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Research Notes in Economics

Weekly Economic Conditions Index for Turkey

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Özet

Bu çalışmada, günlük ve haftalık olarak açıklanan yüksek frekanslı veriler kullanılarak iktisadi faaliyetteki gelişmeleri zamanlı olarak izlemeye imkân veren haftalık frekansta oluşturulmuş bir endeks tanıtılmaktadır. Krediler, banka ve kredi kartıyla yapılan harcamalar, iş ilanları, elektrik tüketimi ve dış ticaret verilerinin haftalık frekansta yıllık yüzde değişimlerinden oluşturulan endeks yardımıyla koronavirüs pandemisinin iktisadi faaliyet üzerine etkileri analiz edilmiştir. Endeks, pandemiye bağlı etkilerin Mart ayının ikinci yarısından itibaren iktisadi faaliyeti olumsuz etkilediğine, Mayıs ayı ile birlikte ise dipten dönüş sinyallerinin başladığına işaret etmektedir. Endeksin milli gelir büyümesini takip etmekte faydalı olduğu bulunmuştur. Bu çerçevede, veri akışı ile birlikte haftalık olarak güncellenebilen endeks kısa dönemli milli gelir tahminlerinde kullanılabilecektir.

Abstract

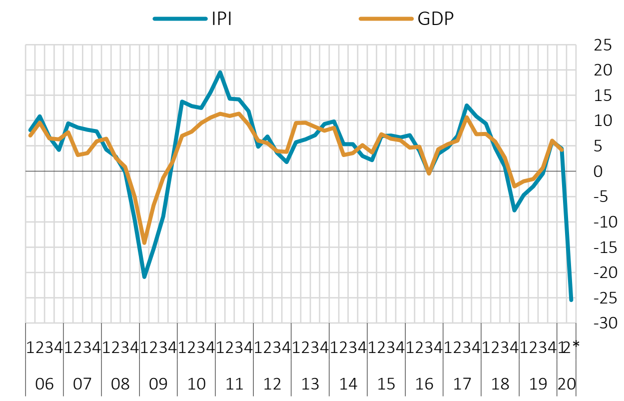
In this study, a weekly index that aims tracking developments in economic activity in a timely manner is introduced. The index is formed by using weekly annual percentage changes of credit growth, expenditures by domestic and foreign cards, total number of job postings, electricity consumption and foreign trade data. Index is used to analyze the effects of the coronavirus pandemic on the economic activity. The index indicates that the pandemic started to affect the economic activity negatively in the second half of March and the economy started to recover starting from the first week of May as the restrictions are started to be eased gradually. Overall, the index is successful in tracking the economic activity in Turkey. As a result, the index, which can be updated on a weekly frequency with the flow of information, can be used to produce timely nowcasts for the GDP growth.

1. Introduction

National accounts and industrial production indicators provide comprehensive information on economic activity. However, these indicators are released with a delay due to the time required for data collection and processing. For example, for Turkish economy as of July 2020, the latest Gross Domestic Product (GDP) data are available for the first quarter of 2020 while the latest industrial production data are available for May 2020 (Figure 1). In this respect, nowcasts for the GDP growth, such as for the second and third quarters of 2020, are produced using hard data, survey variables and financial indicators. At ordinary times, nowcasting models allow researchers to produce accurate early predictions. However, survey indicators that are published on a monthly frequency may not be sufficient to provide timely information about the rapid changes at extraordinary times, such as the situation caused by COVID-19 pandemic disease. We focus on the March production data and survey indicators as an example in this context.

