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A QUEST FOR LEADING INDICATORS OF THE TURKISH UNEMPLOYMENT RATE

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ABSTRACT This paper examines various variables that are likely to be associated with the Turkish non-agricultural unemployment rate in search of indicators to summarize and forecast the state of the labor market. We consider a total of 72 series that reflect aggregate economic activity, labor market conditions, expectations over future economic activity, global economic trends, and credit conditions. We use Granger causality tests, correlation analyses and individual out of sample forecast performance of these series to assess their informativeness about the unemployment rate. We find that Business Tendency Survey indicators and some series that measure the global economic conditions satisfy all three criteria of informativeness. Moreover, the composite index constructed from series selected based upon out of sample predictive power improves short-term forecast performance of the autoregressive benchmark model, where we use only lagged values of the unemployment rate.
JEL C32, E24
Keywords Leading indicator, Unemployment rate, Granger causality test

ÖZ Bu çalışma, işgücü piyasasının mevcut durumunu özetlemek ve tahmin etmek amacıyla, Türkiye'de tarım dışı işsizlik oranı ile ilişkili olabilecek bazı değişkenleri incelemektedir. Bu kapsamda, iktisadi faaliyetin genel gidişatını, iş gücü piyasası koşullarını, iktisadi faaliyete ilişkin beklentileri, kredi koşullarını ve küresel eğilimleri gösteren 72 tane değişken değerlendirmeye alınmıştır. Serilerin bilgi değeri Granger nedensellik testi, bağıntı analizi ve bireysel örneklem dışı tahmin performansı sonuçları esas alınarak ölçülmüştür. Bulgularımıza göre, İktisadi Yönelim Anketi'nde yer alan göstergeler ile küresel iktisadi faaliyetle ilişkili bir takım değişkenler söz konusu üç ölçütü de sağlamaktadır. Bununla birlikte, örneklem dışı tahmin performansına bakılarak seçilen serilerden oluşturulan bileşik endeksin, işsizliğin sadece kendi gecikmeli değerleriyle açıklandığı temel modele kıyasla tahmin performansını iyileştirdiği gözlenmiştir.
TÜRKİYE'DE İŞSİZLİK ORANI İÇİN ÖNCÜ GÖSTERGE ARAYIŞI
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1. Introduction

This paper aims to discover leading indexes for the non-agricultural unemployment rate in order to contribute towards timely assessment of the labor market conditions in Turkey.[1] Having a leading index for timely monitoring of the labor market is especially valuable in Turkey as the unemployment data is released with a three months lag. Moreover, given that unemployment data covers the whole economy and not some specific sectors only, its timely assessment provides valuable information regarding overall economic activity.

This paper investigates a diverse set of data including series related to aggregate economic activity, consumers' and firms' expectations, labor market indicators, global economic trends, and credit conditions in search of leading indicators, as practiced in the literature.[2] We closely follow the methodology suggested by Marcellino (2006) and Gyomai and Guidetti (2012) to investigate the candidate series. As such, we first clean the data from seasonal components and outliers. We remove long run trend from the series so as to focus on the cyclical movements and standardize them as they have different units. We perform Granger causality tests and compute cross correlations of series with the unemployment rate series to assess their leading properties. Moreover, we evaluate series based on their individual marginal predictive power in a way similar to Stock and Watson (1989).

We also use series that are identified as having good leading and forecasting properties to construct various composite indexes, as composite indexes may be informative as well. To judge the informativeness of those composite indexes, we measure their performance to forecast unemployment rate in terms of root mean square errors and compare their performance to a benchmark where unemployment rate is modeled as an AR(2) process. We find that the composite index constructed from series with good out of sample forecasting property outperforms all other composite indexes. It improves one-period ahead forecast by 17 percent relative to the benchmark model.

Leading indicators have long been used to summarize the state of the macroeconomic activity (see Marcellino (2006), Stock and Watson (1989) and references therein). Stock and Watson (1999) analyze business cycle

[1] Henceforth, "unemployment rate" is used instead of "non-agricultural unemployment rate".
[2] Stock and Watson (1989), for instance, use 280 series.

properties of series such as interest rate, prices, employment by sector, among others. Estrella and Mishkin (1998) investigate various financial variables as predictors of US recessions by examining their out of sample forecast performance. Banerjee et al. (2005) evaluate a set of variables for their leading ability of euro area inflation and GDP growth. Composite leading indexes (CLI hereafter) constructed from leading indicators are used as much as leading indicators themselves. Some policy related institutions regularly compute and report CLIs. For instance, OECD reports CLIs for its member countries as well as for some groups of countries such as euro area and European countries, while Bureau of Economic Analysis (BEA) and Conference Board compute and report CLIs for the US economy. Auerbach (1982) analyzes the power of CLI used by BEA, Diebold and Rudebusch (1989) use scoring rules to look at the predictive ability of the CLIs to forecast peaks and troughs of business cycles. Institutions mentioned above use some form of averaging (simple/weighted) to construct composite indexes. There are also studies that use different techniques to investigate leading indicators. For instance, Camba-Mendez et al. (2001) and Bandholz and Funke (2003) use dynamic factor models to get CLIs for some European countries and Germany, respectively, while Groenen et al. (2011) use principal covariate index approach to improve the performance of CLI of the Conference Board.

Aforementioned studies use GDP as the indicator of aggregate economic activity. There are also studies that use other variables, including labor market indicators, as measures of aggregate economic activity.[3] One of the first studies that focus on the employment indicators is Moore (1983) for the United States. He constructs a leading employment index using average workweek and overtime hours in manufacturing industries, number of initial claims for unemployment insurance, the layoff rate, and the ratio of voluntary to involuntary part time employees and then forecasts unemployment.[4] Recently, Claus (2011) constructs seven leading indexes of New Zealand employment and assesses their relative usefulness in terms of forecasting quarterly employment growth. Claus (2001) constructs composite index to forecast employment in Canada.

There are also studies analyzing the leading indexes for the Turkish economy. For instance, Atabek et al. (2005) construct a composite leading index for the economic activity. In doing so, among other variables, they include the number of employees, payments to workers in manufacturing industry and business tendency survey results regarding expected

[3] For summary of the series used to monitor economic activity please see Marcellino (2006).

[4] For more studies that focus on forecasting the employment growth in the US, please see Montgomery et al. (1998), Rothman (1998), Rapach and Strauss (2008), Rapach and Strauss (2010).

employment. Similarly, Altuğ and Uluceviz (2011) and Aruoba and Sarıkaya (2012) also construct indicators for real activity. Aforementioned papers address predicting real activity or inflation. To our knowledge, this is the first paper that focuses on compounding a leading index for the Turkish labor market. The closest to this study is Chadwick and Şengül (2012), which nowcasts the monthly non-agricultural unemployment rate for Turkey using the Google search query data.

The rest of the paper is organized as follows: The following section contains description of the data. Section 3 presents methodology regarding data processing and Granger causality testing procedure. In Section 4, results of Granger causality tests, cross correlation analyses, and out sample forecasting exercise are presented. This section also combines selected leading indicators to produce composite indexes and reports their forecast performance. The last section concludes.

2. Data

Our target series is the Turkish non-agricultural unemployment rate. The source of the unemployment data is the Turkish Household Labor Force Survey (HLFS), which is conducted by the Turkish Statistical Institute (TURKSTAT) on a monthly basis as of 2005. The HLFS data is announced with a delay of three months.

