TÜRKİYE CUMHURİYET MERKEZ BANKASI

RESEARCH NOTES IN ECONOMICS

Forecasting Turkish GDP Growth: Bottom-Up vs Direct?

Mahmut Günay

Özet: Bu çalışmada, milli gelir tahmini için doğrudan ve dolaylı yaklaşımların performansları karşılaştırılmaktadır. Dolaylı yaklaşımda milli gelirin alt kalemleri ayrı ayrı tahmin edilip, bu tahminlerin birleştirilmesiyle milli gelir büyüme tahmini oluşturulmaktadır. Doğrudan yaklaşımda ise milli gelir büyümesinin kendisi modellenmekte ve tahmin edilmektedir. Sonuçlar, dolaylı yaklaşımın tahmin hatalarını azalttığını göstermektedir. Tahminlerin salt rakam sunmaktan ziyade iktisadi bir öykü anlatmak için de kullanıldığı dikkate alındığında, daha kapsamlı analiz yapmaya imkân veren dolaylı yaklaşımın önemi belirginleşmektedir.

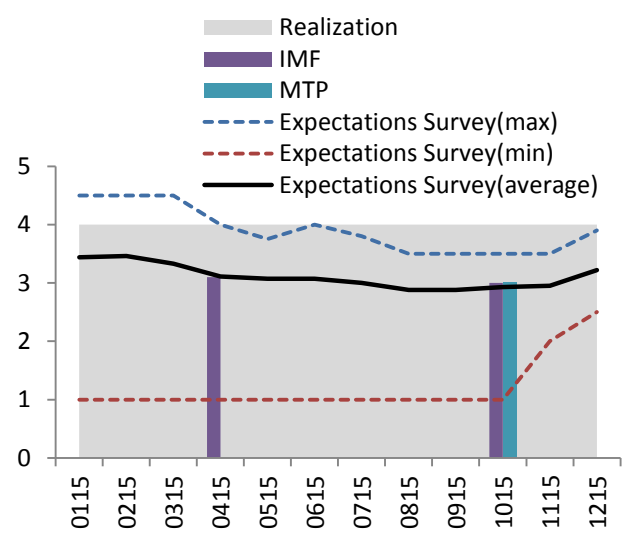
Abstract: In this note, we compare performance of direct and bottom-up approaches to forecasting Turkish GDP growth. In the bottom-up approach, we forecast each component separately and then aggregate these forecasts to reach GDP growth forecast. In the direct approach, we model and forecast GDP growth itself. Results indicate that bottom-up approach helps reduce forecast errors. Importance of the bottom-up approach becomes more evident when we take into account the storytelling dimension of forecasting.

1. Introduction

In 2015, Gross Domestic Product (GDP) growth in Turkey surprised forecasters on the upside. Chart 1 shows the evolution of forecasts for 2015 of the Survey of Expectations (SoE) conducted by the Central Bank of Turkey. We also present forecasts of the IMF and the Medium Term Programs (MTP) prepared by the Ministry of Development, which were released at different times throughout the year. In October 2015, economic growth for 2015 was expected to be 3.0 percent by the IMF and the preliminary MTP. In the SoE, the average of the forecasts of the 66 surveyed was 2.9 percent growth with the maximum forecast being 3.5 percent. TURKSTAT announced at the end of the first quarter of 2016 that the growth in 2015 was 4.0 percent.

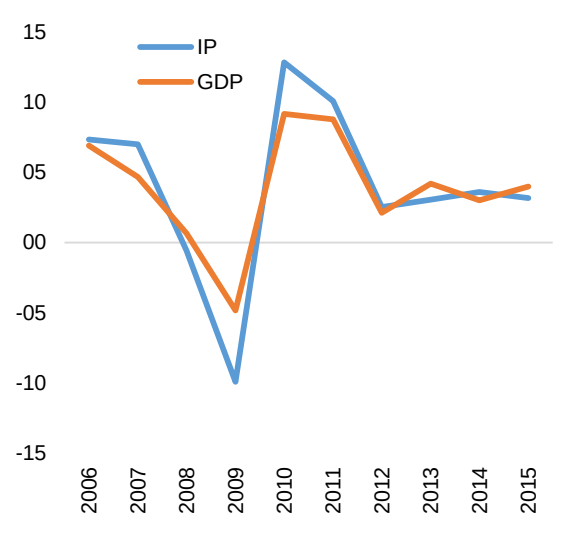
Analyzing market expectations for year on year (yoy) growth rates in each quarter and realizations shows that in all quarters of 2015, GDP growth was realized higher than market expectations. For example, for the third quarter market consensus on growth (according to the survey by Anatolian Agency) was 2.7 percent, while the realized growth rate was 4.0 percent. Similarly, for the last quarter of 2015, market expectation was 4.8 percent while growth was 5.7 percent. This persistent underestimation is one of the reasons that even towards the end of the year, forecasts for GDP growth in 2015 were around 3.5 percent.