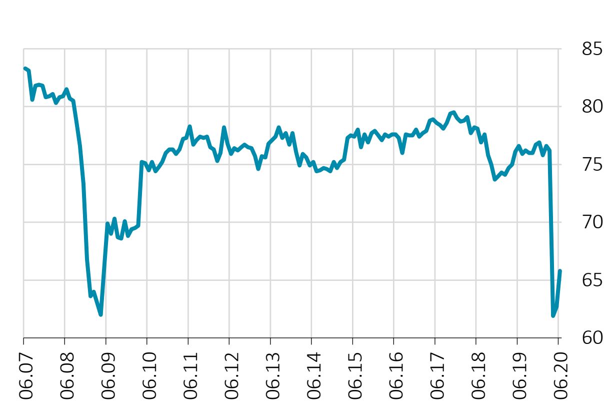
Industrial production declined by 7.1 percent, with real time data, in March compared to February. As of March data, this was the highest month-on-month decline since 2005, when the currently published series starts. However, capacity utilization rate decreased slightly in March (Figure 2). Timing of the surveys is thought to play a role in this situation. The first COVID-19 case in Turkey appeared in mid-March. So, surveys conducted at the first half of the month cannot provide information about the abrupt movements that occur in the rest of the month. Indeed, in April capacity utilization declined by 14.3 percentage points. A similar delay may be observed when the economy enters to the recovery phase. Therefore, more timely signals about the economic activity may help to guide decision makers at times of unusual movements in the economic activity.

Figure 1: Industrial Production Index (IPI) and Gross Domestic Product (Adjusted for Calendar Effects, Annual % Changes)



Source: TURKSTAT.

Figure 2: BTS-Capacity Utilization Rate (CUR) (Seasonally Adjusted, Level)



Source: CBRT.

In this context, in addition to using surveys and financial indicators, early signals about the pace of economic activity can be obtained through certain high frequency data such as electricity consumption and foreign trade statistics, which can be monitored on a daily basis. Obtaining reliable early signals by aggregating information from different indicators in the most appropriate way became even more important during the pandemic. Accordingly, many central banks have started to construct weekly indicators and share them with the public (Lewis et al. (2020) for the US economy and Eraslan and Götz (2020) for the German economy). In this note, a Weekly Economic Conditions Index (WECI) is introduced aiming at tracking developments in the Turkish economic activity in a timely manner.

WECI is constructed by utilizing year-on-year changes of high frequency data published on daily and weekly bases. To compute the WECI, total credit growth, total expenditures by domestic and foreign cards, total number of job postings on Kariyer.net website, electricity consumption, exports and imports are utilized. Principal components approach is used to obtain the common component of these series. After calculating the WECI, its monthly and quarterly averages are calculated and then these are compared with indicators of economic activity such as GDP, industrial production, and capacity utilization. Since WECI can be updated on a weekly basis, it can be used for updating nowcasts for GDP growth in a timely manner. As an example, we present evolution of the nowcasts for GDP growth on a weekly basis with the incoming data for the second quarter.

2. Data and Methodology

2.1 Data

In this note, daily and weekly indicators that are informative about consumption, labor market, and production are utilized. Table 1 lists the variables used in the construction of WECI along with information about their frequency, sample period, lags in publishing days and data sources. Data set consists of total credit growth, total expenditures by domestic and foreign cards, total number of job postings on Kariyer.net website, electricity consumption, exports and imports. While total credit growth and total expenditures by domestic and foreign cards are released on a weekly frequency, total number of job postings, electricity consumption, exports and imports data are published on a daily frequency. The daily flow variables, which are electricity consumption, exports and imports, are converted into weekly frequency by aggregating the daily values of the relevant week. Total number of job postings data are converted into weekly frequency by taking the last day of the relevant week as its weekly data. Then, weekly annual percentage changes are calculated by taking the changes of all variables compared to 52 week ago.

Table 1: Variables used in Weekly Economic Conditions Index (WECI)

	Frequency	Start of the Sample	Lags in Publishing Days*	Source
Total Credit Growth (Adjusted for Exchange Rate Effect)	Weekly	2006	5	Banking Regulation and Supervision Agency (BRSA)
Total Expenditures by Domestic Cards	Weekly	2014	5	Central Bank of the Republic of Turkey (CBRT)
Total Expenditures by Foreign Cards	Weekly	2015	6	Interbank Card Center (ICC), CBRT
Kariyer.net- Total Number of Job Postings	Daily	2013	1	Kariyer.net
Electricity Consumption	Daily	2015	1	Turkish Electricity Transmission Corporation (TETC)
Exports	Daily	2013	1	Ministry of Trade (MT)
Imports	Daily	2013	1	Ministry of Trade (MT)

*Lags in publishing days show how many days the variables are published after the day that they belong to.