We use a wide range of indicators that can be informative to infer the movements of the unemployment rate. Table 1 describes the range of these series and their release dates relative to unemployment rate, as well as data sources. We have 72 different series that can be grouped under the following five categories:

i. Aggregate economic activity indicators: In the absence of monthly GDP data, we use industrial production index (IPI) as a proxy for economic activity. Capacity utilization rate is another indicator considered within this category. Domestic value added taxes also carry information about economic activity. Similarly, a change in value added tax on imports may signal the change in economic activity, as import growth increases along with the economic activity in Turkey. We compute nominal tax series as a ratio to nominal GDP (NGDP). We also use firm entry and exit data since entry/exit decisions are driven by current and expected economic outlook. We also include net number of firm entry data in our analysis.

Given that foreign trade is highly associated with growth in Turkey, real effective exchange rate (REER) that influences countries' competitive position is another potential indicator. Central Bank of the Republic of Turkey releases REER for different baskets of foreign currencies. Thus, we also include the series of developing-countries-based REER and developed-countries-based REER.

ii. Consumer confidence and survey indicators: We use survey data that measure expectations of consumers and firms as survey questions apprehend valuable information about the future course of the economy. With respect to consumers' expectations, we use the overall confidence index compiled from different questions of the Turkish Consumer Confidence Survey (CCS).

We use results of Business Tendency Survey (BTS) to capture firms' expectations regarding change in employment, orders, production, and average unit cost over the next three months. This survey is available at the aggregate level since 2000. These series are called non-weighted as they are simple aggregation of the results. In 2007, the survey went under some changes. Since then, there is data available for subsectors and all series, including the aggregates, are weighted by firm size. Non-weighted aggregate series are still released.

iii. Labor market indicators: We use variables from HLFS such as the number of layoff and quits, discouraged workers, hours worked, first time job seekers. We make use of two additional data sources: Turkish Employment Agency (ISKUR) and Kariyer.net, a private career web site. ISKUR data covers unemployment insurance claims, vacancies, and newly registered unemployed. Kariyer.net data includes job applications and vacancies collected through the web site. We divide variables in levels with three-month average of the latest available non-agricultural labor force (NALF) data to measure them relative to the economically active population.

Another labor market indicator is the Purchasing Managers' Index (PMI) for employment which is directly related to employment in the manufacturing sector. It is derived from a survey question that compares the current level of employment with its level in the previous month.

iv. Global economic conditions: As the global interaction of markets increase, repercussion effects of various macroeconomic variables are felt by all over the world. Hence we use indicators reflecting general course of economy in the European Union (EU), OECD and USA as representative of the global trends. More specifically, we use European economic tendency index, German economic tendency index, OECD-Europe composite leading index (CLI), and OECD and USA CLI.

v. Credit conditions: Expansion of credits is a good indicator for the increase in domestic demand, hence, income and ultimately, employment. In this regard, we make use of the following series: consumer credits, mortgage, vehicle credit, consumer credits and credit cards, and TL and FX denominated commercial credit. We analyze both the level and the quarterly change of credit series. Series are computed as ratio to NGDP.

Table 1. Data Description

Series[a]	Source	Data availability	Released data dates
Non-agricultural Unemployment Rate	HLFS	2005m01 - 2013m03	t-3
Industrial Production Index	TurkStat	2000m01 - 2013m04	t-2
Unemployment Insurance Claims over NALF	HLFS	2005m01 - 2013m05	t-1
Vacancies over NALF[c]	ISKUR	2005m01 - 2013m05	t-1
ISKUR Newly Registered Unemployed over NALF	ISKUR	2005m01 - 2013m05	t-1
Vacancies over Newly Registered Unemployed[c]	ISKUR	2005m01 - 2013m05	t-1
Kariyer.net Vacancies over NALF	kariyer.net	2005m01 - 2013m05	t-1
European Economic Tendency Index	OECD	2000m01 - 2013m07	t
German Economic Tendency Index	OECD	2000m01 - 2013m07	t
OECD-Europe CLI	OECD	2000m01 - 2013m04	t-2
OECD CLI	OECD	2000m01 - 2013m04	t-2
USA CLI	OECD	2000m01 - 2013m04	t-2
Domestic Value Added Tax over NGDP	CBRT	2000m01 - 2013m05	t-1
Value Added Tax on Imports over NGDP	CBRT	2000m01 - 2013m05	t-1
Number of Firm Entry	TurkStat	2000m01 - 2013m05	t-1
Number of Firm Exits	TurkStat	2000m01 - 2013m05	t-1
Net Number of Firm Entry	TurkStat	2000m01 - 2013m05	t-1
Discouraged Workers over NALF	HLFS	2005m01 - 2013m03	t-3
Developing Countries Based REER	CBRT	2003m01 - 2013m05	t-1
Developed Countries Based REER	CBRT	2003m01 - 2013m05	t-1
Consumer Credits over NGDP[d]	CBRT	2000m06 - 2013m05	t-1
Mortgage over NGDP[d]	CBRT	2000m06 - 2013m05	t-1
Vehicle Credit over NGDP[d]	CBRT	2000m06 - 2013m05	t-1
Consumer Credits and Credit Cards over NGDP[d]	CBRT	2000m06 - 2013m05	t-1
TL Denominated Commercial Credit over NGDP[d]	CBRT	2000m06 - 2013m05	t-1
FX Denominated Commercial Credit over NGDP[d]	CBRT	2000m06 - 2013m05	t-1
Non-weighted BTS EP, EE, EO and EUC	CBRT	2000m01 - 2013m05	t-1
Weighted BTS EP, EE, EO and EUC[e]	CBRT	2007m01 - 2013m05	t-1
Non-agricultural Average Working Hours	HLFS	2005m01 - 2013m03	t-3
First Time Job Seekers over NALF	HLFS	2005m01 - 2013m03	t-3
Number of Layoffs over NALF	HLFS	2005m01 - 2013m03	t-3
Number of Quits over NALF	HLFS	2005m01 - 2013m03	t-3
PMI for Employment	Markit	2005m05 - 2013m05	t-1
Capacity Utilization Rate	CBRT	2007m01 - 2013m05	t-1
Kariyer.net Job Application over NALF	kariyer.net	2005m01 - 2013m05	t-1
Kariyer.net Job Application per Vacancy	kariyer.net	2005m01 - 2013m05	t-1

(a) Series abbreviations: CLI: Composite leading indicators; NGDP: Nominal gross domestic product; REER: Real effective exchange rate; EP: Expected production over the next three months; EE: Expected employment over the next three months; EO: Expected orders over the next three months; EUC: Expected average unit cost over the next three months; FX: Foreign Exchange; REER: Real effective exchange rate. (b) Data source abbreviations: ISKUR: Turkish employment agency; TCTS: Turkish consumer tendency survey; BTS: Business tendency survey; kariyer.net: a Turkish private website for employment search; CBRT: Central Bank of the Republic of Turkey. (c) Private sector. (d)We also look at the quarterly change of the series over quarterly NGDP. (e) Data include intermediate, investment, durable, non-durable, consumer and food and beverages goods subsectors. (f) Shows the availability of the data when unemployment rate for time t-3 is announced.

3. Methodology

We closely follow Marcellino (2006) and Gyomai and Guidetti (2012) to assess the leading properties of the series. Gyomai and Guidetti (2012) describe the methodology used in constructing a composite leading index for the OECD. They choose a wide range of series based on economic relevance and practical consideration. More specifically, these series have an economic justification, are high frequency, are available timely and are not subject to significant revisions. Then, these series are seasonally adjusted with outliers removed, de-trended and normalized. These candidate series are evaluated for their cyclical performance in relation to the cyclical turning points of the target series, series that is the reference for the aggregate economic activity. To make sure of the conformity to the cycle in general, not only to the turning points, they also compute cross correlations between the candidate series and the target series. Based on the performances, they select series and aggregate them to construct the composite leading index.

