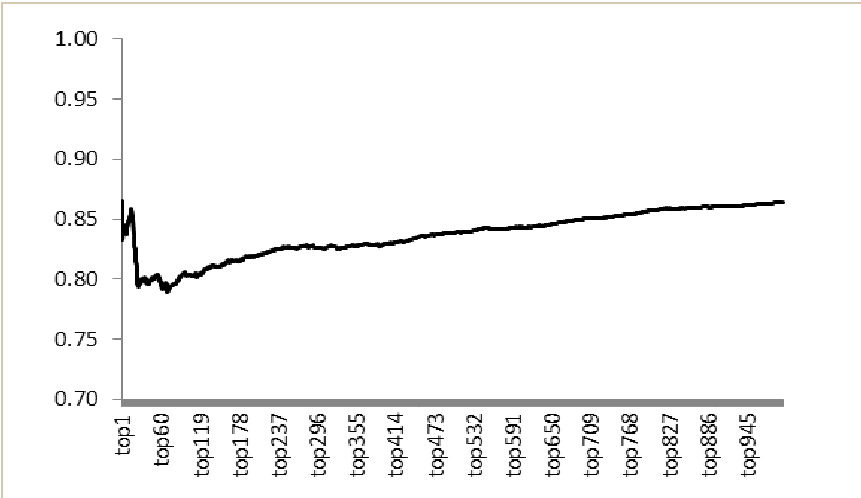

Figure 5.6: Combination of VAR models with three variables

The combination of four-variable VAR models and all VAR models yields more prominent improvement in RRMSFE. For four-variable VAR models, the lowest RRMSFE occurred when forecasts of the top 81 models are combined. We get the RRMSFE of 0.72 (Figure 5.7). The lowest RRMSFE occurred when forecasts of the top 56 models are combined for the case of all VAR models combination. The resulting RRMSFE is 0.75 (Figure 5.8).

