WP/15/269

# IMF Working Paper

## How External Factors Affect Domestic Economy: Nowcasting an Emerging Market

By Serhat Solmaz and Marzie Taheri Sanjani

INTERNATIONAL MONETARY FUND

 WP/15/269

**IMF Working Paper**

**Strategy, Policy, and Review Department**

# How External Factors Affect Domestic Economy: Nowcasting an Emerging Market

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December 2015



## Abstract

External headwinds, together with domestic vulnerabilities, have loomed over the prospects of emerging markets in recent years. We propose an empirical toolbox to quantify the impact of external macro-financial shocks on domestic economies in parsimonious way. Our model is a Bayesian VAR consisting of two blocks representing home and foreign factors, which is particularly useful for small open economies. By exploiting the mixed-frequency nature of the model, we show how the toolbox can be used for "nowcasting" the output growth. The conditional forecast results illustrate that regular updates of external information, as well as domestic leading indicators, would significantly enhance the accuracy of forecasts. Moreover, the analysis of variance decompositions shows that external shocks are important drivers of the domestic business cycle.

**JEL Classification Numbers:** C11, C53

**Keywords:** Nowcasting, Bayesian estimation, VAR, Emerging Market

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[1] The authors would like to thank Michal Andrle, Gregorio Impavido, Helene Poirson Ward, Mika Kortelainen, Ernesto Ramirez, Antonio Spilimbergo, Alexander Tieman, Ivanna Vladkova Hollar, and Kevin Wiseman for useful comments.

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# I. INTRODUCTION

**Emerging market (EM) vulnerabilities to external headwinds and their intrinsic domestic fundamentals have returned to the center of policy discussions.** Post global financial crisis (GFC) spillover of advanced economies' policies, along with various uncertainty factors, tangled with weak domestic fundamentals, loom over emerging markets with large trade links and high exposure to the global financial cycle.

**This paper proposes a methodology to quantify the impact of external and domestic macro-financial impulses in explaining the dynamic of home economy.** Our proposed framework allows for both forward looking and historical analysis. Historical analysis sheds light on the roles of both external and domestic conditions in explaining the business cycle in EMs, while the forward-looking analysis can guide policy by measuring the impact of new information on forecasts. By limiting the model to key explanatory variables, we aim to focus on the main channels of propagation and spillover.

**Our methodology is based on a Mixed-Frequency Bayesian VAR (MFBVAR), which consists of two blocks, home and foreign.** While the home economy can be any open economy exposed to global factors through trade and financial channels, we have selected Turkey as the home economy for our methodology. The mixed-frequency feature of our model allows us to combine monthly and quarterly information, which we use to compute our conditional forecast, or "nowcast."

**To illustrate the application of our proposed methodology, we apply it to the case of Turkey.** Turkey, a very open economy that exports to major advanced economies, especially Europe,[2] is completely dependent on the importation of primary commodities, and has major trade links with many countries in its region. Moreover, financial factors such as risk taking

[2] While Turkey's trade links with Europe have been traditionally large and important, Turkey has various trading partners and their relative share change over time. For example in 2013 Iraq was the Turkey's 2nd biggest export market.

channel and capital flow are also important. These characteristics make it an ideal test case. This toolbox can be used for other small open economies. To do so the practitioner needs to identify the relevant external variables to be included in the model, by assessing the statistics concerning the main trading and financial trading partners, the degree of trade and financial openness and the reliance on oil and other commodities. Table 4 in appendix presents descriptive statistics of the variables in the model and their interdependence. We try to keep the model minimal, in order to make it easy to use.

**The choices of leading indicators and relevant global factors are guided by theory and application in order to describe the evolution of the domestic economy properly.** Application dictates the choice of the variables in the model. In our case, the framework is designed for GDP nowcasting.[3] The leading indicators in the home economy should have thorough information content about investment, trade, and financial activities. The external factors that form the foreign block of our model are chosen to reflect the macroeconomic state of the main trading and financial partners of the home economy. The home block consists of five variables, while our foreign block consists of only three variables. The information content of global oil prices, US corporate risk spread, and US industrial production, can signal shocks related to global demand, finance, and trade.

**We find that external shocks can account for more than 50% of the GDP growth dynamic in Turkey.** Historical variance decompositions illustrate that a decrease in the risk-taking appetite in the US or strong US industrial production (IP) provide positive impulses for our emerging market economy's output growth. Our counterfactual simulations show that external shocks play a key role in explaining the recession and subsequent rebound. By exploiting the mixed-frequency nature of the model, nowcasting can be used to quantify the direction of macroeconomic developments, as the high frequency data become available. We should note that our model improves upon the benchmark naïve model.

[3] For example, for an inflation forecasting exercise we need different indicators than a GDP forecasting case.

**The paper is organized as following.** Section 2 discusses the model's specifications and database. Sections 3 to 6 present the results, namely: impulse response function, variance decomposition analysis, counterfactual simulations, and conditional forecast results, respectively. Section 7 concludes. References and Appendices are in Sections 8 through 11.

## II. MODEL AND DATA

1. **We use a mixed-frequency Bayesian Vector Autoregression (VAR) model for our analysis, consisting of two blocks**: **a home economy and a foreign economy,** See, Österholm and Zettelmeyer (2008); Abrego and Österholm (2008); and Andrle, Ho and Saltos (2013). The VAR model is an effective tool for studying complex, dynamic interrelation in data. The empirical analysis of this model is four-fold. First, by estimating the impulse response functions using VAR, we can trace out the effects of policy, innovations from external factors, and risk on the economy. Second, we analyze historical variance decompositions to demonstrate the impact of external and domestic shocks in explaining the volatility of the domestic economy. Third, we compute the in-sample conditional forecasts to assess the information-optimality of the external and domestic factors independently. Finally, we provide a nowcast of GDP growth using monthly information releases. In what follows, we describe the model specification.