Marcellino (2006) describes the methodology of constructing (non-model based) composite index as selection, transformation and weighting. Data selection step is deciding which component series to use. Like Gyomai and Guidetti (2012), Marcellino (2006) advises choosing series that are economically relevant and practical. Economic relevance implies an economic relationship between the component and the target series. The series should also have a relatively wide economic coverage so as to be better able to capture the current economic conditions. The series we use, which are described in the data section, are related to unemployment either directly or through affecting economic activity and employment. These series are practical to use as they are monthly, they are not subject to revisions and long compared to other available data.[5]

We need to transform (filter) the series chosen as potential leading indexes. We seasonally adjust all series and sort out outliers before filtering.[6] Then, we utilize the Hodrick-Prescott (HP) filter to remove the long-run trend. This filtering is used by the OECD and it is one of the methods suggested by Marcellino (2006).[7] We use smoothing parameter

[5] We had to exclude some potentially informative series as they failed to conform with practicality critera. More specifically, Industrial Labor Input Indices and Trade and Services Indices disclosed by TurkStat were not used as they are quarterly and they are announced with a delay. Sectoral Tendency Statistics disclosed by TurkStat were not used because of short span. They start from 2011 January. There is also data on sectoral wages (agriculture, industry, construction and services) that is announced by Social Security Institution on a monthly basis. These series were not included in the analysis as they are highly volatile.

[6] We correct the data for additive outliers and transitory changes, and remove the irregular noise component from the series using Demetra+ Software.

[7] The filtering process involves removing long term trend (de-trending) in the first step and keeping the trend of short term cycles in the second. We do not implement the second step as removing short term cycles results in spuriously high explanatory power (R2).

λ=814 to remove cycles longer than 7.5 years, which is the longest cycle observed in Turkey, as documented by Alp et al. (2011).[8] Finally, series are normalized. As such, we subtract the mean and divide by the standard deviation and add 100. We use these normalized series for the analysis described in the following sections whereas we use leading indicators of other countries as they are, since these series have already gone through these processes.

After processing the component series, we check their conformity to the target series, the unemployment rate, which also has gone through the same processes. For this purpose, we use cross correlations and Granger causality, both of which are suggested by Gyomai and Guidetti (2012) and Marcellino (2006) and also used by Stock and Watson (1999). Note that the series that are used are the cyclical components of the original series.

Below, we describe the Granger causality test procedure in more detail.

3.1. Granger Causality

We test for Granger Causality (GC) between each of the potential leading indicators and the non-agricultural unemployment rate. Under Granger framework, test of causality running from X to Y is the test of whether lagged values of X improve the forecast of Y over the information provided by the lagged values of Y alone (Granger, 1969). In other words, GC tests the predictive power of X in the equation for Y. More formally, within the two variable simple causal model framework, definition of GC is as follows;

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t^{'} \quad (1)$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \varepsilon_t^{''} \quad (2)$$

Definition: Let Ω denote the information set available at time t. If the prediction error for the variable Y is larger when X is excluded from the information set, then, we say that X is causing Y.

Looking at equations, definition of causality implies X Granger causes Y if $c_j \neq 0$ for some j. Similarly Y causes X if $b_j \neq 0$ for some j. If both of these events occur, there is said to be a feedback relationship between X and

[8] Most of the series are detrended from 2005 onwards. Industrial production and unemployment rate data is available at lower frequencies before 2005. We make use of this additional data to better HP filter these series. As such, for IPI, we linearly interpolate the quarterly data from 2000Q1 to 2004Q4 to change the frequency to monthly and merge that with the monthly data from 2005 onwards. Unemployment data, on the other hand, is available from 1988 to 1999 in biannual frequency and from 2000 to 2004 in quarterly frequency. We first convert the quarterly data to monthly using linear interpolation then implement the same technique for the biannual data. After filtering, we use data after 2005.

Y. In practice, given that the residuals from these equations are uncorrelated white noise series, once the optimal lag (m) is determined, standard F-test could be used to test the restriction that coefficients of the lagged values of variable X on the variable Y are jointly equal to zero.

Lag selection is an important step in the testing process. One widely used approach is to estimate the equation system as defined above in a Vector Auto Regression (VAR) framework, varying lag order from one up to a predetermined upper limit. Then, the optimal lag is determined using one of the model selection criteria, mostly Akaike (AIC) or Schwartz Information Criteria (SIC).

We proceed as follows: Given that our sample is small, we use single equation sequential testing procedure proposed by Hsiao (1981), which is based on Granger's concept of causality and Akaike's final prediction error (AFPE) criterion (Equation 3).[9] We prefer single equation testing over a VAR-based lag selection as the number of parameters grows with the square of the number of variables in VAR approach, and hence exhausting the degrees of freedom. First, we run an autoregressive model for variable X and determine the optimal lag order using SIC.

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{n} b_j Y_{t-j} + u_t \qquad (3)$$

Next, given the optimal lag for X, we add lags of Y and run the model by varying lags from one to the maximum order. And then, we choose the optimal lag order for Y based on SIC. According to Hsiao (1981)'s methodology for testing GC, we compare SIC of the autoregressive process for variable X with that of the model estimated including the lags of variable Y. If the former is greater than the latter, we say that Y Granger causes X and the optimal model for predicting X is the one including m lags of X and n lags of Y. Along with this methodology, we also test the joint significance of the lagged values of Y. Instead of standard F-test, we use Wald test, which is robust to serial correlation.[10] We prefer Wald test as our equations may suffer from serially correlated residuals due to overlapping data problem associated with the unemployment rate. More specifically, unemployment rate represents three month survey results even though it is announced at a monthly frequency.

[9] In the original paper AIC is used as a selection criteria. We prefer to use SIC because it performs better in terms of choosing the correct model when there is serial correlation in the residuals (Hurvich and Tsai, 1996).
[10] Coefficient covariance matrix used in Wald test is the robust and consistent estimator for autocorrelated disturbances as suggested by Newey and West (1987).

4. Results

To determine whether the series in consideration can be employed as a leading indicator, we carry out three different types of analysis. The first one is based on GC test results, while the second one is on the correlation structure between the series and the target. Additionally, we look at the out of sample forecast performance of the candidate series. In Section 4.1, we discuss the results for series that Granger cause the unemployment rate based on the methodology described in the previous section. In Section 4.2, we interpret the association of the series with the unemployment rate using cross correlation analysis. In Section 4.3, we determine the series that improve forecast of the benchmark model based on Root Mean Square Error (RMSE) measure. Then, we use results of these analyses to form composite leading indicators and interpret their one period ahead forecast performance.

4.1. Granger Causality Test Results

GC test requires that series must be covariance stationary. Thus, as a first step, stationarity of the transformed variables is tested using methodology proposed by Phillips and Perron (1988), which allow us to control the serial correlation in the residuals. Appendix Table A.1 reports our unit root test results for all the series, using Phillips-Perron specification.[11] As reported in Table A.1, the presence of the unit root is rejected at 5-percent significance level for most of the variables. Even though the series may be stationary in the longer run, our short data span may lead to misleading test results. Hence, we include failed series as well.[12]

GC test results that follow from the procedure mentioned in the previous section are displayed in Table 2. Only the series that both pass Wald test and SIC criteria are reported here. We find that majority of Business Tendency Survey indexes Granger cause the unemployment rate. For ease of presentation, we only display aggregated indexes (others can be found in Appendix Table 6.2). Among indicators of economic activity, industrial production index, value added tax on imports and developing countries based REER Granger cause the unemployment rate. Indicators of global outlook are also informative. As for labor market indicators, Kariyer.net vacancies pass GC test. Among indicators regarding credits, only TL denominated commercial credit fulfills the criteria for passing the GC test. Some of the series only partially fulfill the criteria for passing GC Test. Although lags of these series are jointly significant in the equation for the unemployment rate, they fail the SIC criteria proposed by Hsiao (1981). These indicators given in Table A.2 are unemployment insurance claims

[11] Since these series are already detrended, we include only a constant term when performing the test.