Before constructing the index, moving holidays arises as an issue to be dealt with (Yüncüler, 2015). Due to the moving religious and national holidays, working and trading days can change substantially from year to year. For example, when a public holiday shifts from a week to previous week, year-on-year growth rates of some of the indicators exceed 500 percent. To control for the calendar day effects, we implement a smoothing process by using the trends of the weeks before and after the relevant week in order to eliminate sharp positive and negative annual growth rates. This procedure facilitates the interpretation of the index by correcting the high volatilities observed in the past periods. In the factor model approach, some sort of smoothing practice is also applied in the literature. For instance, for the indicators that are used for factor extraction, Stock and Watson (2005) replace the values larger than the 6 times of the inter-quantile range with the median value of the 5 preceding observations.

2.2 Methodology

As a response to the challenges posed by the COVID-19, a number of recent studies attempt to use high frequency indicators for monitoring the developments in the economic activity in a timely manner (Table 2). In these studies, indicators like spending by bank cards, electricity consumption/production, and online job postings are utilized to obtain early signals about the pace of the economic activity. These indicators are available on a daily or weekly basis with very short publication lags. Some of these studies are descriptive and track the movement in these series. On the other hand, Levis et al. (2020) use a more comprehensive data set to construct a weekly index for the economic activity in the USA. After constructing the index, they analyze how closely their weekly economic conditions index tracks the real sector variables, such as industrial production and GDP. Eraslan and Götz (2020) produce a weekly economic conditions index for German economy following the Levis et al. (2020) approach. In this note, we also use factor model approach to extract the common factor of indicators as in Levis et al. (2020).

Table 2: Recent Studies with High Frequency Indicators

Authors	Institution	Date	Target Variable	Indicators Used in the Analysis
Lewis, Mertens and Stock	NY Fed	March 2020	US Real Sector Variables (IP and GDP) ABD	Same store sales, consumer confidence, initial unemployment insurance claims, continued unemployment insurance, staffing index, withholding tax collections, raw steel production, fuel sales, railroad traffic and electricity output
Adrjan and Lydon	CB of Ireland	April 2020	Employment (Ireland and Selected Countries)	Indeed.com online job postings
Hopkins and Sherman	CB of Ireland	April 2020	Ireland Consumer Spending	Spending with bank card and ATM cash withdrawals
Carvalho, Garcia, Hansen, Ortiz, Rodrigo, Mora and Ruiz	U. Cambridge, U. Edinburgh, Imperial College, BBVA	April 2020	Consumer Spending in Spain	BBVA banking transactions
Eraslan and Götz	Bundesbank	May 2020	Economic Activity in Germany	Electricity, toll (road charge), flights, google search trends for unemployment and short-time work, cash withdrawal and air pollution

We briefly explain the mechanics of the methodology we employ. Factor model approach can be summarized as in Equation 1. In this representation, X shows the indicators used for factor extraction, Λ are the loadings, F is the factor and e is the idiosyncratic term. There are different approaches for estimating the factors. Barhoumi et al. (2014) and Stock and Watson (2016) review the literature on the factor models. Levis et al. (2020) find that factors obtained from state-space method are sensitive to the model specification such as the lag length and sample size. So, they proceed with the principal component approach for estimating the factors.