The model is a structural VAR with only one lag, due to the short sample size and in order to avoid the over parameterization problem. All the variables in the model are stationary and have a zero mean, since we demeaned and detrended all the data using the Hodrick-Prescott (HP) filter. The model converges to a steady state. With *Y(t)* being the vector of endogenous variables with *n* entries, assume the economy evolves as:

$$Y_t = c + \sum_{r=1}^{p} A_r Y_{t-r} + \varepsilon_t,\ \varepsilon_t \sim i.i.d(0, \boldsymbol{\Sigma}), \qquad (\mathbf{1})$$

where the constant term $c$ is a $v$x1 vector, but in our case it is zero since the data is demeaned, where $v$ is the number of variables, $A_r$ is a $v$x $v$ autoregressive matrix, and $\varepsilon_t$ is a

$v$x1 white noise process with covariance matrix $\boldsymbol{\Sigma}$. Since we demean the model, the closed-form notation of the model is:

$$Y_t = AY(t-1) + \varepsilon_t,\ \varepsilon_t \sim i.i.d(0, \boldsymbol{\Sigma}). \qquad (\mathbf{2})$$

**The identification assumption ensures no spillover from the domestic economy to the external block while, the external block does affect the domestic economy.** We estimate the model with the standard OLS estimates by imposing block erogeneity condition. We use a multi-step forecasting error approach to evaluate the forecasting power of our model by recursively computing the h-step ahead forecast, see Marcellino, Stock, and Watson (2006).

We analyze the period after the banking crisis of 2001 in Turkey. The data cover the period 2003Q2 to 2014Q1. The number of explanatory variables in the model is kept to a minimum, so that we can track through the main channels of propagations. The information content of variables in the model signals macro-financial developments in aggregate output. Specifically, we use only the price of oil, US industrial production,[4] and US risk spread (defined as the spread between Moody's BAA and AAA corporate bond rates) in the foreign economy block. Intuitively, global oil price and US IP reflect the dynamic of commodity cycle and demand pressure respectively; US risk spread signal foreign investors risk taking appetite. Note that there are various risk indicators such as EMBI, VIX, FSI (financial stress index), which can be used for other small open economies, nevertheless for the case of Turkey we found that US risk spread suits the nowcasting application better.[5]

Generally to tailor the model for other economies' nowcasting, the practitioner should choose the domestic variables by analyzing all possible *soft* and *hard* leading indicators for which data is available. For example, other potential candidates include consumer and business confidence indicators, unemployment, consumption expenditure, manufacturing trade sales,

[4] Hard data such as industrial production or imports carries a lot of information about the GDP growth in Turkey (See Akkoyun and Gunay, 2012).

[5] One way of comparing the explanatory power of various indicators is to check mean square forecast error.

stock price index, capital utilization and exchange rate. In choosing the external variables, the real and financial variables of the main trading partners are the key.

We have examined a panel of High Frequency Indicators (HFIs) in order to choose domestic leading indicators. In the domestic economy block we use real GDP, industrial production, three-month weighted average interest rates, imports, and loans to the private sector. Loans to the private sector are a particularly informative leading indicator for Turkey, in the context of a small open economy, since it contains relevant information about capital inflows and credit availability. IP reflects production performance, import can shed light on the trade dynamic, and interest rate present saving-investment dynamic. Variables are seasonally adjusted by official sources and authors' computations (X12 ARIMA standard procedure).

$$\text{Data } (Y_t) = \left( \begin{array}{l} \textbf{Global} \left\{ \begin{array}{l} Global\ Price\ of\ Oil \\ US\ Industrial\ Production \\ Risk\ Spread\ (BAA - AAA) \end{array} \right\} \textbf{External} \\ \hline \textbf{Turkey} \left\{ \begin{array}{l} Real\ GDP \\ Industrial\ Production \\ Interest\ rates \\ Credit\ (Loan\ to\ Private\ Sector) \\ Import \end{array} \right\} \textbf{Domestic} \end{array} \right)$$

In the domestic block, we order slow-moving variables[6] first so that they can contemporaneously affect fast moving variables.[7] Cholesky decomposition is used to

[6] Note that GDP is quarterly and the rest of the variables are monthly.

estimate an orthogonal covariance matrix of the residuals. The ordering of the variables in the model, our vector of data, is specified as follows. Our identification implies that external shocks have an impact on domestic variables.[8] Moreover, in the domestic block GDP is presumed to be uncorrelated with other (non-GDP) domestic shock processes.

To make the series stationary, we compute cyclical components of the data. These are obtained by applying the HP filter to 100 times the natural log of data. We apply the HP filter only to the level of domestic economy interest rates and US financial risk spread data. Since we use leading indicators in this forecasting exercise, the cyclical components are quite crucial for signaling the drivers of forecast in rapid growth, stable, and slowdown periods. Hence, calculations based on the cyclical component improve the forecast performance of the model.

## III. IMPULSE RESPONSE ANALYSIS

**By comparing the impulse responses of GDP growth to external shocks, one can observe that oil shock can lead to the largest drop in output growth.**

Figure **1** reports the median of the posterior distribution of the impulse responses to adverse shocks of risk spread, US IP, and global oil price. The spread shocks are financial shocks, affecting the supply of funds, while oil price and US IP shocks are demand shocks. Upon the impact of a one-standard-deviation oil shock (spread shock and US IP), output drops 1.3 (0.7 and 1) percentage points relative to its steady state. IP, credit, and imports commove with output growth. The interest rate increases in response to adverse supply shocks, reflecting the tradeoff between output and inflation stabilization objectives, while it decreases in response to the demand shocks.