[12] We have also tested for a unit root in the series using Augmented Dickey-Fuller (ADF) test. In that case, for all the series, presence of a unit root is rejected at 5 percent.

from ISKUR, non-farm average working hours and number of quits from HLFS and quarterly change in commercial credits denominated in FX.

Table 2. Test Results and Diagnostics for Series that Pass Granger Causality Test

	Wald Test Statistic	Lag Target	Lag Series	R2	LM Test Prob. (Max)	LM Test Prob. (Min)	SIC (Base)	SIC (Base+)
Industrial Production Index	14.67	2	1	0.88	0.41	0.07	0.990	0.857
Kariyer.net Vacancies/NFLF	35.5	2	3	0.88	0.59	0.01	0.990	0.960
European Economic Tendency Index	4.68	2	1	0.86	0.65	0.04	0.990	0.967
German Economic Tendency Index	4.84	2	1	0.86	0.55	0.05	0.990	0.960
OECD-Europe CLI	4.78	2	1	0.86	0.61	0.04	0.990	0.962
OECD CLI	4.92	2	1	0.86	0.57	0.05	0.990	0.962
USA CLI	4.92	2	1	0.86	0.62	0.04	0.990	0.970
Value Added Tax on Imports/NGDP	14.46	2	3	0.87	0.72	0.04	0.990	0.975
Developing Countries Based REER	4.79	2	1	0.86	0.61	0.07	0.990	0.972
TL Denominated Commercial Credit /NGDP	4.51	2	1	0.86	0.29	0.04	0.990	0.956
Non-weighted EP	9.43	2	1	0.88	0.10	0.00	0.990	0.869
Non-weighted EE	13.99	2	1	0.87	0.16	0.02	0.990	0.872
Non-weighted EO	12.75	2	1	0.88	0.12	0.00	0.990	0.838
Weighted EP	18.34	2	1	0.89	0.73	0.03	0.990	0.947
Weighted EO	16.57	2	1	0.90	0.85	0.02	0.990	0.927

Note: Note: For each equation, the first column is the Wald test statistic concerning the joint significance of the lags of the explanatory variable. This test statistic is compared with the cut of value from the Chi-squared distribution at 5 percent. Following columns are; optimal lag lengths for the dependent and explanatory variable; minimum and maximum LM test probabilities from the residual serial correlation tests for lags from one up to 12; SIC of the autoregressive equation that only includes the lags of the dependent variable (SIC Base) and that of equations that include both variables (SIC Base +).

4.2. Cross Correlation Analysis

In this section we investigate the correlation between the unemployment rate and leads and lags of the candidate indicators, up to 12 lags. This exercise provides valuable information on the cyclical association of the candidate series with the target. We require correlations to be significant at 1 percent, and variables to lead the target. The location of the highest significant correlation is an indicator of the average lead time. However, for this information to be reliable, we would expect to observe cluster of strong correlations that are in the neighborhood of the highest correlation. Therefore, along with the location of highest correlation, we also check that of the second and third, to be consistent. Results for the series that lead the unemployment rate at 1 percent significance level are presented in Table 3, while the results for the rest are given in Appendix Table A.3. Similar to the GC test results, most of the BTS series satisfy the criteria as defined above.

Since their results are similar to the aggregate indexes, they are also given in the appendix for ease of display.

Table 3. Correlation Structure of Selected Variables

	Contemporaneous Correlation	Correlation Values Highest	2nd Highest	3rd Highest	Correlation Lags Highest	2nd Highest	3rd Highest	Lead/Lag Structure
Industrial Production Index	-0.71*	-0.76*	-0.73*	-0.71*	-1	-2	0	leads
Unemployment Insurance Claims/NFLF	0.68*	0.7*	0.68*	0.68*	-1	0	-2	leads
ISKUR Newly Registered Unemployed/NFLF	0.24**	0.63*	0.58*	0.55*	-5	-6	-4	leads
Kariyer.net Vacancies/NFLF	-0.7*	-0.75*	-0.7*	-0.68*	-1	0	-2	leads
Turkish Consumer Confidence Index	0.07	-0.55*	-0.53*	-0.52*	-9	-10	-8	leads
European Economic Tendency Index	-0.43*	-0.54*	-0.53*	-0.52*	-3	-2	-4	leads
German Economic Tendency Index	-0.44*	-0.56*	-0.55*	-0.54*	-3	-2	-4	leads
OECD-Europe CLI	-0.41*	-0.56*	-0.55*	-0.54*	-3	-4	-2	leads
OECD CLI	-0.45*	-0.55*	-0.55*	-0.52*	-2	-3	-4	leads
USA CLI	-0.49*	-0.54*	-0.53*	-0.51*	-2	-1	-3	leads
Value Added Tax on Imports/NGDP	-0.41*	-0.41*	-0.4*	-0.39*	0	-3	-1	coincident
Number of Firm Entry	-0.35*	-0.54*	0.53*	-0.53*	-4	6	-3	leads
Number of Firm Exits	-0.18	-0.46*	-0.45*	-0.45*	-6	-7	-5	leads
Net Number of Firm Entry	-0.31*	-0.43*	-0.42*	-0.41*	-3	-2	-4	leads
Discouraged Workers/NFLF	0.72*	0.72*	0.66*	0.62*	0	-1	1	coincident
Developing Countries Based REER	-0.31*	-0.43*	-0.42*	-0.4*	-2	-3	-1	leads
Non-weighted EP	-0.37*	-0.62*	-0.59*	-0.56*	-2	-3	-1	leads
Non-weighted EE	-0.45*	-0.69*	-0.67*	-0.62*	-2	-3	-1	leads
Non-weighted EO	-0.39*	-0.65*	-0.62*	-0.58*	-2	-3	-1	leads
Non-weighted EUC	-0.69*	-0.69*	-0.69*	-0.61*	0	1	-1	coincident
Weighted EP	-0.25**	-0.74*	-0.7*	-0.68*	-3	-4	-2	leads
Weighted EE	-0.58*	-0.79*	-0.79*	-0.73*	-2	-3	-4	leads
Weighted EO	-0.27**	-0.76*	-0.72*	-0.7*	-3	-4	-2	leads
Number of Layoffs /NFLF	0.83*	0.83*	0.81*	0.73*	0	1	-1	coincident
Number of Quits /NFLF	0.46*	0.46*	0.43*	0.36*	0	-1	1	coincident
Capacity Utilization Rate	-0.74*	-0.74*	-0.69*	-0.67*	0	-1	1	coincident
Kariyer.net Job Application per Vacancy	0.76*	0.76*	0.72*	0.7*	0	1	-1	coincident
Quarterly change (QC) in consumer credits/ Quarterly NGDP	-0.34*	-0.37*	-0.36*	-0.34*	-1	-2	0	leads
QC mortgage/Quarterly NGDP	-0.26**	-0.33*	-0.31*	-0.31*	-2	-3	-1	leads
QC consumer credits and credit cards/Quarterly NGDP	-0.37*	-0.39*	-0.37*	-0.37*	-1	0	-2	leads
QC commercial credit denominated in TL/Quarterly NGDP	-0.43*	-0.47*	-0.46*	-0.45*	-2	-1	-3	leads
QC commercial credit denominated in FX/Quarterly NGDP	-0.65*	-0.7*	-0.65*	-0.65*	-1	-2	0	leads

Note: * and ** indicate statistical significance at the 1 and 5 percent level.