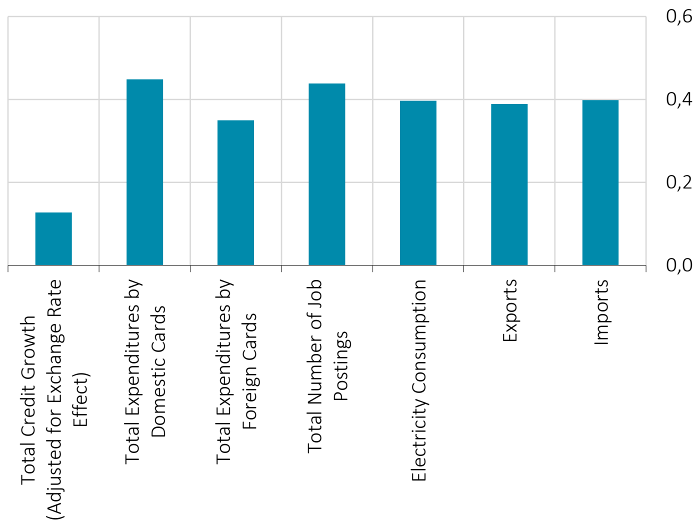
$$X_t = \Lambda F_t + e_t \tag{1}$$

One additional issue that we have to deal with is the missing data at the beginning of the sample for some indicators. As given in Table 1, while credit data start in 2006, other indicators are available from 2013, 2014, and 2015. We extract the factor from 52-week percentage change of these indicators starting from 2014. So, we have missing data for expenditures by bank cards and electricity consumption. We use Expectation Maximization algorithm proposed by Stock and Watson (2002). McCracken and Ng (2016) summarize the steps in this algorithm as follows:

i. Create a balanced data set by filling in the missing values by the sample mean of the indicators,
ii. Obtain factors and factor loadings from this balanced panel of standardized indicators,
iii. Update the missing values by the value obtained from "*estimated loading*estimated factor*",
iv. Multiply these values with the standard deviation of the sample and add the sample mean,
v. Treat these newly obtained values as data and then obtain sample mean and sample standard deviation and standardize the data again,
vi. Obtain factors and loadings,
vii. Iterate the above steps until factors do not change more than a given threshold.

We present the final loadings after performing the above steps (Figure 3). Except for the credit growth, loadings are close to each other.

Figure 3: Loadings of the Indicators Used in WECI



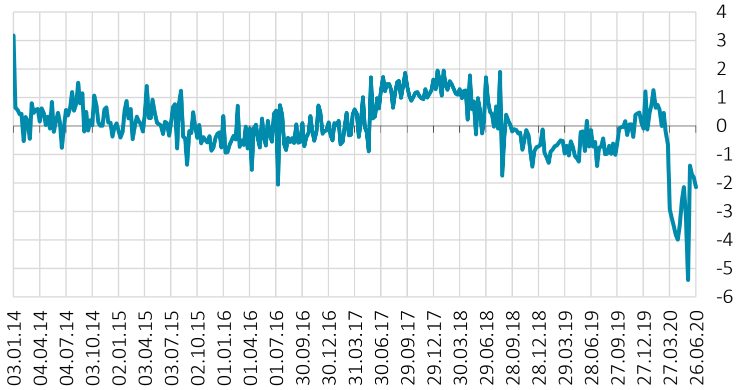
Source: Authors' own calculations.

3. Estimation Results

3.1 WECI and Event Analysis

WECI that is obtained by using the available data as of 26th of June is presented in Figure 4. We standardize the index so that its mean is 0 and standard deviation is 1. So, the final value of -2.1 means that the index is 2.1 standard deviation lower than its average in the analysis sample. WECI peaks at the beginning of 2018, then declines until the middle of 2019 and then rises until the beginning of 2020. Recent expansionary cycle came to an end after the pandemic starts to affect the economy. The lowest level for the index is observed at the week ending on the 29th of May with the effect of the 4-day lockdown applied throughout the country during Ramadan Feast. The second lowest level was observed at the week ending on the 24th of April. After that week, the index shows improvement indicating that economy starts to recover from the effect of the pandemic.