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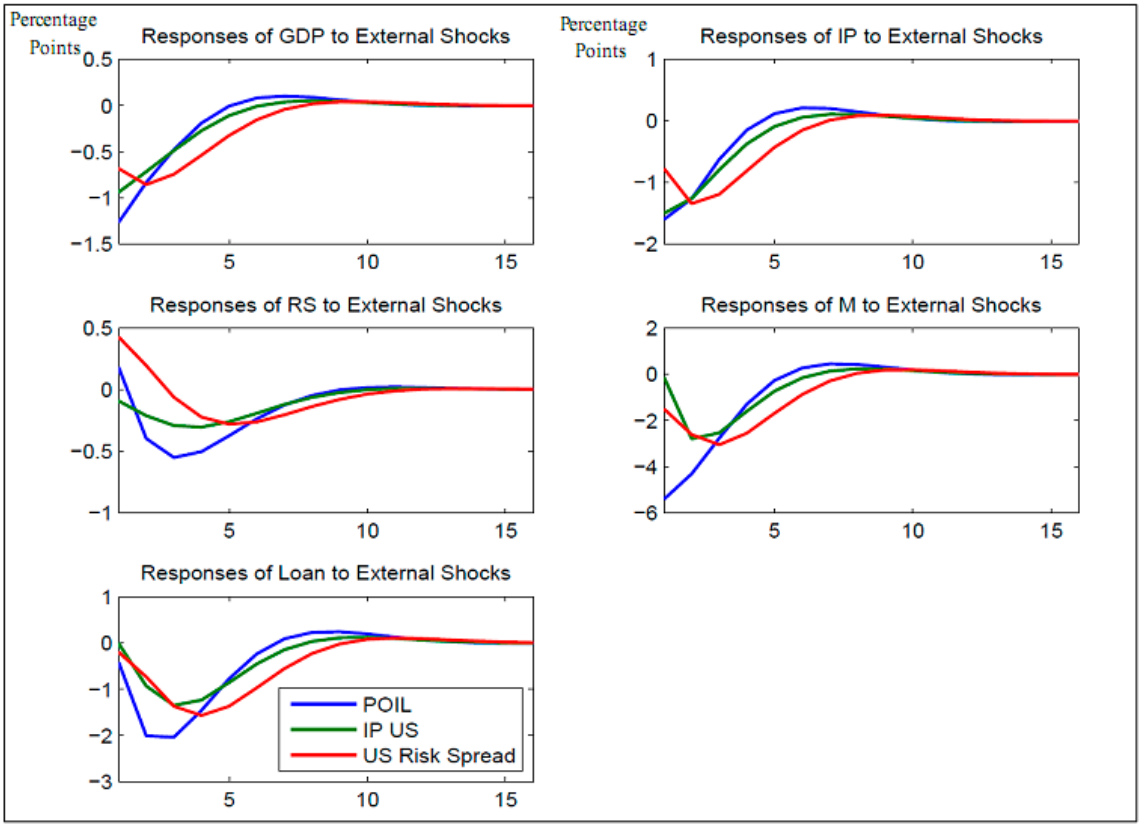
[7] Giannone et. al (2015) also place GDP as the first variables. We have done some robustness check by changing the ordering of the variables in the domestic block and we found that the main finding of the paper stays qualitatively the same.

[8] This identification will not be applicable for US economy since it is a large open economy with complex links to the global economy.

**Figure 1. External Shocks and Responses of Domestic Variables**




# IV. VARIANCE DECOMPOSITION

## A. Forecast Error Variance Decompositions (FEVD)

**By using variance decomposition analysis, we quantify the impact of external shocks on the domestic economy at different horizon.** This exercise demonstrates that global factors have significant impacts on our small open emerging economy, which could further have important policy implications. By computing variance decomposition we essentially project the dynamic of an endogenous variable into the different shocks component of the VAR, in order to measure the information content of relative importance of each shock in explain the variables in the VAR. We can rewrite the model using the lag operator as following:

$$Y_t = ALY_t + \varepsilon_t \rightarrow Y_t = (I - AL)^{-1}\varepsilon_t = B(L)\varepsilon_t, \qquad (3)$$

and the error in forecasting Y(t) for each horizon h is:

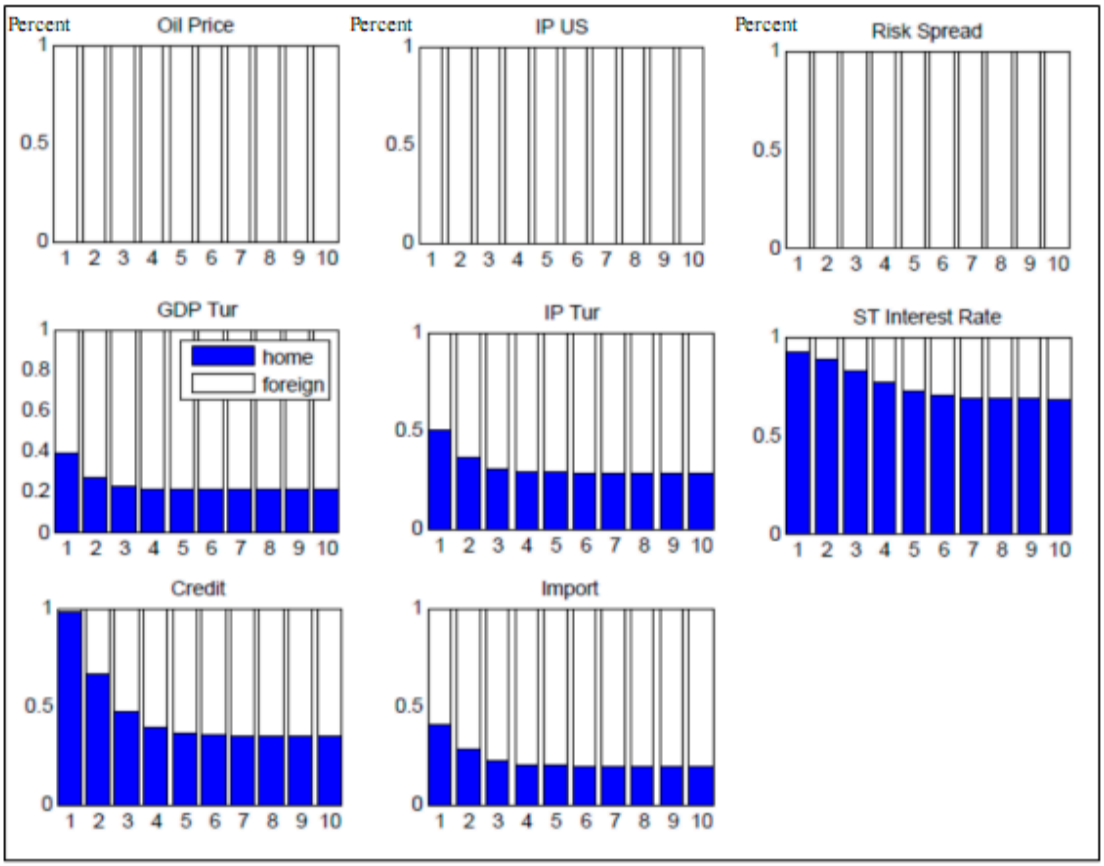
$$Y_{t+h} - Y_t(h) = B(L)\varepsilon_{t+h}, \quad (4)$$

Hence, the variance of the total forecasting error is given by:

$$var(Y_{t+h} - Y_t(h)) = B(L)\Sigma B(L)', \quad (5)$$

We can compute individual shock's variance decomposition as the individual share of the total variance decomposition. To compare the domestic versus external shocks, we aggregate FEVD of all the domestic shocks together and call it "home"; we do the same for the external shocks and we call them "foreign". Figure 2 shows total forecast error variance decomposition over 10 quarters following aggregated shocks to the home economy. The blue bars show the aggregate contribution of the domestic shocks, while the white bars explain the aggregated external shocks. All shocks in the model are considered unanticipated. The large share of white bars in the panel suggests that most of the volatility in the domestic indicators is explained by external factors.