We find that many of the indicators that pass the GC test also have strong correlation between their lagged values and the unemployment rate. These series are industrial production index, kariyer.net vacancies data, indicators for global economic conditions, and aggregate BTS series. In addition, unemployment insurance claims, ISKUR newly registered unemployed data, number of firm entry, QC in commercial credit denominated in FX and TL, and Turkish consumer confidence index are found to lead the target, whereas capacity utilization rate, Kariyer.net job application per vacancy, discouraged workers and number of layoffs and quits are coincident with the unemployment rate.[13]

4.3. Forecast Performances of Candidate Series

We also investigate the forecast performance of candidate series. Forecast performance of individual series is measured by root mean square error (RMSE) of the forecasts relative to a benchmark model. As benchmark, we model unemployment rate as an autoregressive process and based on Schwarz Information Criterion (SIC), the process is AR(2). Then, we estimate another equation to forecast the unemployment rate by including lags of unemployment rate and a candidate series. The optimal lag of unemployment rate and the candidate series are again chosen based on SIC. In estimated models autocorrelation and heteroscedasticity corrected covariance matrices are used to account for possible serial correlation in the residuals.

We use root mean square errors (RMSE) to measure forecast performances. As such, we run forecast models for 12 consecutive periods and compute the average RMSE for these 12 data points. Since we need the realization of the unemployment rate to compute RMSE values and data for unemployment rate end in March 2013, our forecasting period starts from April 2012. Resulting relative RMSE values, as well as the R^2 values, for series that outperform the benchmark are provided in Table 4.

[13] Developing countries based REER also has a significant correlation coefficient and leads the target but the sign of the correlation is the opposite of what is expected.

Table 4. Forecast Performance of Single Variables

Explanatory variable	R2	RRMSE	Explanatory variable	R2	RRMSE
Benchmark Model	0.864	1	First Time Job Seekers/NFLF	0.882	0.975
Weighted EE	0.893	0.933	Kariyer.net Job Application per Vacancy	0.868	0.980
German Economic Tendency Index	0.875	0.943	Purchasing Managers' Index for Employment	0.869	0.986
ISKUR Newly Registered Unemployed/NFLF	0.867	0.946	Non-weighted EP	0.89	0.991
Non-weighted EE	0.890	0.951	Turkish Consumer Confidence Index	0.866	0.992
European Economic Tendency Index	0.874	0.957	Kariyer.net Job Application/NFLF	0.865	0.996
QC commercial credit denominated in TL/Quarterly NGDP	0.870	0.966	TL Denominated Commercial Credit /NGDP	0.878	0.996
QC commercial credit denominated in FX/Quarterly NGDP	0.879	0.969	Non-weighted EO	0.899	0.996
OECD-Europe CLI	0.875	0.970	Number of Layoffs/NFLF	0.883	0.997
Domestic Value Added Tax/NGDP	0.865	0.971	FX Denominated Commercial Credit /NGDP	0.866	0.997
Discouraged Workers/NFLF	0.866	0.975			

Note: RMSE of the benchmark model is 0.223. Benchmark forecasting equation is AR(2). All but one (First Time Job Seekers/NFLF) of the remaining forecasting equations contain two lags of the target and one lag of the related variable.

4.4. Composite Indexes

Following the literature, we compute different composite indexes. In constructing of composite indexes, we need to decide on the aggregation method. Following OECD's approach, we construct composite indexes using simple averaging. However, notice that since the series are normalized by their standard errors, simple average aggregation implicitly implies an aggregation weighted by the standard errors of the series. Even though there are different ways of aggregating series into a composite index (see Marcellino, 2006), we choose this simple method as it is practical and there is no strong evidence in favor of other ways.[14]

We begin with series that pass the GC test. Note that among them, there are group of series that measure relatively similar concepts, and including all of them would implicitly increase their weight in the composite index. Hence, from such groups we select few that are prominent in terms of fulfilling the GC criteria and representative. Among indicators that measure economic activity abroad, we use German Economic Tendency Index and OECD CLI. We also exclude net number of firm entry as we already include number of entrant firms. Among BTS indicators passing GC test, we only use aggregated indexes as they are representative of the overall survey. Within aggregate indexes, expected production and expected orders are

[14] We also did weighted averaging using the highest correlation value between the target and the series as weights. For some of the composite indexes there was only a slight improvement.

highly correlated. Thus among the two series we only include expected orders. Some of the series that are reported to pass GC test in Table 2 are also Granger caused by the target. Since this may potentially mitigate the performance of the leading composite index, we also construct an alternative composite index that excludes these series. By filtering series in the aforementioned way we form two composites based on GC test results (GC-I and GC-II).

Similarly, we construct a composite index (Corr-I) from series that have desired cross correlation structures as displayed in Table 3. In doing so, among the series that have similar information context, we select only some of them as opposed to using them all. Notice that some of the series in Table 3 are coincident with the target. Therefore, to enhance the leading property of the composite index, we construct an alternative index excluding such series (Corr-II).

We also construct a composite index (FP) that contains only series that improve forecast performance over the benchmark model. Computation of the RMSE measure and the benchmark model are same as those used for evaluating individual series' performances in Section 4.3. Details regarding indicators that are used to construct each composite index are provided in Appendix Table A.4.

Table 5 also reports relative predictive power of the composite indexes. Only the composite index composed of series that have marginal predictive power (FP) performs better than the benchmark model in terms of RMSE. It improves benchmark model's performance by 17 percent.

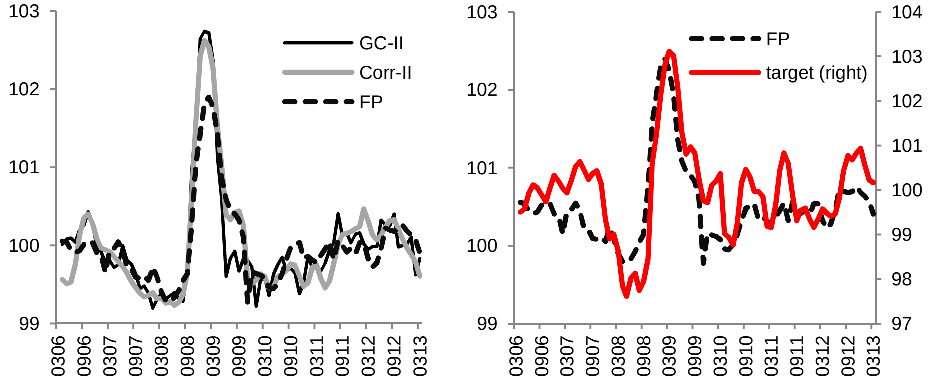
Table 5. Forecast Performances of Composite Indexes

Explanatory variable	R2	RRMSE
Benchmark Model	0.864	1
GC-I	0.892	1.038
GC-II	0.898	1.068
Corr-I	0.888	1.126
Corr-II	0.889	1.088
FP	0.892	0.833

Note: RMSE of the benchmark model is 0.223. Benchmark forecasting equation is AR(2). All of the forecasting equations contain two lags of the target and one lag of the related composite index.