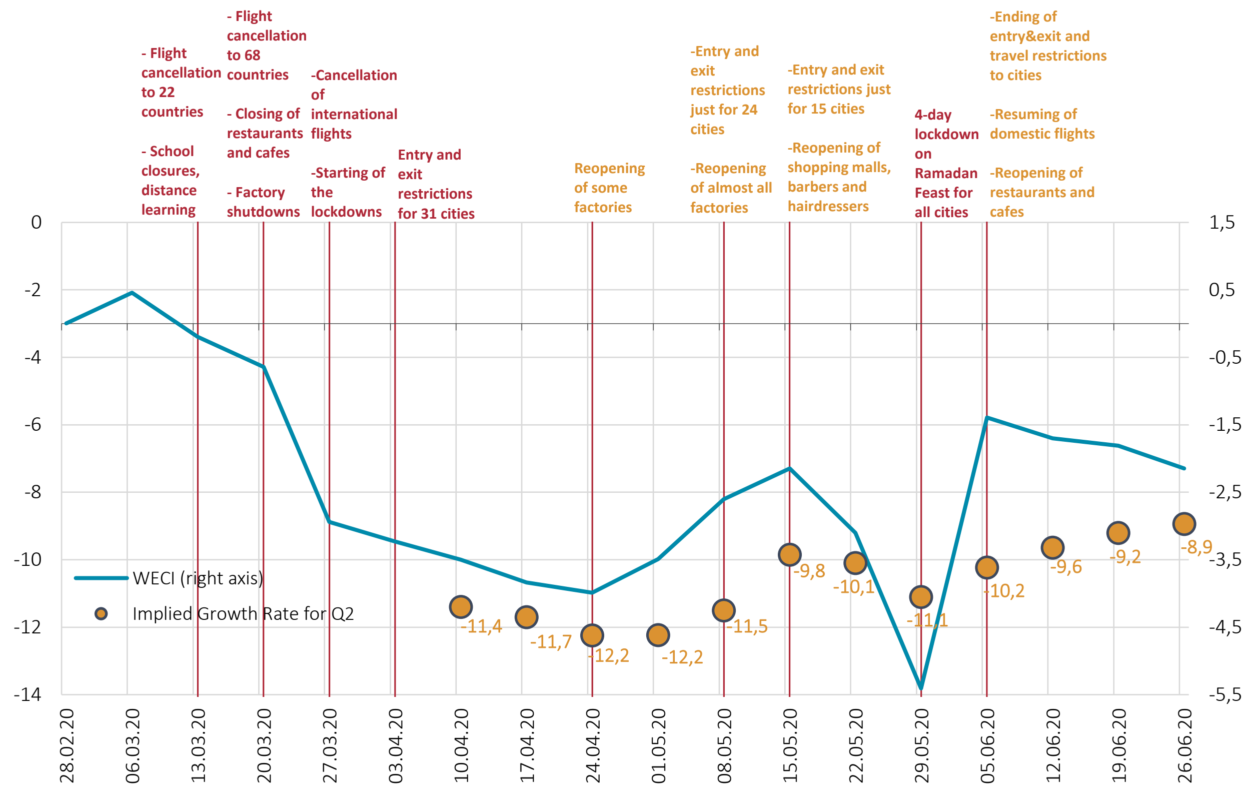
Figure 4: Weekly Economic Conditions Index (WECI)



Source: Authors' own calculations.

In Figure 5, we present the index starting from February 2020 and highlight the key events over this period. We see that with the introduction of restrictions on mobility and travel, interruption of production in factories, and temporary suspension of the activities of the restaurants and cafes, index posted a noticeable decline from the second half of March to the end of April. As the measures against COVID-19 outbreak are eased and the partial normalization steps are implemented, recovery signals in economic activity are observed starting from the first week of May. The index, which declines due to the temporary measures in the second half of May, starts to increase with the widening of the scope of normalization steps in June.