**Figure 2. Forecast Error Variance Decompositions of Home and Foreign Shocks**



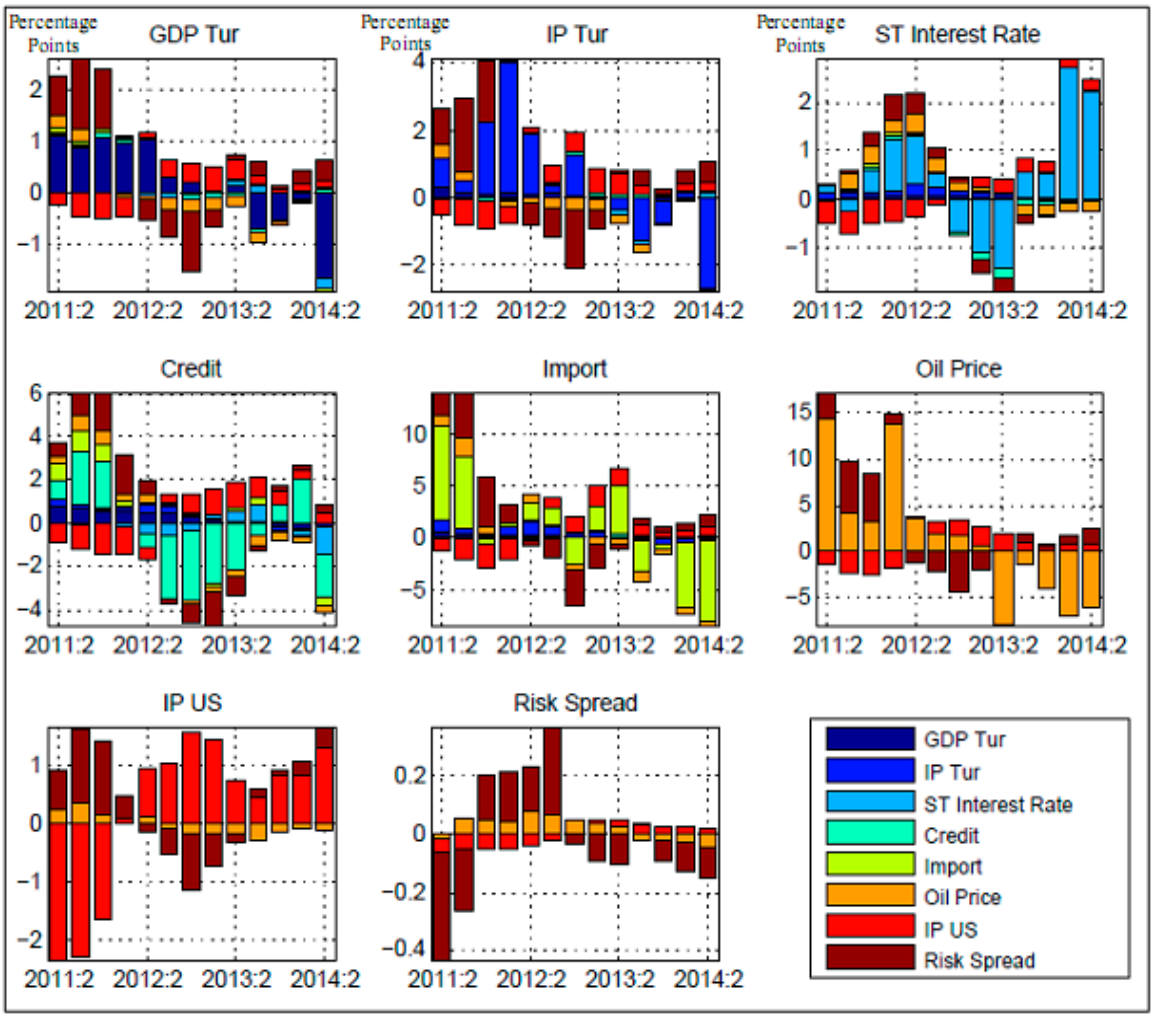
Note that, by construction, our identification assumption implies that there is no spillover from the domestic economy to the external variables; therefore, the FEVDs of external variables is merely explained by the shocks originating in the foreign block. By investigating the panel, one can draw the following observations. First, the impact of domestic shocks in the first quarter is the strongest. Second, more than 60% of output FEVD is driven by external factors. While the response of the loans to private sector is determined largely by domestic factors in the short term, in the medium-to-long-term the share of external shocks increases. This is due mainly to capital flows that are converted to credit in the home economy. Similarly, the response of short-term interest rates is explained mainly by the domestic factors, as the monetary policy responds to business cycle shocks.

Figure **7** in the Appendix shows the individual variables' structural historical variance decompositions. The large impact of external variables on domestic economy is not surprising, as Turkey has become increasingly open economy after 2001. Both pull and push factors, global financial cycle, appreciated currency, and improved domestic prospect, played role in increasing capital inflow into the economy.

## B. Historical Variance Decompositions

**Drivers of the domestic business cycle can be determined by computing the dynamic contribution of each shock in explaining the historical path of the variables.** Figure 3 shows the year-on-year, historical variance decompositions (HVD) of the variables in the model. Intuitively given a variable, such as GDP, we project the variable in the orthogonal space of the shocks; hence, each colored bar represents the contribution of the related shock in explaining the dynamic of the variable of interest. Such quantitative analysis of business cycle drivers can help tailor the policy mix. For example, in episodes of high external spillover in the domestic economy, identifying whether the spillover is uncertainty driven or due to change in the fundamentals can help domestic policy makers choose their policy instruments more effectively.