Figure 1 compares best performing composite index with those based on Granger causality and correlation analysis (left panel), as well as with the unemployment rate over the sample period (right panel). Although they follow a similar trend, there are differences in terms of magnitudes of cyclical movements between composite indexes. Even with the best performing index, high frequency movements of the unemployment rate are captured to a limited extent. One possible explanation could be that our indicators may not successfully capture high frequency movements in unemployment that are driven by movements in participation to the labor force, which is highly volatile in the Turkish labor market.

Figure 1. Composite Indexes

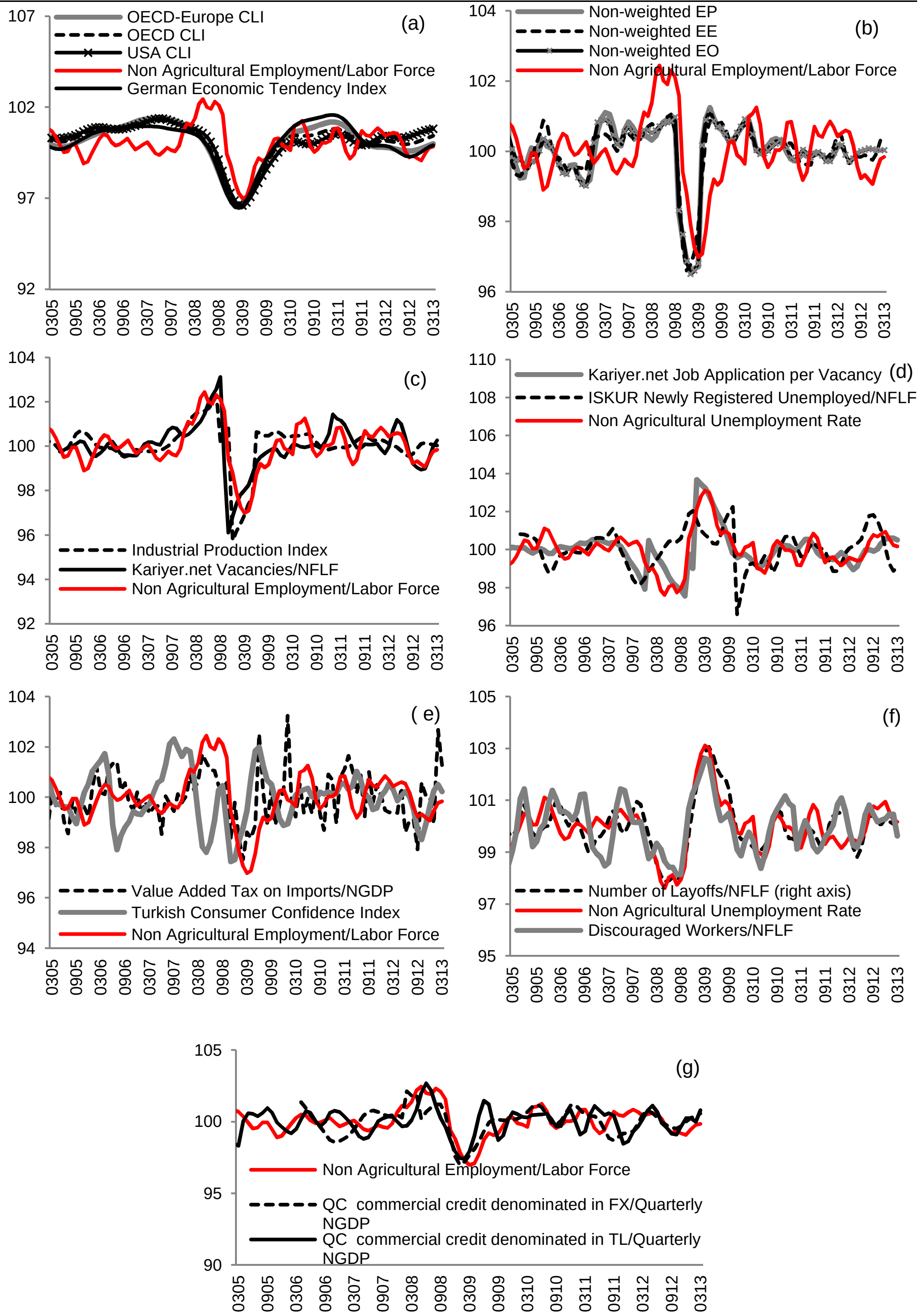


Note: Series are seasonally adjusted, de-trended and normalized.

5. Overall Evaluation and Conclusion

This paper analyses an extended set of variables regarding Turkish economy in search of leading indicators for the non-agricultural unemployment rate. As such, we employ Granger causality test, cross correlation analysis and individual out of sample predictive power of candidate variables. We use seasonally adjusted, outlier detected, HP detrended and standardized series to carry out these analyses.

Figure 2. Selected Series and the Target



Note: Series are seasonally adjusted, de-trended and normalized.

Based on Granger causality tests, cross correlations, and forecast performances, some of the series stand out as the leading indicators of the unemployment rate. Series that indicate the global economic conditions, namely German and European Economic Tendency Indexes, and OECD-Europe CLI, emerge as good indicators of the movements in unemployment based on all of the three methods. Figure 2.a displays these series together with the employment to labor force ratio. Business tendency survey data also passes all three means of testing the informativeness of the candidate series. Their movements with the employment to labor force ratio is displayed in Figure 2.b

Series that are directly linked to the labor markets cannot pass all three tests. Among those, Kariyer.net vacancies data, ISKUR's registered newly unemployed series, Kariyer.net job application per vacancy satisfy the criteria of two out of three methods. Movement of these series along with other series that perform well with respect to at least two of the methods, namely VAT on imports, consumer confidence index, discouraged workers, number of layoffs, QC in commercial credits denominated in TL and FX, are also displayed in Figure 2.

Finally, we construct several composite indexes using series that are found to be informative and compare these composite indexes by their performance to forecast the unemployment rate. Only the composite index constructed based on individual out of sample forecast performance improve upon the benchmark model which is an AR(2) process of the unemployment rate. It improves forecast performance by 17 percent.