Chart 1. GDP Growth Forecasts for 2015 (Year on Year Growth)*



Source: CBRT, Ministry of Development, TURKSTAT and IMF WEO.
*IMF forecasts are taken from WEO, MTP is the Medium Term Program.
Shaded area shows the realization.

Chart 2: GDP and Industrial Production (Year on Year Growth)



Source: TURKSTAT.

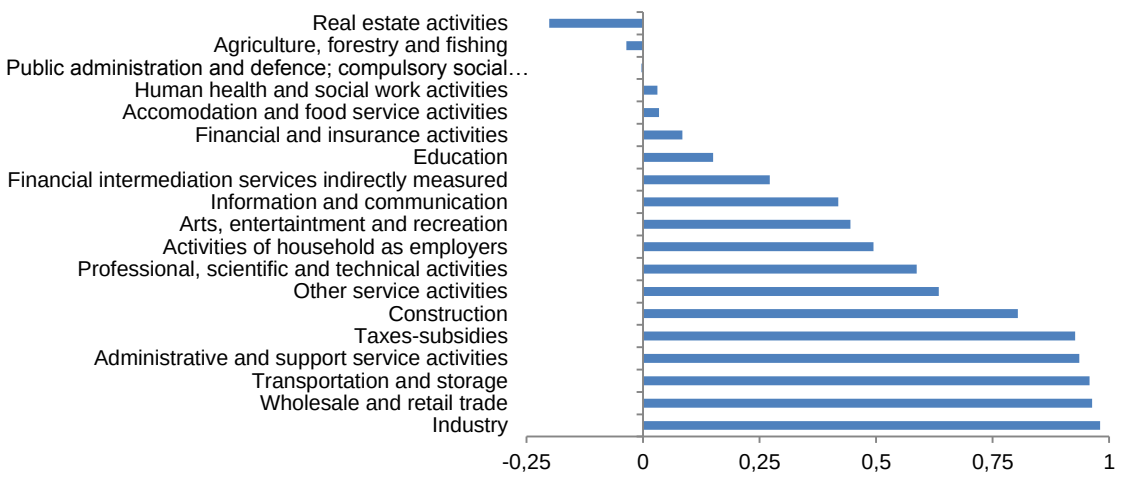
Industrial production (IP) is also considered to be an important indicator for monitoring economic activity. As shown in Chart 2, while GDP growth was above expectations in 2015,

IP growth was relatively weaker (3.2 percent growth). Motivated by the higher than expected growth in 2015 and the diverging strengths of IP and GDP growth, in this note we revisit the issue of forecasting GDP growth in Turkey. In particular, we compare one-step ahead forecasting performance of direct versus bottom-up approaches. In the former approach, we model and forecast aggregate GDP data with relevant indicators, such as IP. In the latter, we forecast components of GDP from the production side separately and aggregate these forecasts to reach one-step ahead forecast of GDP growth. Our results show that using the bottom-up approach reduces forecast errors relative to the direct forecasting approach.

2. Industrial Production, GDP and GDP Components from the Production Side

Chart 2 has shown that IP and GDP can post relatively close growth rates as in recent periods, or considerably different growth rates as in 2009-2010 period. We analyze the correlation of IP with GDP components from the production side to see the relation of GDP components with IP. Chart 3 shows that there is a great heterogeneity. As expected, industrial value added is the component most correlated with IP. We note that correlations of trade, transportation and storage and net taxes with IP are also very high. On the other hand, the correlation of IP with real estate activities is negative, and it is zero with agriculture. Against this background, depending on the source of growth, GDP and IP growth may diverge from each other. For instance, if the fluctuations are driven mostly by agriculture, as in recent periods, GDP growth may be higher than IP growth. Hence, it may be important to take into account the dynamics of different components for producing more accurate forecasts. Bottom-up approach aims to achieve this.