**Figure 3. Historical Variance Decompositions**




The GDP dynamic shows a large degree of persistence between 2011 and 2013. The external channels, both real and financial, have been very important during the turmoil of 2012-2013. A combination of Euro Area double-dip recession, uncertainty around the US fiscal cliff, Turkey's political unrest, and other factors led to an increase in volatility and market perception of risk in emerging markets.[9] Hence, US IP is playing a negative but small role, while US risk spread is playing a large and positive role in explaining the domestic economy's business cycle between 2012 and mid-2013. This is intuitive, as US IP is a proxy

[9] With large declines in portfolio investment, gross capital inflows to central and southeastern Europe turned sharply negative in the third quarter of 2013 and dropped substantially for Turkey (Figure 2.4, WEO April 2014, page 57).

for external real activity, and US risk spread is a proxy for the risk-taking appetite of foreign investors. Hence, the contribution of the US IP has an opposite effect compared to the contribution of the risk spread, highlighting the countercyclical nature of the risk spread.[10] Finally, one can observe that the real GDP chart in the top left hand-side commoves with the IP in the top middle chart.[11]

Domestic factors have a minor role in explaining the dynamic of short-term rates. Moreover, in 2012 the contribution of risk spread has been positive and significant, but the explanatory role of the spread is diminishing in the latter part of the sample. Credit commoves with GDP, but nonetheless, the role of domestic factors is decreasing toward the end of the sample.

## V. COUNTERFACTUAL SIMULATIONS

**How important are external shocks in explaining historical data?** We answer this question by computing three counterfactual economies: (i) a simulated economy with all the shocks included; (ii) a simulated economy where we exclude domestic shocks, but the external shocks still affect the model dynamic; and finally, (iii) a simulated economy where we exclude external shocks, while the domestic shocks are still operating. To compute these counterfactual economies we first estimate the parameters and historical paths of shocks of the model using the whole information set; then we simulate our BVAR model using a subsample of the shocks by setting zero coefficients on the selected residuals, specifically, external shocks (ii) and domestic shocks (iii). The simulated paths now correspond to a hypothetical economy with no forecast errors in the residuals of the foreign block and domestic block, respectively.

Figure **4** presents a panel of the domestic variables' historical paths under the above three scenarios. The red curves denote the baseline economy in the presence of all the shocks. The

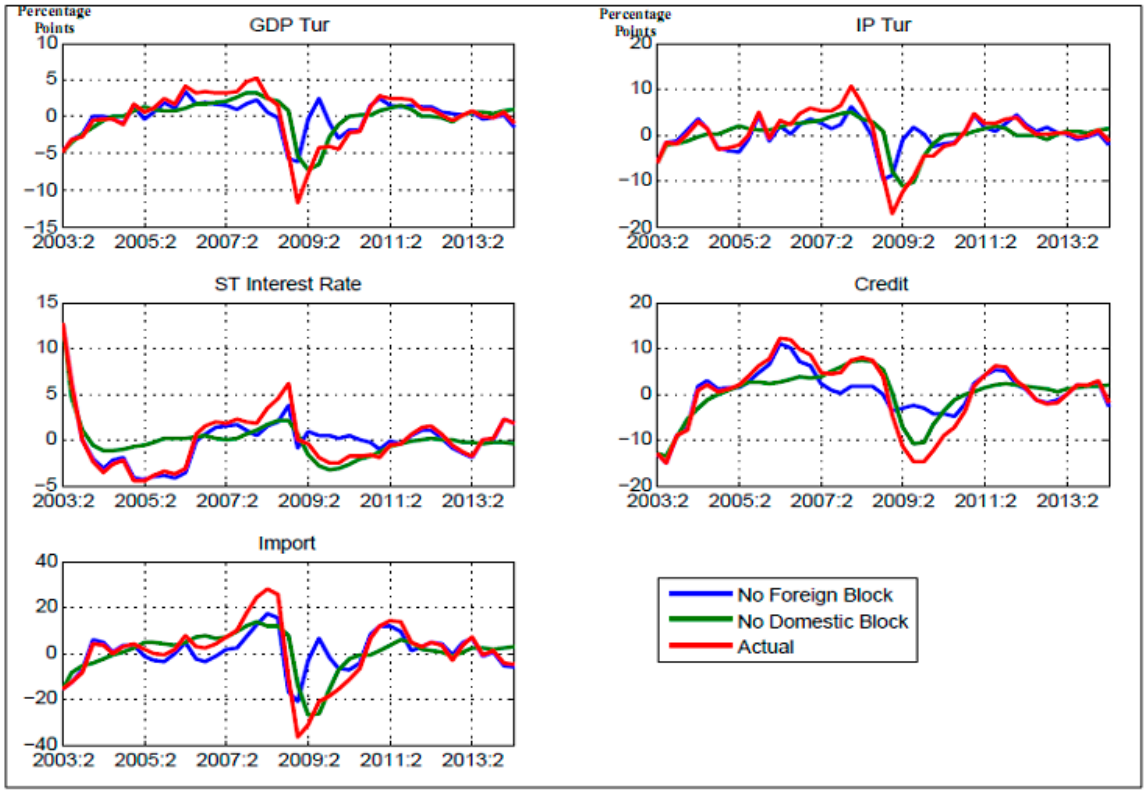
[10] When US economy is growing, foreign investors' home bias increases; as a result FDI to emerging economies shrinks, which further affects credit dynamic in domestic economy. The increase in US corporate risk spread has an opposite effect.

[11] This is mainly due to the methodology used by Turkish Statistical Institute (TurkStat) to construct the Real GDP, which assigns a high weight on IP.

blue curves illustrate our counterfactual economy in which we turn off the external shocks. Finally, the green curves show the counterfactual economy without domestic shocks. By comparing the three curves, one can assess the information content of different shocks in explaining the historical paths of the variables in the economy.

In the wake of the recent global financial crisis, the Turkish economy experienced a recession and a subsequent rebound in 2009 and 2010, partially due to the negative spillover from the US economy. The periods before and after the 2009 recession are considered *normal times* in this paper. By comparing the green and blue curves in the
**Figure 4**, one can observe that, while domestic shocks play an important role in explaining the business cycle dynamic during normal times, the external shocks can explain the joint dynamic of *downturn and rebound* better. A model that does not account for external shocks predicts a shorter duration for the 2009 downturn episode and a too-speedy recovery.