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Appendix

Table A.1. Philips-Perron Test Results

	Test Statistic			Test Statistic	
Unemployment rate	-2.94	**	Non-Durable goods EP	-2.74	***
Non-farm unemployment rate	-3.04	**	Non-Durable goods EE	-4.48	*
Industrial production index	-5.49	*	Non-Durable goods EO	-2.9	***
Unemployment insurance claims/Non-farm labor force(NFLF)	-3.31	**	Non-Durable goods EUC	-3.56	*
Vacancies (private sector)/NFLF	-3.61	*	Consumer goods EP	-3.45	**
Job applications/NFLF	-3.84	*	Consumer goods EE	-3.27	**
Vacancies (private sector)/Job applications	-3.6	*	Consumer goods EO	-2.94	**
Kariyer.net vacancies/NFLF	-3.53	*	Consumer goods EUC	-3.2	**
Turkish consumer confidence index	-2.96	**	Food and beverages EP	-2.59	***
European economic tendency index	-2.58	***	Food and beverages EE	-2.79	***
German economic tendency index	-2.7	***	Food and beverages EO	-2.81	***
OECD Europe composite leading indicators(CLI)	-2.67	***	Food and beverages EUC	-2.1	
OECD CLI	-2.68	***	Non-weighted EP	-4.3	*
USA CLI	-2.54		Non-weighted EE	-4.13	*
Domestic value added tax/Nominal gross domestic product (NGDP)	-19.75	*	Non-weighted EO	-4.42	*
Value added tax on imports/NGDP	-9.5	*	Non-weighted EUC	-4.31	*
Number of firm entry	-5.06	*	Weighted EP	-2.6	***
Number of firm exits	-4.93	*	Weighted EE	-2.00	
Number of net firm entry	-4.88	*	Weighted EO	-3.09	**
Discouraged workers/NFLF	-3.9	*	Weighted EUC	-3.01	**
Developing Countries Based Real Effective Exchange Rate (REER)	-3.8	*	Non-farm average working hours	-4.52	*
Developed Countries Based REER	-3.63	*	First time job seekers/NFLF	-3.22	**
Consumer credits/NGDP	-5.4	*	Number of layoffs/NFLF	-2.98	**
Mortgage/NGDP	-6.06	*	Number of quits/NFLF	-2.89	***
Vehicle credit/NGDP	-4.67	*	Purchasing Managers' Index for Employment	-3.96	*
Consumer credits and credit cards/NGDP	-6.08	*	Capacity utilization rate	-3.29	**
TL denominated commercial credit /NGDP	-4.09	*	Kariyer.net number of job application/NFLF	-3.04	**
FX denominated commercial credit /NGDP	-2.57		Kariyer.net number of job application per vacancy	-3.55	*
Intermediate goods EP	-2.84	***	Quarterly change (QC) in consumer credits/ Quarterly NGDP	-3.68	*
Intermediate goods EE	-2.68	***	QC mortgage/Quarterly NGDP	-3.45	**
Intermediate goods EO	-2.82	***	QC vehicle credit/Quarterly NGDP	-5.13	*
Intermediate goods EUC	-2.42		QC consumer credits and credit cards/Quarterly NGDP	-3.45	**
Investment goods EP	-3.38	**	QC commercial credit denominated in TL/Quarterly NGDP	-3.35	**
Investment goods EE	-3.46	**	QC Commercial credit denominated in FX/Quarterly NGDP	-3.09	**
Investment goods EO	-3.63	*			
Investment goods EUC	-2.73	***			
Durable goods EP	-4.18	*			
Durable goods EE	-4.02	*			
Durable goods EO	-2.65	***			
Durable goods EUC	-13.29	*			

Note: * , ** and *** indicate statistical significance at the 1, 5 and 10 percent level.

Table A.2. Test Results and Diagnostics for Series that Fail Granger Causality Test

	Wald Test Statistic	Lag Target	Lag Series	R2	LM Test Prob. (Max)	LM Test Prob. (Min)	SIC (Base)	SIC (Base+)
Causality: Series GC Target (Series that Pass Wald Test but fail SIC criteria)								
Unemployment Insurance Claims/NFLF	9.64	2	2	0.87	0.56	0.01	0.991	1.009
ISKUR Newly Registered Unemployed/NFLF	353.13	2	6	0.89	0.37	0.03	0.991	1.029
Intermediate Goods EUC	5.5	2	1	0.86	0.84	0.13	0.991	1.210
Investment Goods EP	8.71	2	1	0.88	0.94	0.00	0.991	1.117
Durable Goods EP	7.06	2	1	0.87	0.73	0.22	0.991	1.174
Non-Durable Goods EP	5.95	2	1	0.87	0.79	0.22	0.991	1.137
Food&Beverages EP	4.73	2	1	0.88	0.79	0.13	0.991	1.117
Food&Beverages EO	4.44	2	1	0.87	0.42	0.09	0.991	1.127
Weighted EE	10.3	2	1	0.88	0.55	0.05	0.991	1.054
Non-farm Average Working Hours	4.23	2	1	0.85	0.75	0.05	0.991	1.028
Number of Quits and Layoffs/NFLF	31.57	2	4	0.87	0.37	0.11	0.991	1.003
QC commercial credit denominated in FX/Quarterly NGDP	6.54	2	1	0.87	0.24	0.00	0.991	1.056
No causality								
Vacancies (private sector)/NFLF	0.00	2	1	0.85	0.78	0.03	0.991	1.070
Vacancies/Newly Registered Unemployed (ISKUR, private sector)	0.44	2	1	0.85	0.74	0.01	0.991	1.065
Turkish Consumer Confidence Index	1.4	2	1	0.86	0.52	0.02	0.991	1.023
Domestic Value Added Tax/NGDP	0.92	2	1	0.85	0.67	0.04	0.991	1.034
Number of Firm Entry	2.72	2	1	0.86	0.59	0.01	0.991	0.996
Number of Firm Exits	2.05	2	1	0.86	0.77	0.00	0.991	1.010
Net Number of Firm Entry	1.42	2	1	0.86	0.69	0.00	0.991	1.007
Discouraged Workers/NFLF	0.57	2	1	0.85	0.64	0.05	0.991	1.033
Developed Countries Based REER	1.47	2	1	0.85	0.73	0.05	0.991	1.030
Consumer Credits/NGDP	0.59	2	1	0.85	0.63	0.04	0.991	1.030
Mortgage/NGDP	0.35	2	1	0.85	0.73	0.03	0.991	1.036
Vehicle Credit/NGDP	1.17	2	1	0.86	0.60	0.03	0.991	1.016
Consumer Credits & Credit Cards/NGDP	1.5	2	1	0.86	0.38	0.01	0.991	1.010
FX Denominated Commercial Credit /NGDP	0.27	2	1	0.86	0.82	0.05	0.991	1.111
Investment Goods EUC	2.05	2	1	0.86	0.91	0.14	0.991	1.230
Durable Goods EE	1.22	2	1	0.86	0.76	0.12	0.991	1.238
Durable Goods EO	0.29	2	1	0.86	0.95	0.06	0.991	1.260
Durable Goods EUC	1.9	2	1	0.86	0.97	0.09	0.991	1.263
Non-Durable Goods EUC	0.97	2	1	0.86	0.98	0.10	0.991	1.255
Consumer Goods EUC	3.73	2	1	0.86	0.97	0.13	0.991	1.238
Food and Beverages EUC	2.12	2	1	0.86	0.96	0.11	0.991	1.236
Non-weighted EUC	2.42	2	1	0.86	0.77	0.05	0.991	1.022
Weighted EUC	3.1	2	1	0.86	0.98	0.11	0.991	1.233
First Time Job Seekers/NFLF	0.44	2	1	0.85	0.75	0.04	0.991	1.033
Number of Layoffs/NFLF	5.1	2	2	0.86	0.37	0.06	0.991	0.997
Purchasing Managers' Index for Employment	2.01	2	1	0.86	0.67	0.05	0.991	1.047
Capacity Utilization Rate	1.02	2	1	0.86	0.83	0.11	0.991	1.244
Kariyer.net Job Application/NFLF	0.94	2	1	0.85	0.77	0.04	0.991	1.063
Kariyer.net Job Application per Vacancy	1.39	2	1	0.86	0.70	0.01	0.991	1.008
Quarterly change (QC) in consumer credits/ Quarterly NGDP	1.64	2	1	0.86	0.69	0.05	0.991	1.023
QC mortgage/Quarterly NGDP	1.54	2	1	0.85	0.65	0.04	0.991	1.025
QC vehicle credit/Quarterly NGDP	1.01	2	1	0.85	0.72	0.04	0.991	1.031
QC consumer credits and credit cards/Quarterly NGDP	1.7	2	1	0.86	0.68	0.06	0.991	1.023
QC commercial credit denominated in TL/Quarterly NGDP	1.13	2	1	0.86	0.68	0.01	0.991	1.016

Note: See the note below Table 2.