Chart 3. Correlation between Annual Growth Rates of GDP Components and Industrial Production (2006-2015)



Source: TURKSTAT

Chart 4: Value Added of Agriculture and Industrial Production (Year on Year Growth)

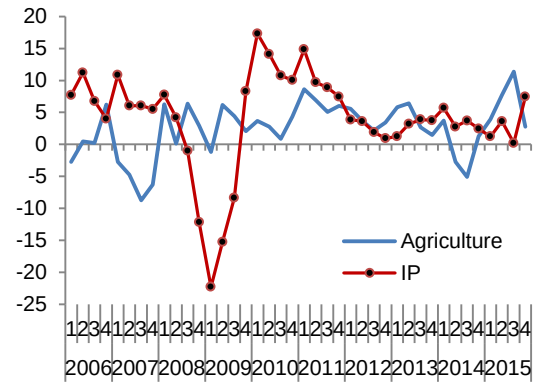


Chart 5: Industrial Value Added and Production (Year on Year Growth)

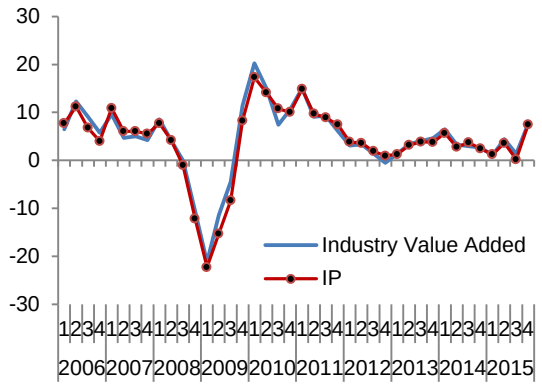


Chart 6. Value Added of Construction and Industrial Production (Year on Year Growth)

Chart 7. Value Added of Trade, Transport-Storage and Industrial Production (Year on Year Growth)

Chart 8. Value Added of Other Services and Industrial Production (Year on Year Growth)

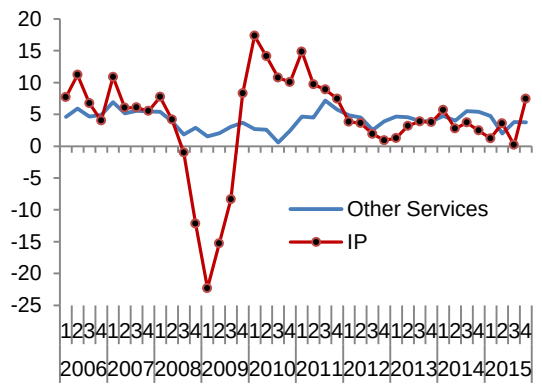
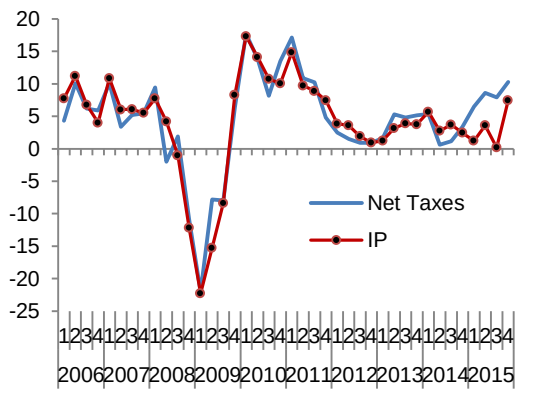


Chart 9. Net Taxes and Industrial Production (Year on Year Growth)



Source: TURKSTAT.