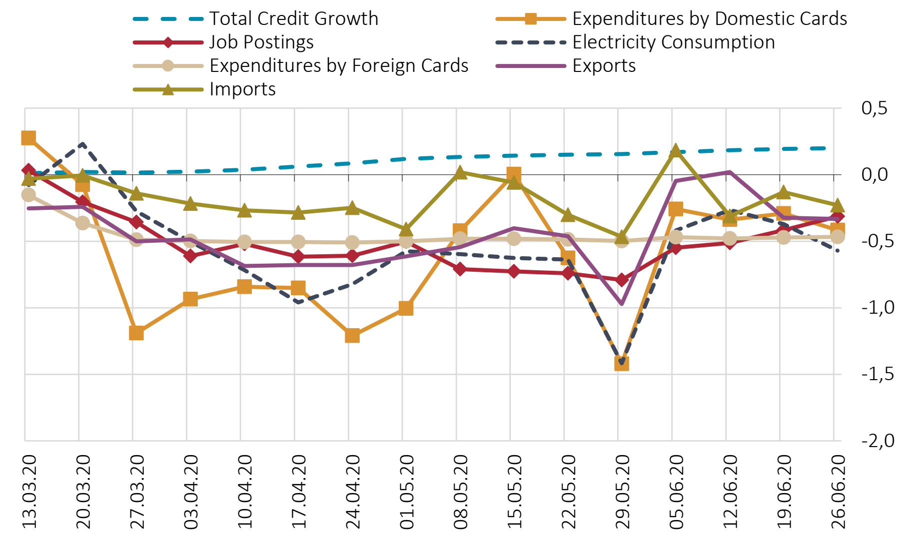
Figure 5: Weekly Economic Conditions Index (WECI) and Event Timeline



Source: Authors' own calculations.

We can decompose the contribution of each indicator to the index in Figure 6. This will enable us to see which indicator drives the movement at certain weeks. We see an increasing positive contribution from credit growth. All other indicators, most notably spending with domestic cards, negatively affect the index starting from the second half of March. Due to the lockdowns at the end of May, there is a sharp decline in economic activity while the following week there is a strong rebound. Electricity consumption and spending by domestic cards are the two components that contributed most negatively to the index over this period. Recently, contribution of the labor market indicator steadily improves while contribution from expenditure by the foreign cards remain weak which is related to the outlook in the tourism activity.

Figure 6: Contributions of Indicators to the WECI over Weeks (% Points)

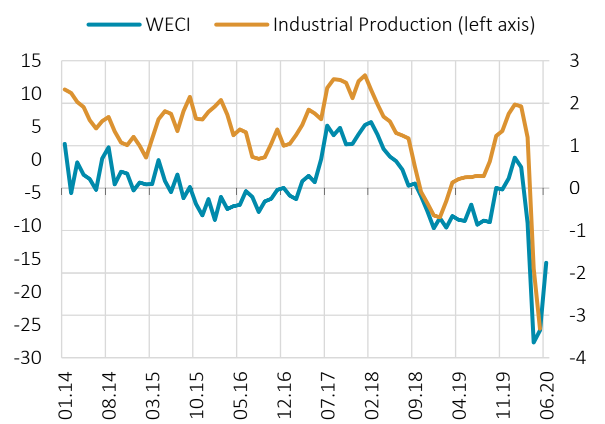


Source: Authors' own calculations.

3.2 WECI and Macroeconomic Indicators

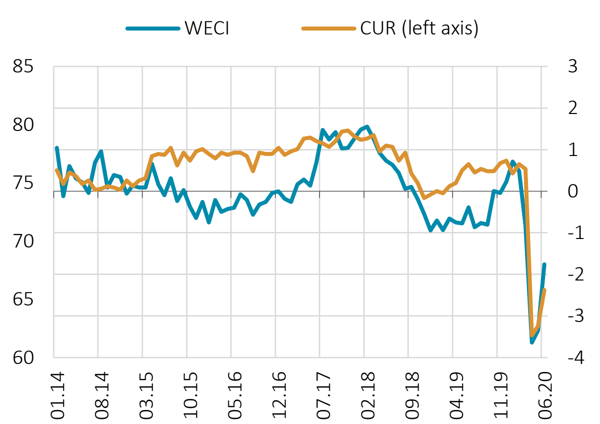
Next, we look at whether the WECI can track the developments in the key macroeconomic indicators closely. We start with the annual percentage change of the industrial production index (IPI). Since IPI is a monthly indicator, we calculate the average of the WECI on a monthly basis. Figure 7 shows that WECI tracks the developments in the IPI closely. Figure 8 shows the capacity utilization and WECI. Correlation in two series is somewhat weak. In April, both WECI and capacity utilization rate declines considerably and then they both starts to recover.