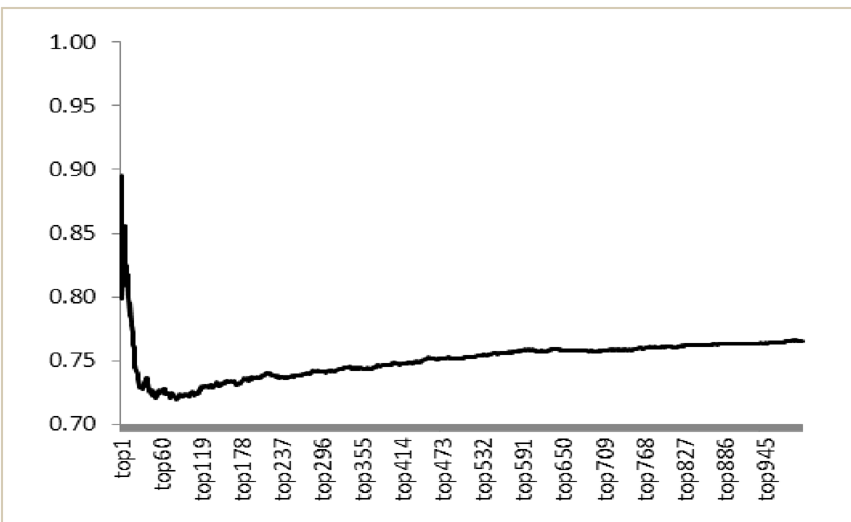

Figure 5.7: Combination of VAR models with four variables

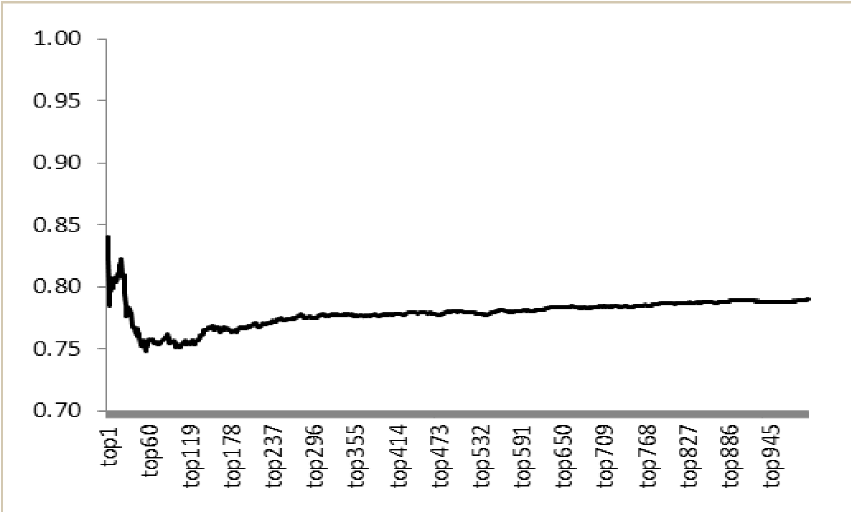

Figure 5.8: Combination of all VAR models

As a result, by using VAR models with four variables and utilizing combination forecasts method, we get most accurate forecasts for industrial production.

CHAPTER VI

CONCLUSION

There have been important structural changes in Turkey, after 2001 banking crisis. Turkey implemented implicit inflation targeting till 2006, and thereafter has adopted inflation targeting regime. In this regime, one of the important variables of the policy decision variables to assess inflationary pressure is the level of economic activity, which can be measured by GDP or industrial production. In this paper, we construct different models to get short-term forecasts for industrial production, using pseudo out-of-sample forecasting method. We use univariate models, VAR models to forecast industrial production. Furthermore, we combine VAR models' forecasts using combination forecast method to benefit from a larger information set.

When we compare the univariate and VAR models according to RRMSFE criterion, forecasting performance of VAR models are poorer than univariate models. While the best performing univariate models yields an improvement of 0.18 in RRMSFE, the best performing VAR models with two, three and four endogenous variables yield improvements of 0.13, 0.13 and 0.11, respectively. To benefit from larger information set of VAR models, we evaluate VAR models in four different ways using combination forecast method. There are three types of VAR models in our analysis, according to the number of variables they include. Initially we analyze these three types of models separately. Then we pool all VAR models and analyze them altogether. By using VAR models with four variables and utilizing combination forecasts method, we get most accurate forecasts for industrial production, giving an RRMSFE of 0.72.

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APPENDIX

Table A.1: Series Descriptions

Series Name	Source	Abbreviation
Industrial Production Index	IFS[12]	ipi
Capacity Utilization Rate	Turkstat [13]	cur
Electricity Production	TET [14]	elec
Production Of Agricultural Machines	AMA [15]	trac
Production Of Buses	AMA	bus
Production Of Automobiles	AMA	auto
Production Of Truck	AMA	truck
Production Of Van	AMA	van
Production Of Midibus	AMA	midi
Exports	Turkstat	exp
Imports	Turkstat	imp
Unit Value Of Export	Turkstat	expuv
Unit Value Of Import	Turkstat	impuv
Intermediate Goods Imports	Turkstat	intimp
Capital Goods Imports	Turkstat	capimp
Consumer Price Index	Turkstat	cpi
Producer Price Index	Turkstat	ppi
US Consumer Price Index	IFS	uscpi
VAT Revenue	MF [16]	vat
Real VAT Revenue	*	vatr
Credit Default Swaps (CDS), 2-year	Bloomberg	cds2
Credit Default Swaps (CDS), 5-year	Bloomberg	cds5
JP Morgan EMBI Global Index for Turkey	Bloomberg	embig
JP Morgan EMBI+ Index for Turkey	Bloomberg	embip
ISE 100 Index	ISE [17]	ise100
Real ISE 100 Index	*	ise100r
Gross International Reserves	CBRT [18]	res
Central Bank's Gross FX Reserves	CBRT	rescb
International Gold Reserves	CBRT	resgold
S&P 500 Index	Bloomberg	spx
Real S&P 500 Index	*	spxr
VIX Index	Bloomberg	vix
European VIX Index	Bloomberg	vixe
M1	CBRT	m1
Real M1	*	m1r
M2	CBRT	m2