Table A.3. Correlation Structure of Candidate Series

	Contemporaneous Correlation	Correlation Values Highest	2nd Highest	3rd Highest	Correlation Lags Highest	2nd Highest	3rd Highest	Lead/Lag Structure
Vacancies (private sector)/NFLF	-0.21 **	-0.29 *	-0.27 **	0.26 **	1	2	12	lags
Vacancies/Newly Registered Unemployed (ISKUR, private sector)	-0.29 *	0.4 *	0.34 *	-0.32 *	12	11	-5	lags
Domestic Value Added Tax/NGDP	0.08	-0.13	-0.12	-0.11	7	9	8	lags
Developed Countries Based REER	-0.26 **	-0.26 **	-0.26 **	0.25 **	-1	0	12	leads
Consumer Credits/NGDP	0.08	0.26 **	-0.23 **	-0.22 **	-12	8	7	leads
Mortgage/NGDP	0.11	0.2 **	0.12	0.11	-12	-11	0	leads
Vehicle Credit/NGDP	0.16	-0.4 *	-0.4 *	-0.4 *	10	9	11	lags
Consumer Credits and Credit Cards/NGDP	0.18	-0.38 *	-0.37 *	-0.34 *	8	7	9	lags
TL Denominated Commercial Credit /NGDP	0.2 **	-0.51 *	-0.5 *	-0.47 *	7	8	6	lags
FX Denominated Commercial Credit /NGDP	-0.23 **	-0.57 *	-0.56 *	-0.53 *	4	5	6	lags
Intermediate Goods EP	-0.35 *	-0.76 *	-0.73 *	-0.69 *	-3	-2	-4	leads
Intermediate Goods EE	-0.57 *	-0.77 *	-0.75 *	-0.72 *	-2	-3	-1	leads
Intermediate goods EO	-0.34 *	-0.76 *	-0.72 *	-0.7 *	-3	-2	-4	leads
Intermediate Goods EUC	-0.63 *	-0.63 *	-0.61 *	-0.6 *	0	-1	1	coincident
Investment Goods EP	0.06	-0.67 *	-0.64 *	-0.58 *	-4	-5	-3	leads
Investment Goods EE	-0.38 *	-0.79 *	-0.74 *	-0.73 *	-3	-2	-4	leads
Investment Goods EO	-0.07	-0.58 *	-0.55 *	-0.49 *	-3	-4	-2	leads
Investment Goods EUC	0.03	-0.39 *	-0.38 *	0.38 *	5	6	-4	lags
Durable Goods EP	-0.22 **	0.58 *	0.51 *	0.49 *	5	6	4	lags
Durable Goods EE	-0.48 *	-0.55 *	-0.55 *	-0.49 *	-2	-2	-3	leads
Durable Goods EO	0.03	0.44 *	-0.44 *	0.43 *	9	-10	8	lags
Durable Goods EUC	0.02	-0.2 **	-0.19	-0.15	-10	-9	-11	leads
Non-Durable Goods EP	-0.37 *	0.68 *	0.67 *	-0.65 *	7	8	-3	lags
Non-Durable Goods EE	-0.48 *	-0.69 *	-0.66 *	-0.62 *	-2	-3	-1	leads
Non-Durable Goods EO	-0.53 *	-0.78 *	-0.76 *	-0.7 *	-2	-3	-1	leads
Non-Durable Goods EUC	-0.15	0.27 **	0.27 **	0.24 **	-11	-10	-12	leads
Consumer Goods EP	-0.44 *	-0.66 *	-0.63 *	0.59 *	-2	-3	6	leads
Consumer Goods EE	-0.56 *	-0.75 *	-0.7 *	-0.69 *	-2	-1	-3	leads
Consumer Goods EO	-0.48 *	-0.75 *	-0.73 *	-0.67 *	-2	-3	-4	leads
Consumer Goods EUC	-0.24 **	-0.33 *	-0.32 *	0.31 *	-3	-2	-12	leads
Food&Beverages EP	-0.44 *	0.82 *	0.8 *	0.76 *	8	7	9	lags
Food&Beverages EE	-0.61 *	-0.8 *	-0.78 *	-0.74 *	-2	-3	-1	leads
Food&Beverages EO	-0.56 *	-0.72 *	0.69 *	-0.68 *	-2	8	-1	leads
Food&Beverages EUC	-0.38 *	-0.39 *	-0.38 *	-0.38 *	-1	-2	0	leads
Weighted EUC	-0.37 *	0.54 *	0.49 *	-0.39 *	12	11	-1	lags
Non-farm Average Working Hours	-0.12	0.26 **	0.25 **	0.18	8	9	10	lags
First Time Job Seekers/NFLF	0.2 **	-0.24 **	-0.21 **	-0.21 **	-12	-11	6	leads
Purchasing Managers' Index for Employment	-0.45 *	0.64 *	0.59 *	-0.57 *	6	7	-2	lags
Kariyer.net Job Application/NFLF	0.2 **	-0.45 *	-0.43 *	-0.42 *	11	10	12	lags
QC vehicle credit/Quarterly NGDP	-0.21 **	-0.23 **	-0.22 **	-0.21 **	-1	-2	0	leads

Note: * and ** indicate statistical significance at the 1 and 5 percent level.

Table A.4. Composite Index Descriptions

	GC-I	GC-II	Corr-I	Corr-II	FP
Industrial Production Index	1	1	1	1	0
Unemployment Insurance Claims/NFLF	0	0	1	1	0
ISKUR Newly Registered Unemployed/NFLF	0	0	1	1	1
Kariyer.net Vacancies/NFLF	1	0	1	1	0
Turkish Consumer Confidence Index	0	0	1	1	1
German Economic Tendency Index	1	0	1	1	1
OECD-Europe CLI	0	0	0	0	1
OECD CLI	1	1	1	1	0
Domestic Value Added Tax/NGDP	0	0	0	0	1
Value Added Tax on Imports/NGDP	1	0	1	0	0
Number of Firm Entry	0	0	1	1	0
Number of Firm Exits	0	0	1	1	0
Discouraged Workers/NFLF	0	0	1	0	1
Developing Countries Based REER	1	1	1	1	0
Consumer Credits and Credit Cards/NGDP	0	0	0	0	1
TL Denominated Commercial Credit /NGDP	1	1	0	0	1
FX Denominated Commercial Credit /NGDP	0	0	0	0	1
Non-weighted EE	1	1	1	1	1
Non-weighted EO	1	1	1	1	1
Non-weighted EUC	0	0	1	0	0
First Time Job Seekers/NFLF	0	0	0	0	1
Number of Layoffs and Quits/NFLF	0	0	1	0	1
Purchasing Managers' Index for Employment	0	0	0	0	1
Capacity Utilization Rate	0	0	1	0	0
Kariyer.net Job Application/NFLF	0	0	0	0	1
Kariyer.net Job Application per Vacancy	0	0	1	0	1
Quarterly change (QC) in consumer credits/ Quarterly NGDP	0	0	1	1	0
QC mortgage/Quarterly NGDP	0	0	1	1	0
QC consumer credits and credit cards/Quarterly NGDP	0	0	1	1	0
QC commercial credit denominated in TL/Quarterly NGDP	0	0	1	1	1
QC commercial credit denominated in FX/Quarterly NGDP	0	0	1	1	1

Note: These are all the series that pass either GC, cross correlation analysis or forecast evaluation based on RRMSE. In the table, 1 (0) indicates that series is included in (excluded from) the composite index.