Figure 7: Industrial Production Index (2-Month Moving Averages, Adjusted for Calendar Effects, Annual % Changes) **and WECI**



Source: TURKSTAT, Authors' own calculations.

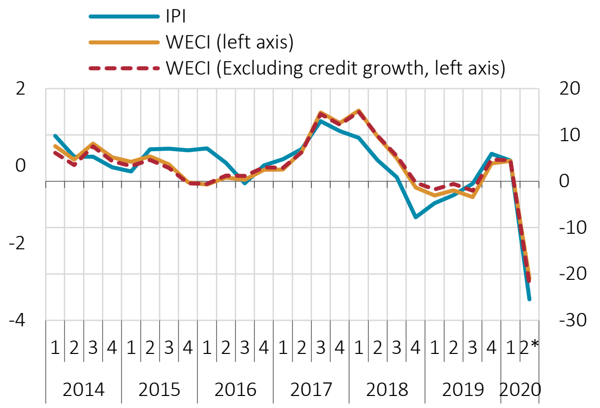
Figure 8: BTS-Capacity Utilization Rate (Seasonally Adjusted, Level) **and WECI**



Source: CBRT, Authors' own calculations.

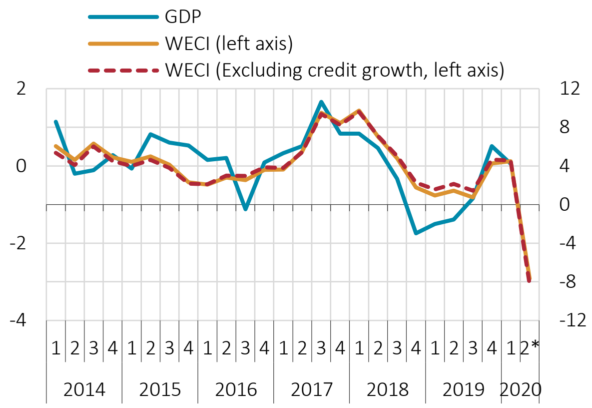
Finally, we look at the relation of GDP and quarterly industrial production with WECI. By considering the strong course in credit growth in recent times, we also extract the common component of indicators excluding credit growth. In this respect, we also present WECI that is constructed excluding the credit growth. To compare with the quarterly GDP data, quarterly average of the WECI is calculated. From the inspection of Figure 9 and 10, it is seen that there is correlation between WECI and two indicators of economic activity to a certain degree. Recent data about WECI suggests that the effects of the pandemic disease on economic activity are felt strongly in the second quarter of 2020.

Figure 9: Industrial Production Index (Adjusted for Calendar Effects, Annual % Changes) **and WECI**



Source: TURKSTAT, Authors' own calculations.

Figure 10: Gross Domestic Product (Adjusted for Calendar Effects, Annual % Changes) **and WECI**

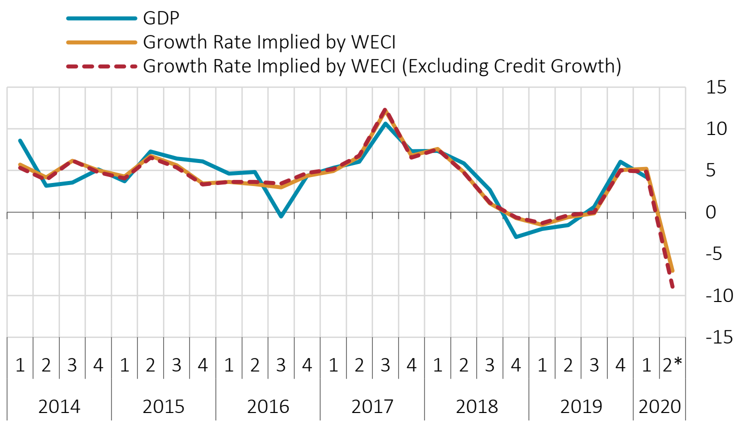


Source: CBRT, Authors' own calculations.