[12] IMF International Financial Statistics
[13] Turkish Statistical Institute
[14] Turkish Electricity Transmission Company
[15] Automotive Manufacturers Association
[16] Ministry of Finance
[17] Istanbul Stock Exchange
[18] Central Bank of the Republic of Turkey
* Based on our calculations

Table A.1 (cont'd)

Real M2	*	m2r
M2Y	CBRT	m2y
Real M2Y	*	m2yr
M3	CBRT	m3
Real M3	*	m3r
Total Credit	CBRT	credit
Total Real Credit	*	creditr
Brent Oil Price	Bloomberg	brent
Real Brent Oil Price	*	brentr
West Texas Intermediate (WTI) Oil Price	Bloomberg	wti
Real WTI Oil Price	*	wtir
Gold Price	Bloomberg	gold
Real Gold Price	*	goldr
US $/TL Nominal Exchange Rate	CBRT	usdtl
Euro/TL Nominal Exchange Rate	CBRT	eutl
Nominal Exchange Rate Basket ($ + €)	*	basket
Real Effective Exchange Rate	BIS[19]	rer
Central Bank Policy Rate	CBRT	policy
Benchmark Interest Rate, 2-year maturity	Bloomberg	bench
Overnight Interest Rate	CBRT	onir
US 1-month Interest Rate	Bloomberg	usir1
US 3-month Interest Rate	Bloomberg	usir3
US 6-month Interest Rate	Bloomberg	usir6
US 12-month Interest Rate	Bloomberg	usir12

[19] Bank for International Settlements

Table A.2: Augmented Dickey-Fuller Test Results

Variable	Transformation	ADF test statistics
cur	Level	2.20
cur	1^{st} difference	11.71^{***}
elec	Level	3.48^{**}
trac	Level	1.97
trac	1^{st} difference	12.61^{***}
bus	Level	3.21^{**}
auto	Level	4.66^{***}
truck	Level	4.27^{***}
van	Level	3.01^{**}
midi	Level	6.72^{***}
exp	Level	2.71^{*}
imp	Level	2.76^{*}
expuv	Level	2.77^{*}
expuv	1^{st} difference	6.54^{***}
impuv	Level	4.12^{***}
intimp	Level	2.75^{*}
capimp	Level	2.55
capimp	1^{st} difference	9.70^{***}
cpi	Level	6.31^{***}
ppi	Level	7.36^{***}
uscpi	Level	3.49^{***}
vat	Level	3.74^{***}
vatr	Level	3.36^{**}
cds2	Level	2.80^{*}
cds2	1^{st} difference	10.69^{***}
cds5	Level	2.75^{*}
cds5	1^{st} difference	10.77^{***}
embig	Level	2.46
embig	1^{st} difference	9.97^{***}
embip	Level	2.48
embip	1^{st} difference	9.97^{***}
ise100	Level	2.95^{**}
ise100r	Level	2.89^{*}
res	Level	2.65^{*}
res	1^{st} difference	11.08^{***}
rescb	Level	2.99^{**}
resgold	Level	3.71^{***}
spx	Level	2.54
spx	1^{st} difference	7.46^{***}
spxr	Level	2.51
spxr	1^{st} difference	7.57^{***}
vix	Level	3.32^{**}
vixe	Level	3.53^{***}
m1	1^{st} difference	13.71^{***}

*** Significant at 1 % level.
** Significant at 5 % level.
* Significant at 10% level.

Table A.2 (cont'd)