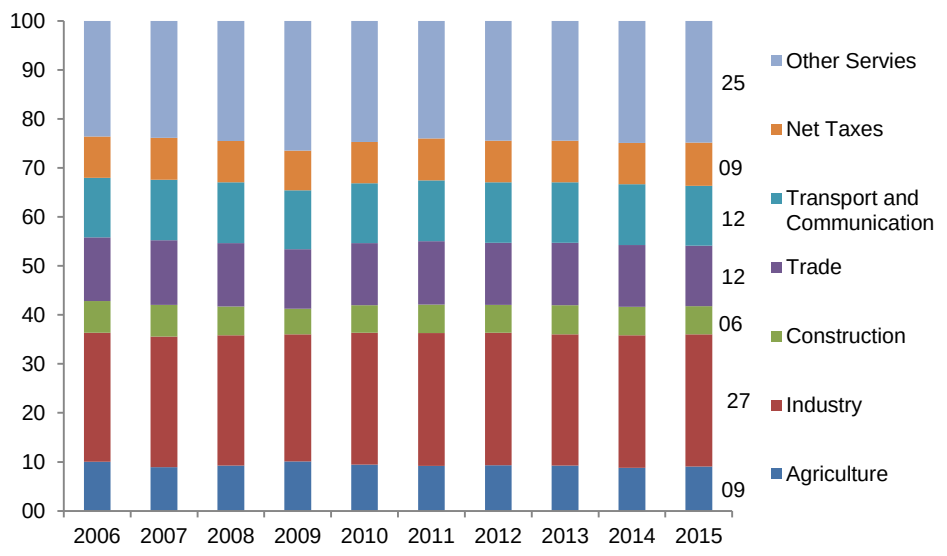
For the bottom-up approach, we group GDP components into 7 categories based on the correlations presented in Chart 3 as shown in Equation 1 (see Charts 4 to 9 for the growth rate of these components and IP).

$$GDP = Agriculture + Industry + Construction + Trade + Transport\ and\ Storage + Other\ Services + Taxes\ and\ Subsides \quad (1)$$

In a nutshell we can say that IP growth may be helpful for forecasting industrial value added, trade, transport and storage and net taxes, but it gives almost no information for agriculture and "other services". Moreover, in 2015 net taxes component also performed much stronger than IP growth.

It may be wondered why we stress IP heavily in this note. Chart 10, which presents the shares of groups, defined above, in GDP, offers an answer. It is observed that components of GDP that are highly correlated with IP, namely industrial value added, trade, transport and storage and net taxes, account for almost 60 percent of GDP. Hence, even though industrial value added alone is around 27 percent of GDP (with constant prices), when we take into account components that are closely related to industrial production, the share of components that are moving in tandem with IP increases substantially. Moreover for other services, which account for almost a quarter of GDP, the share is rather stable. Hence, modelling with IP would capture most of the variation in GDP.

Chart 10. Shares of the Components in GDP (with Constant Prices, Percent)



Source: TURKSTAT

3. Methodology and Data

In this note we use bridge equations for one-step ahead forecasting of GDP. In the bridge equation approach, we convert monthly indicators to quarterly data and then use these indicators in forecasting GDP.[1]

a. Forecast Horizon

Since GDP data are published with considerable delay, different names are given to the predictions of GDP growth with reference to its timing. Predictions after the end of a quarter are called backcast, predictions made within a quarter are called nowcast and predictions for the coming quarters are called forecast.[2] In this note we are interested in backcasting GDP growth. We backcast GDP growth by using data available in two months after the end of the reference quarter. As we discuss in the introduction part, even when all three months' data are available for indicators that can be used for predicting GDP growth, there can still be significant difference between expectations and the realization.

b. Direct and Bottom-up Forecasting Approaches

As their names suggest, in the direct approach one models and forecasts GDP growth itself. In the bottom-up approach (also named as disaggregate approach), one forecasts each component separately and then weights those forecasts to come up with GDP forecast.

As explained in the previous section, GDP components can move differently. Naturally, dynamics of these series may be affected from different forces. Indeed, while IP is informative about some of the components, it is silent on the series like agriculture or other services. Hence, modelling each series with different indicators and different lag length structures and then aggregating the forecasts of those components may reduce forecast errors. Hendry and Hubrich (2005) analyze the relation between direct and bottom-up forecasts both theoretically and empirically. Disaggregation in the bottom-up approach can be across regions of an economy, across time and across variables such as sub-indices of a price measure. They show theoretically that using information of in the disaggregate components cannot lower predictability of a given aggregate. However, this result is dependent on the assumption that the data generating process is known. If the data generating process is not known so that the model has to be estimated then it is ambiguous whether aggregate or disaggregate forecasts will make lower error. They note that forecasts may be affected from model selection, estimation uncertainty, data measurement error and structural breaks. Hence, it is not surprising that empirical evidence on this matter is mixed.

[1] See Gunay (2015) for a discussion on the use of bridge equations for short term forecasting.
[2] Figure 1.1 in Günay (2015) elaborates on this issue in detail.