4. Implied Growth Rate for GDP

In the nowcasting literature, it is customary to perform pseudo out-of-sample forecasting analysis to evaluate the short-term forecasting performance of the models. However, we cannot perform pseudo out-of-sample nowcasting analysis due to short sample size. So, we look at the in-sample performance of the WECI along with the evolution of nowcasts on a weekly basis for the second quarter. For this aim, we run a regression of calendar day adjusted annual GDP growth on a constant, WECI, fourth lag of the dependent variable to capture the base effects and finally a dummy variable which takes 1 from the fourth quarter of 2017 onwards. This dummy captures changes in the mean of the GDP as in our sample mean GDP growth changes over time. Figure 11 shows the fitted value from this regression for the growth rate of the GDP that is calculated by using the 26th June observation of WECI. Regressions are done both with the WECI calculated including and excluding credit growth. Overall, in-sample performance of the model is relatively successful. For the second quarter, models imply that there may be a significant annual contraction in the national income data.

Figure 11: GDP (Adjusted for Calendar Effects, Annual % Changes) **and Implied Growth Rate for GDP**



Source: Authors' own calculations.

We use coefficients estimated from the aforementioned regression for updating the nowcasts on a weekly basis. We average the WECI that would be available in a given week for a quarter and calculate the implied growth rates using these coefficients. Dots in the Figure 5 shows the weekly evolution of the nowcasts with the flow of information. It is seen that nowcasts improved with the incoming data except the week ending in 29th of May which corresponds to the lockdowns due to public holidays. Overall, we see that nowcasts from WECI improved around 3 percentage points from the start of the second quarter to the end of the quarter.

5. Conclusion

In this note, a weekly index that aims tracking developments in economic activity in a timely manner is introduced. The index is formed by weekly annual percentage changes of credit growth, expenditures by domestic and foreign cards, total number of job postings, electricity consumption and foreign trade data. Principal components approach is utilized in the estimation of the index. In-sample analysis suggests that WECI can track the developments in GDP relatively successfully. So, by using WECI, nowcasts for GDP growth can be updated on a weekly basis.

6. References

Adrjan, P., & Lydon, R. (2020). Covid-19 and the global labour market: Impact on job posting. Central Bank of Ireland, Economic Letter, Vol. 2020, No: 3.

Barhoumi, K., Darné, O., & Ferrara, L. (2014). Dynamic factor models: A review of the literature. OECD Journal: Journal of Business Cycle Measurement and Analysis, 2013(2), 73-107.

Carvalho, V. M., Garcia, J. R., Hansen, S., Ortiz, A., Rodrigo, T., Rodriguez Mora, J. V. & Ruiz, J. (2020). Tracking the Covid-19 Crisis with High-Resolution Transaction Data. Cambridge-Inet Working Paper Series, No: 2020/16.

Eraslan, S., & Götz, T. (2020). Weekly activity index for the German economy, Deutsche Bundesbank.

Hopkins, A., & Sherman, M. (2020). How has the COVID-19 Pandemic Affected Daily Spending Patterns? Central Bank of Ireland, Behind the Data.

Lewis, D., Mertens, K., & Stock, J. H. (2020). US economic activity during the early weeks of the SARS-Cov-2 outbreak (No. w26954). National Bureau of Economic Research.

McCracken, M. W., & Ng, S. (2016). FRED-MD: A Monthly Database for Macroeconomic Research. Journal of Business & Economic Statistics, Vol. 34(4), 574-589.

Stock, J. H., & Watson, M. W. (2002). Macroeconomic forecasting using diffusion indexes. Journal of Business & Economic Statistics, 20(2), 147-162.

Stock, J. H., & Watson, M. W. (2005). Implications of dynamic factor models for VAR analysis (No. w11467). National Bureau of Economic Research.

Stock, J. H., & Watson, M. W. (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In Handbook of macroeconomics (Vol. 2, pp. 415-525). Elsevier.

Yüncüler, Ç. (2015). Estimating the Bridging Day Effect on Turkish Industrial Production. Central Bank of the Republic of Turkey, Research Notes in Economics, No: 2015-15.

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