m1r	Level	2.67^{*}
m1r	1^{st} difference	12.78^{***}
m2	1^{st} difference	8.33^{***}
m2r	Level	3.05^{**}
m2y	Level	6.28^{***}
m2yr	Level	2.89^{**}
m3	1^{st} difference	9.20^{***}
m3r	Level	2.93^{**}
credit	1^{st} difference	3.24^{**}
creditr	1^{st} difference	2.95^{**}
brent	Level	3.51^{***}
brentr	Level	3.44^{**}
wti	Level	3.66^{***}
wtir	Level	3.63^{***}
gold	Level	2.91^{**}
goldr	Level	2.79^{*}
usdtl	Level	2.52
usdtl	1^{st} difference	3.11^{**}
eutl	Level	5.74^{***}
basket	Level	5.90^{***}
rer	Level	4.72^{***}
policy	Level	3.44^{**}
bench	Level	2.95^{**}
onir	Level	2.10
onir	1^{st} difference	25.80^{***}
usir1	1^{st} difference	6.62^{***}
usir3	1^{st} difference	5.72^{***}
usir6	1^{st} difference	5.90^{***}
usir12	1^{st} difference	7.83^{***}
ADF Test critical values		
1 % level	5 % level	10 % level
3.49	2.89	2.58

Table A.3: RRMSFEs of Univariate ADL Models

Benchmark AR Model	RMSFE: 6.15	
Variable	**Transformation**	**Relative RMSFE**
cur	level	1.01
cur	1st difference	0.98
elec	level	0.94
trac	level	1.08
trac	1st difference	1.14
bus	level	1.03
auto	level	0.82
truck	level	1.04
van	level	1.04
midi	level	1.16
exp	level	0.84
imp	level	0.82
expuv	level	1.17
expuv	1st difference	1.15
impuv	level	1.24
intimp	level	0.83
capimp	level	0.92
capimp	1st difference	0.94
cpi	level	1.06
ppi	level	1.06
uscpi	level	1.14
vat	level	1.09
vatr	level	1.04
cds2	level	1.03
cds2	1st difference	1.38
cds5	level	0.99
cds5	1st difference	1.15
embig	level	1.14
embig	1st difference	1.31
embip	level	1.14
embip	1st difference	1.33
ise100	level	1.04
ise100r	level	1.10
res	level	1.11
res	1st difference	1.08
rescb	level	1.11
resgold	level	1.06
spx	level	0.99
spx	1st difference	1.03
spxr	level	1.07
spxr	1st difference	1.04
vix	level	1.15
vixe	level	1.06
m1	1st difference	1.07
m1r	level	1.09
m1r	1st difference	1.17

Table A.3 (cont'd)

m2	1st difference	1.21
m2r	level	1.22
m2y	level	1.03
m2yr	level	1.03
m3	1st difference	1.09
m3r	level	1.10
credit	1st difference	1.02
creditr	1st difference	1.04
brent	level	1.10
brentr	level	1.04
wti	Level	1.11
wtir	Level	1.05
gold	Level	1.39
goldr	Level	1.30
usdtl	Level	1.01
usdtl	1st difference	0.97
eutl	Level	0.99
basket	Level	1.04
rer	Level	1.13
policy	level	1.31
bench	Level	1.22
onir	Level	1.20
onir	1st difference	1.06
usir1	1st difference	1.21
usir3	1st difference	1.20
usir6	1st difference	1.07
usir12	1st difference	1.06

TEZ FOTOKOPİ İZİN FORMU

ENSTİTÜ

Fen Bilimleri Enstitüsü [ ]

Sosyal Bilimler Enstitüsü [x]

Uygulamalı Matematik Enstitüsü [ ]

Enformatik Enstitüsü [ ]

Deniz Bilimleri Enstitüsü [ ]

YAZARIN

Soyadı : Değerli ....

Adı : Ahmet ....

Bölümü : İktisat ....

TEZİN ADI (İngilizce): Short-term Industrial Production Forecasting for Turkey

....

....

TEZİN TÜRÜ : Yüksek Lisans [x] Doktora [ ]

1. Tezimin tamamı dünya çapında erişime açılsın ve kaynak gösterilmek şartıyla tezimin bir kısmı veya tamamının fotokopisi alınsın. [ ]

2. Tezimin tamamı yalnızca Orta Doğu Teknik Üniversitesi kullanıcılarının erişimine açılsın. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına dağıtılmayacaktır.) [ ]

3. Tezim bir (1) yıl süreyle erişime kapalı olsun. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına dağıtılmayacaktır.) [x]

Yazarın imzası .... Tarih ....