**Figure 4. Counterfactual Simulations**



## VI. CONDITIONAL FORECAST

**The mixed-frequency nature of our model allows for using the new release of information in updating the forecast of the GDP.** This is particularly useful because GDP has a slow release and is available on a quarterly basis, but it can be estimated using higher-frequency variables. This work belongs to the strand of literature that studies "nowcasting GDP." Nowcasting is an exercise for computing the current-quarter forecast of key indicators of real economic activity, namely GDP, using the information flow. Any release of high frequency data might convey economically significant information, which has an impact on GDP. Following Giannone, Reichlin, and Small(2008), the conditional forecast problem is defined as following:

$$\underbrace{\mathrm{E}_t\{GDP_{t+1}^{Q} \,|\Delta_t^{M+1}\}}_{nowcast} = \underbrace{\mathrm{E}_t\{GDP_{t+1}^{Q}|\Delta_{\mathrm{t}}{}^{M}\}}_{Unconditional\ Forecast} + \underbrace{\mathrm{E}_t\{\, GDP_{t+1}{}^{Q}|\delta_{\mathrm{t}}{}^{M+1}\}}_{Revisions\ due\ to\ the\ news} \quad (6)$$

$$\Delta_t = \{\Delta_t^M, \Delta_t^Q\} = \{y_t, y_{t-1}\, y_{t-2}, \dots y_0\} \quad (7)$$

$$GDP_t^Q = GDP_t^M + GDP_t^{M+1} + GDP_t^{M+2},\ Q = \{\, M_1, M_2\, , M_3\}, \quad (8)$$

where the $\underbrace{\mathrm{E}_t\{GDP_{t+1}{}^{Q}|\Delta_{\mathrm{t}}{}^{M+1}\}}_{nowcast}$ shows the nowcast of quarterly GDP at period *t*, conditional on the information set available up to month $M$+1, $\Delta_{\mathrm{t}}{}^{M+1}$. $Q$ stands for quarters and $M$ stands for months. Every month, with new data available, the forecast is revised $\mathrm{E}_t\{\, GDP_{t+1}{}^{Q}|\delta_{\mathrm{t}}{}^{M+1}\}$, using the Kalman filter to account for the missing observations.

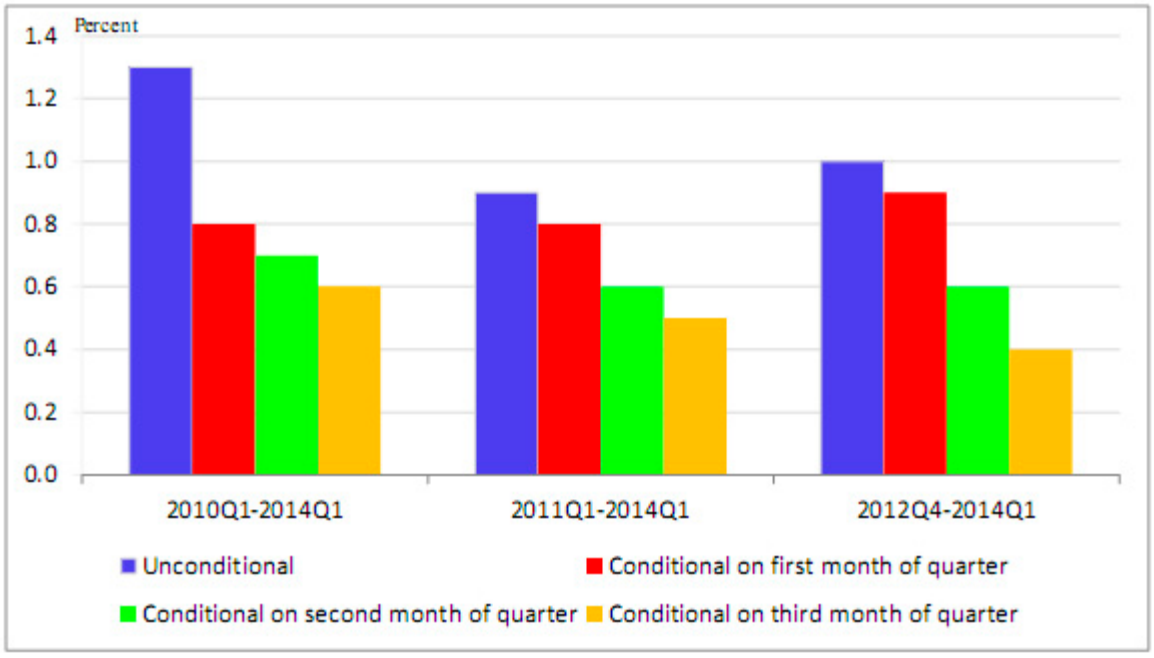
Nowcasting improves as new information becomes available throughout the month. We evaluate the forecasting power of the model by computing one-quarter ahead root-mean-square errors (RMSEs) over different horizons and different vintages. The RMSEs of the model's forecast for GDP growth of Turkey are calculated as:

$$RMSE_h = \sqrt{\frac{\sum_{t=2011Q1+h}^{2012Q2}\left(GDP_t^{Actual} - GDP_t^{Forecast}\right)^2}{N}}, \quad (9)$$

where $h = 1\ and\ N = 6$.

Figure **5** summarizes the RMSE results. The blue bars are unconditional forecasts; the red, green, and yellow bars correspond to the nowcast conditional on the data available up to the first, second, and third months of each quarter; and finally, the yellow bars correspond to the nowcast conditional on the data available up to the third month of each quarter.

**Figure 5. RMSEs for Different Time Vintages** (quarterly nowcast of output growth)




We also compared our annual forecasts with the World Economic Outlook (WEO) forecast for the recent four years, including the 2009 recession and 2010 recovery. To compute the out-of-sample forecast for any given year *i*, we restrict ourselves to the data available up to the previous year *i*-1.[12]

Table **1** and

Table **2** show the comparison between out-of-sample annual (four steps ahead) forecast errors and RMSEs of our model with the spring WEO forecast. Forecast errors are calculated as the difference between the forecast and actual. For example, Table 1 shows that WEO's

[12] We use final estimate for the year instead of initial estimates.

forecast of 2009 GDP growth has been 4% above the actual, while our model predicted the 2009 recession with a somewhat bigger trough. Althoguh using a VAR framework with domestic leading indicators and global variables provides us with a parsimonious forecasting framework, with a good accuracy, practitioner should be careful relaying only on single forecasting model. Usually combination of several forecasting techniques should be used to more meaningfully understand the future developments in the economy.