As an example consider Hubrich (2005) who compares forecasting consumer price index for euro area directly and aggregating forecasts of sub-indices. Hubrich uses univariate and multivariate models for forecasting inflation and components at different horizons and concludes that it is not necessarily better to use disaggregated approach for forecasting inflation. One reason for this result may be the correlated shocks. This stems from the fact that shocks affecting the sub-indices like oil price shock affect many components simultaneously. So, forecast errors of sub-indices do not cancel out in the aggregation step due to correlated errors. Drechsel and Scheufele (2013) analyze this issue for forecasting German GDP. They obtain disaggregate results both from the production and expenditure side. They find that disaggregated forecasts from the production side produce better result than those from the expenditure side. In some cases, aggregating forecasts from the production side can produce lower forecast errors than the direct approach, albeit marginally. There are studies showing that the bottom-up approach is better than the direct approach. For example, Marcellino et al. (2003) show that aggregating country forecasts to get the aggregate euro area forecast lowers the forecast errors. In summary, while theory implies that disaggregate forecasts should not perform worse than aggregate forecasts, it is ultimately an empirical question to understand which approach would perform better for a specific sample for a given period.

c. Forecast Equation

We use three types of forecast equations for modelling yoy growth rates. In the first type, we fit an AR model to each series and then get a forecast from it. In the second forecast equation, we use only the indicators along with their lags. In the third equation type, we have the most general form. Using different equations enable us to have some idea about the impact of using autoregressive terms of the dependent variable. For example, comparing the performance of AR model with that of the Indicator AR Model will guide us about the role of using indicators for forecasting a given component. For some components we analyze different combinations of the indicators. Choice of the indicators is done by going over TURKSTAT manuals, by following practices in the literature and also by expert judgement. We report the performance of each of these specifications in Table 1.

$$\boldsymbol{AR\ Model}: y_t = \alpha + \beta(L)y_t + \varepsilon_t \tag{2}$$

$$\boldsymbol{Indicator\ Model}: y_t = \alpha + \phi(L)x_{t+}\varepsilon_t \tag{3}$$

$$\boldsymbol{Indicator\ AR\ Model}: y_t = \alpha + \beta(L)y_t + \gamma(L)x_{t+}\varepsilon_t \tag{4}$$

where y is the variable that we want to forecast, x is the vector of indicators that we think to be helpful at forecasting. β(L), γ(L) and ϕ(L) are the lag operators. Note that we allow contemporaneous values of the indicators. Lag lengths are chosen with Bayesian Information Criterion.

We should note that from a strictly technical point of view, since we work with year on year changes, using lags as explanatory variables may make OLS estimates unreliable and tests based on the residuals may not be valid due to autocorrelation in the residuals. However, in this note our primary interest is in forecasting and we limit our attention to the pseudo out-of-sample forecasting performance of the models. This approach is used in forecasting practice as well (see for example Vosen and Schmidt (2011) and Esteves and Rua (2012)).

d. Pseudo Out-of-Sample Forecasting Exercise

We use quarterly data for yoy percentage changes from the first quarter of 2006 to the fourth quarter of 2015. The choice of 2006 as the start of the estimation sample stems from the fact that TURKSTAT started to publish a new IP series from 2005. We evaluate the forecasting performance of these models using recursive pseudo out-of-sample forecasting exercise. This approach is standard in forecasting literature (see for instance Stock and Watson (2003)). We evaluate models for 2010-2015 period.

4. Results

We evaluate forecast performance of three types of equations for each component in Table 1. We discuss each part of the table below:

a. Agriculture

Modelling time series dynamics of agriculture is difficult. There may be abrupt movements due to weather conditions. For example Hahn and Skudelny (2008), who forecast Euro area GDP by bottom-up approach from the production side, use only AR models for forecasting agriculture. Due to productivity issues, employment of the agriculture is not helpful in monitoring output of the sector. Instead, we use food price inflation in our forecast equations. We see that using this indicator does not change the forecast errors (RMSE is 3.15 for the AR model and 3.10 for the Indicator-AR Model).

Table 1. Root Mean Squared Forecast Errors for 2010Q1-2015Q4					
Agriculture					
			AR	Indicator	Indicator-AR
Food Price Inflation			3.15	3.38	3.10
Construction					
			AR	Indicator	Indicator-AR
Production of Other Minerals			3.11	4.24	2.25
Production of Other Minerals	Construction Employment		3.11	4.22	2.49
Production of Other Minerals	Construction Employment	Heavy Commercial Vehicles	3.11	4.42	2.76
Other Services					
			AR	Indicator	Indicator-AR
Employment in Services			1.24	1.31	1.16
Industrial Value Added					
			AR	Indicator	Indicator-AR
Industrial Production			3.93	1.12	1.22
Industrial Production	Import Quantity Index (excl. Gold)		3.93	1.11	1.23
Industrial Production	Import Quantity Index (excl. Gold)	Employment in Industry	3.93	1.23	1.28
Trade					
			AR	Indicator	Indicator-AR
Industrial Production			4.21	2.63	2.54
Industrial Production	Import Quantity Index (excl. Gold)		4.21	2.01	1.71
Transportation-Communication					
			AR	Indicator	Indicator-AR
Industrial Production			3.51	2.30	2.22
Industrial Production	Import Quantity Index (excl. Gold)		3.51	1.91	1.86
Net Taxes					
			AR	Indicator	Indicator-AR
Industrial Production			3.85	2.64	2.67
Industrial Production	Import Quantity Index (excl. Gold)		3.85	2.47	2.58
Industrial Production	Import Quantity Index (excl. Gold)	Production of Petroleum Products	3.85	2.01	2.00
Bottom-up GDP Forecasts					
Disaggregate-AR			2.25		
Disaggregate-Indicator				0.98	
Disaggregate- Indicator AR					0.92
GDP					
			AR	Indicator	Indicator-AR
Industrial Production			2.44	1.33	1.31
Industrial Production	Import Quantity Index (excl. Gold)		2.44	1.19	1.22
Industrial Production	Import Quantity Index (excl. Gold)	Nonagricultural Employment	2.44	1.35	1.31

Notes: We report the RMSE for different specifications. For a given component, for each specification we use same AR model. We obtain bottom-up forecasts by weighting the forecast of a component with its weight in the GDP for the previous year. We pick the model with the lowest RMSE for the components.

b. Construction

Construction value added is a very persistent series. Hence, using autoregressive terms is expected to be helpful for forecasting purposes. Of course, due to cyclical movement of the series, in turning points these terms will have little predictive power. So augmenting the AR equation with additional indicators may be necessary. Results show that using only an AR model does better than using only indicators. Specification that uses autoregressive terms and production of other mineral goods as an indicator, which is the sector that produces goods related to construction such as cement, yields lower forecast errors than specifications using additional indicators in Indicator AR type forecast equation.

c. Other Services

Growth of other services is a relatively smooth series. Hahn and Skudelny (2008) use only AR models for forecasting this component. In fact, using employment in services reduces forecast error only slightly.

d. Industrial Value Added

We model industrial value added with IP, import quantity index and employment in industry. We see that modelling industrial value added with IP only produces relatively low forecast errors.

e. Trade and Transport-Communication

We model two services components, namely trade and transport-communication using IP and import quantity index. For both components, using these two indicators along with the autoregressive terms produce the lowest error in this period.

f. Net Taxes

A model for growth in net taxes that uses IP and import quantity works fine until 2014. However, net taxes decoupled from the industrial production and posted very strong growth rates in 2015 (Chart 9). Indeed, contribution of the net taxes played a major role in 2015 for the GDP growth which outperformed expectations. We analyze the correlation of net taxes with each of the industrial production sectors (Table 2). Correlation of manufacture of petroleum products and other manufacturing is very high in the last two years. In this respect, we try these two sectors as additional regressors.

We get a substantial improvement for forecasting net taxes value added when we use petroleum products for 2014-2015. Performance deteriorated when we also use other

manufacturing, so we report only the model that is augmented with manufacture of petroleum products.

Table 2. Correlation of Net Taxes Value Added Year on Year Change with the Industrial Production Sectors*

	Period:2006-2015	Period:2014-2015
Manufacture of coke and refined petroleum products	0.70	0.96
Other manufacturing	0.30	0.89
Repair and installation of machinery and equipment	0.42	0.69
Manufacture of motor vehicles, trailers and semi-trailers	0.86	0.62
Manufacture of wearing apparel	0.65	0.46

**In the table we show the top 5 sectors with the highest correlation with net taxes for 2014-2015.*

Data mining for specific periods and finding an indicator that works fine is against the spirit of out-of-sample forecast evaluation. This is due to the fact that one can always look back and find some variables that improve the forecasting performance in certain periods. In this respect, we choose indicators that are mainstream for all models except the last model for net taxes. For example, IP or employment indicators are natural candidates to be informative about components from production side. So, analyzing their performance for the past may be helpful for the future. Yet, since net taxes played an important role in the near past we augment its basic model with petroleum production. Of course, we still need more observations to verify whether decoupling from IP is certainly due to strength of the petroleum production.

g. GDP

We model GDP using three indicators; IP, imports and employment. Günay (2015) explores a wide range of models for forecasting quarter-on-quarter GDP growth. We restrict our attention to a limited number of indicators. A study for a horse race similar to Hahn and Skudelny (2008) is left for further research. We see that using IP and imports without autoregressive terms of GDP produces the lowest RMSE.