**Table 1. Out of Sample Forecast Errors for Different Time Vintages**

| Forecast Turkey's output Growth | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|
| WEO | 4.0 | 4.2 | -0.2 | 0.6 |
| Our Model | -2.3 | 2.3 | 0.4 | -0.1 |

**Table 2. Out of Sample RMSEs for Different Time Vintages**

| Forecast Turkey's output Growth | 2009-2012 | 2010-2012 |
|---|---|---|
| WEO | 2.9 | 2.4 |
| Our Model | 1.6 | 1.3 |

## VII. CONCLUSION

This paper proposes a nowcasting toolbox for output growth by specifying an explicit role for global factors. By presenting impulse response functions, variance decompositions, and counterfactual simulations, we illustrate how external shocks, together with domestic shocks, can explain the dynamic of variables in the economy. This empirical setup parsimoniously combines the information content of domestic and external leading indicators; hence, it is suitable for any small open economy that has large trade and financial links to advanced economies. To illustrate the application of our proposed methodology, we apply it to the case of Turkey. Our conditional forecast results suggest an improvement in forecasting power, as we not only exploit the mixed-frequency nature of the model, we can also measure the impulses from external factors.

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# IX. Appendix

## A. Data

**Table 3. Data Description and Sources**

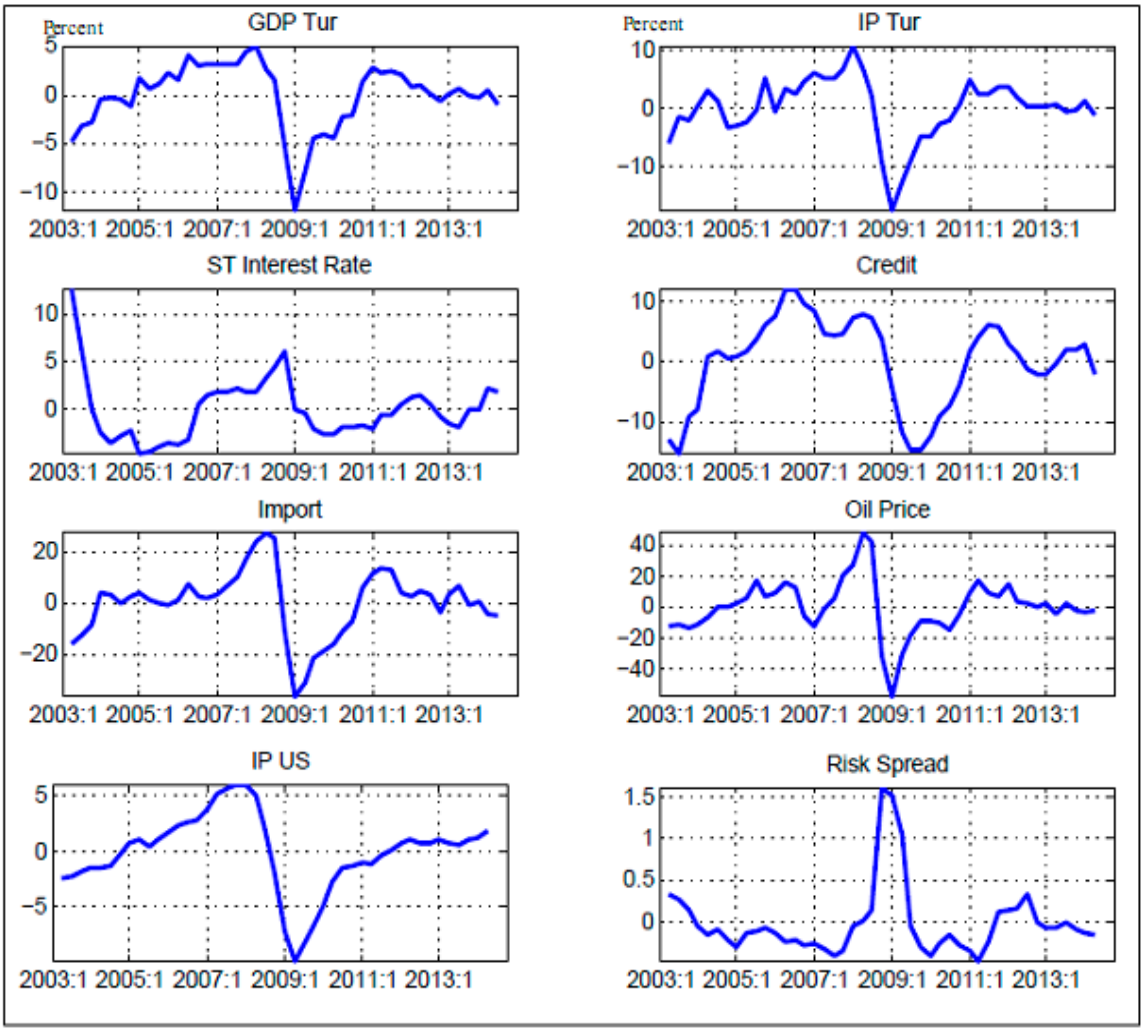
| Variable | Source |
|---|---|
| Gross Domestic Product (SWDA, Thous.98.TL) | TurkStat |
| Industrial Production: Total Industry (SA, 2010=100) | TurkStat |
| Foreign Trade: Total Merchandise Imports, c.i.f. (SA, Mil.US$) | TurkStat |
| Deposit Money Banks Loans: Private Sector (EOP, SA, Thous.TL) | Central Bank of the Republic of Turkey |
| Weighted Average Interest Rates for TL Deposits {Ex Sight/Interbank}: Up to 3Mo (%) | Central Bank of the Republic of Turkey |
| World Crude Oil {Petro}: Brent,WTI,Dubai Fateh Spot Price Avg.( US$/Bbl) | IMF |
| US: Industrial Production excluding Construction (SA, 2007=100) | Federal Reserve Board |
| Risk Spread | Baa-Aaa |
| Moody's Seasoned Baa Corporate Bond Yield (% p.a.) | Moody's |
| Moody's Seasoned Aaa Corporate Bond Yield (% p.a.) | Moody's |