5. Direct vs. Bottom-up?

In this section, we compare and discuss the forecast performance of bottom-up and direct approaches. We start with comparing forecasting with AR models. As seen in Table 1, in the case of direct AR forecasting, RMSE is 2.44. Modelling each component separately with an AR model and then aggregating those forecasts results in lower RMSE of 2.25. Aggregating indicator models also results in lower forecast error compared to direct forecasting with indicators (1.19 for direct vs. 0.98 for aggregate). The lowest RMSE for the disaggregate approach is obtained with the Indicator-AR type models (0.92). In summary,

bottom-up approach results in lower forecast error in this sample with bridge equations for backcasting GDP growth.

As noted by Günay (2016), analyzing forecasts for a relatively long period of time may hide changing dynamics of models. In this respect, we present moving eight quarter RMSEs for direct and bottom-up approaches. We also provide RMSE of market expectations for GDP growth forecasts. We should stress that market expectations are not directly comparable with our models' forecasts. Market participants forecast in real time while we use revised data. Moreover, as we write this note we know about the problems in the forecasting process and what variables might be good at forecasting (such as using petroleum products for forecasting net taxes). Of course, forecasters cannot know these issues at the time of forecasting. Yet, we provide RMSE for market forecasts to give some idea about forecast errors in these periods.

Chart 11 shows moving eight quarter RMSE for different specifications. Bottom-up approach with Indicator-AR type forecast equation performs relatively well over time. Finally, in Chart 12 we present backcast errors from best performing specification and the market consensus. Promising results for bottom-up approach is also observed in this chart.

Chart 11. Eight Quarter Moving Root Mean Squared Errors

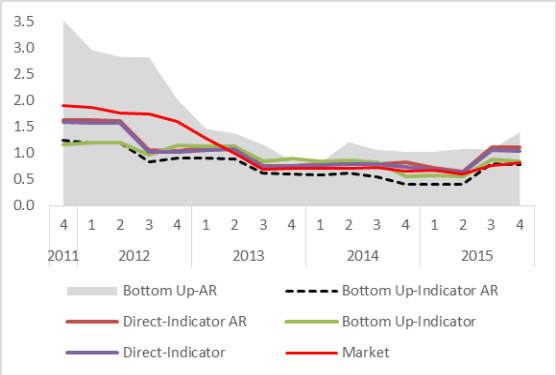
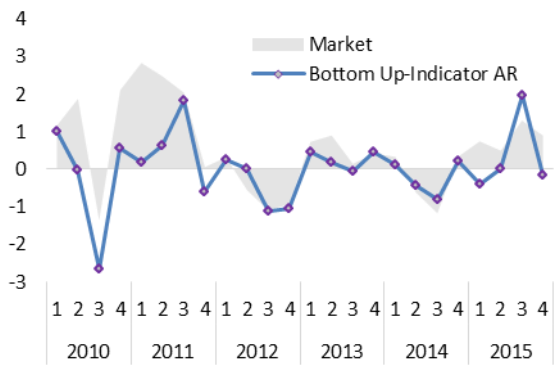


Chart 12. Backcast Errors



6. Conclusion

We evaluate the performance of forecasting GDP directly with that of bottom-up approach where we forecast each component separately and then aggregate those disaggregated forecasts. For the bottom-up approach, we model seven components from production side. Some components have a strong relation with industrial production while some of them are hard to model. We analyze each component separately and come up with different models. Results suggest that bottom-up forecast approach reduces forecast errors.

A natural caveat is in order. This note only considered a comparison between two approaches with single equation models for backcasting. Of course, with different modelling techniques for different forecast horizons relative performance may change in favor of direct forecasting approach. Yet, taking into account the fact that richer stories can be told with bottom-up approach and the fact that for our forecast environment it performed relatively well, we think bottom-up approach should be in the toolkit of forecasters.

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