**Table 4. Cross-Correlation of Output Gap with following Variables**

***(Cyclical component of series (HP filtered))***

| | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 |
|---|---|---|---|---|---|---|---|
| **Output GAP** | 0.33 | 0.56 | 0.82 | 1 | 0.82 | 0.56 | 0.33 |
| **Domestic IP** | 0.3 | 0.55 | 0.79 | 0.94 | 0.76 | 0.51 | 0.22 |
| **Short-term Rate** | 0.5 | 0.4 | 0.21 | -0.12 | -0.29 | -0.38 | -0.38 |
| **Import** | 0.39 | 0.64 | 0.83 | 0.89 | 0.62 | 0.23 | -0.03 |
| **Credits** | 0.69 | 0.83 | 0.87 | 0.75 | 0.52 | 0.31 | 0.15 |
| **Nominal POIL** | 0.26 | 0.51 | 0.7 | 0.79 | 0.56 | 0.13 | -0.13 |
| **US IP** | 0.62 | 0.8 | 0.9 | 0.85 | 0.67 | 0.44 | 0.19 |
| **US Financial Riskness** | 0.38 | 0.05 | -0.35 | -0.68 | -0.77 | -0.61 | -0.52 |

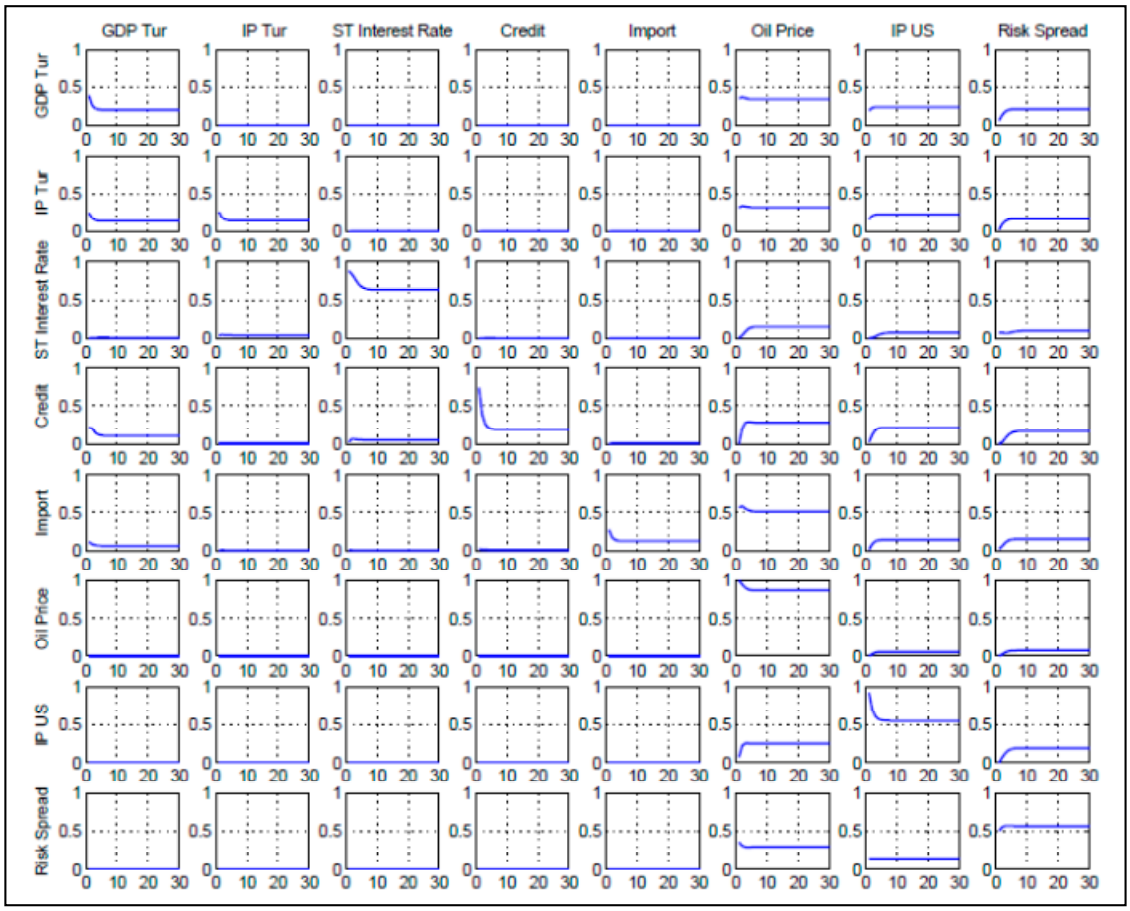
**Figure 6. Stylized Facts: Model Variables** (HP filtered)




## X. STRUCTURAL FORECAST ERROR VARIANCE DECOMPOSITIONS

Figure **7**, below, shows the individual variables' structural forecast error variance decompositions. The rows illustrate the indicators, and the columns illustrate the shocks. Each chart shows the relative contributions of residuals. By investigating the variance decomposition of the Real GDP on the top row, one can highlight the important role of global risk factors, captured by the price of oil, and US investment risks, captured by the spread, through the capital flows and foreign financing channels.

**Figure 7. Structural Forecast Error Variance Decompositions**




## XI. NOWCASTING IN PRACTICE

**In this section, we give an example of how we use monthly information in producing a nowcast of GDP within each quarter.** We assume that the Turkish GDP is available up to 2014Q2; this exercise aims at computing a point forecast of 2014Q3. The domestic variables, except short-term interest rates, are available up to 2014M7, while external variables are available up to 2014M8. As new monthly information is published, we update our estimate of the variance-covariance matrix and update the nowcasts. Our results support the findings in the literature regarding the importance of both IP and imports as leading indicators of Turkish aggregate output. In addition, we find that loans to the private sector have useful

information as a leading indicator. We are using a conditional forecast to parsimoniously combine high frequency information in nowcasting real activities.

**Table 5. Calendar of Turkey's GDP Releases**

| Month | Release Date | Reference Quarter |
|---|---|---|
| March/April | Last week of March or 1st week of April | Q4 |
| June | After first week | Q1 |
| September | 2nd week | Q2 |
| December | 2nd week | Q3 |

Therefore, nowcasting will be implemented using available information based on **Figure 8**. Conditional forecasting on M1 includes information of first month of quarter for all the monthly variables. Conditional forecasting on M2 includes information of second month of quarter only for short-term interest rate and external variables in the model.

**Figure 8. GDP Growth (% YoY) and Nowcast**