# Türkiye | Advances on GDP Nowcasting: Data, Frequency & Methodology

Garanti BBVA Research

October 2022

Creating Opportunities

# Our motivation

- Enhancing our existing nowcasting analysis:
  - Data: adding new variables, dropping less relevant ones and making it ready to regular updates
  - Methodology: Improvements to our Dynamic Factor Model (DFM)
- Benefiting from daily big data proxies
- Generating a reliable in-house «Weekly GDP Tracker»
  - Alternative to the Central Bank's Tracker (which is not publicly shared in detail)
  - Improvement over OECD's Weekly Tracker (based on Google trends)
- Quantitative tool to compute real-time responses to policy impulses in a period of rapidly changing shocks

# GDP nowcasting: data, methodology and weekly GDP tracker

- Improvement in data coverage:
  - Two separate datasets: (i) 14 variables including soft data in the first weeks of nowcasting, (ii) 5 variables of mainly hard data in the backcasting of the quarter.
  - Adding new big data proxies and keeping it open to revisions
  - Dealing with calendar day effects in weekly nowcast
  - Managing deflators when calculating variables in real terms
- Expanding methodological approaches: (i) DFM; (ii) Mixed Frequency Bayesian VAR; (iii) Mixed Data Sampling (Factor MIDAS)
- Checking models' forecast performance by adding in-house IP forecasts in advance
- Introducing a Weekly GDP Tracker
- Model averaging in order to reduce errors
- Enhancing high frequency approach to maximize observable responses to immediate policy impulses

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# 01

# Data Advances

Creating Opportunities

# We list candidate variables and check their individual fit

## CANDIDATE VARIABLES

| VARIABLE | LASSO | ELASTIC NET | CORRELATION | VARIABLE | LASSO | ELASTIC NET | CORRELATION |
|---|---|---|---|---|---|---|---|
| **IP - Industrial Production** | 0.229 | 0.041 | 0.95 | Tax - Total Tax Income | 0.005 | 0.016 | 0.72 |
| **IP - Intermediate Goods** | . | 0.031 | 0.93 | Tax - Income Tax | . | 0.019 | 0.73 |
| IP - Durable Goods | 0.021 | 0.023 | 0.82 | Tax - Stamp Duty | 0.051 | 0.037 | 0.78 |
| IP - Nondurable Goods | . | 0.040 | 0.88 | Tax - VAT | . | . | 0.46 |
| IP - Energy | . | . | 0.62 | **Tax - VAT on Imports** | 0.012 | 0.009 | 0.70 |
| IP - Capital Goods | 0.041 | 0.029 | 0.91 | **Electricity Production** | . | . | 0.72 |
| IP - Electrical Equipment | . | 0.023 | 0.89 | Electricity Consumption | . | . | 0.80 |
| IP - Machinery and Equipment | . | 0.016 | 0.50 | Credits - Total Loans (fx adj) | . | . | 0.36 |
| IP - Motor Vehicles | . | 0.012 | 0.84 | **Credits - Consumer** | . | . | 0.37 |
| IP - Non metalic mineral | . | 0.007 | 0.80 | **Credits - Commercial (fX adj)** | . | . | 0.30 |
| **Retail Sales** | 0.106 | 0.055 | 0.92 | Credits - Mortgage | . | . | 0.45 |
| Turnover - Total Industry | . | 0.000 | 0.75 | Credits - Fx adj Trend | . | . | 0.08 |
| Turnover - Energy | . | . | 0.50 | **SURVEY - Economic Confidence** | 0.000 | 0.000 | 0.64 |
| Turnover - Capital Goods | . | 0.008 | 0.82 | SURVEY - Services Confidence | 0.000 | 0.000 | 0.44 |
| Turnover - Intermediate Goods | . | . | 0.72 | SURVEY - Construction Confidence | . | 0.000 | 0.49 |
| Turnover - Durable Goods | . | . | 0.66 | SURVEY - Retail Trade Confidence | . | . | 0.21 |
| Turnover - Nondurable Goods | . | 0.004 | 0.70 | SURVEY - Consumer Confidence | . | . | 0.22 |
| **Turnover - Total** | . | 0.014 | 0.84 | SURVEY - Real Sector Confidence | . | 0.000 | 0.77 |
| Turnover - Construction | 0.023 | 0.018 | 0.68 | SURVEY - Manufacturing PMI | . | 0.000 | 0.69 |
| Turnover - Trade | . | 0.013 | 0.82 | **SURVEY - Capacity Utilization** | . | 0.001 | 0.85 |
| Turnover - Services | 0.020 | 0.015 | 0.72 | **EXT - Import Volume Index** | . | . | 0.49 |
| **EMP - Number of Employed** | . | 0.023 | 0.72 | EXT - Export Volume Index | . | . | 0.32 |
| EMP - Number of Unemployed | . | . | 0.42 | EXT - Tourist Arrivals | . | . | 0.56 |

Source: Garanti BBVA Research.

# We employ a *variable selection algorithm** to find a better combination

- Select 4-5 monthly core variables that span main dimensions of the economy (IP, retail sales, employment, etc.)
- Estimate a common factor (tracker) using a DFM
- From the available list of variables, choose the one that has the highest correlation with the tracker
- Add that variable to the current chosen list and estimate a new factor
- If the correlation of the new tracker with GDP increases -> keep the variable in the chosen list
- If the correlation of the new tracker with GDP decreases -> drop the variable from the list
- Return to step 3 and continue until all available variables are chosen or dropped

* Cuevas, A., Pérez-Quirós, G., & Quilis, E. M. (2017). Integrated model of short-term forecasting of the Spanish economy (MIPred model). Revista de Economía Aplicada, 25(74), 5-25.

# Variable Selection Algorithm Results (with different core sets)

| | TIME SPAN: 2012Q1-2022Q1<br>All Variables excl Big Data | | | | TIME SPAN: 2015Q1-2022Q1<br>All Variables |
|---|---|---|---|---|---|
| Core Variables | IP - Industrial Production | IP - Industrial Production | IP - Industrial Production | IP - Industrial Production | IP - Industrial Production |
| | Retail Sales | Retail Sales | Retail Sales | Retail Sales | Retail Sales |
| | EMP - Number of Employed | EMP - Number of Employed | Ciro - Toplam | EMP - Number of Employed | EMP - Number of Employed |
| | SURVEY - Economic Confidence | Capacity Utilization | Capacity Utilization | Capacity Utilization | Capacity Utilization |
| Selected Variables from Algorithm | **IP - Intermediate Goods** | IP - Capital Goods | IP - Non Durable Goods | Electricity Production | Electricity Consumption |
| | IP - Non Durable Goods | **Tax - VAT on Imports** | IP - Durable Goods | IP - Capital Goods | Turnover - Trade |
| | **Turnover - Total** | **SURVEY - Economic Confidence** | IP - Non metalic mineral | **Tax - VAT on Imports** | IP - Capital Goods |
| | **Tax - VAT on Imports** | Tax - Total Tax Income | **Tax - VAT on Imports** | **SURVEY - Economic Confidence** | **GB BBVA IP Proxy** |
| | **Capacity Utilization** | Tax - Stamp Duty | **SURVEY - Economic Confidence** | Tax - Total Tax Income | IP - Energy |
| | Turnover - Services | Turnover - Construction | Turnover - Services | Tax - Stamp Duty | **GB BBVA Retail Good Cons** |
| | SURVEY - Services Confidence | IP - Machine and Equipment | Tax - Total Tax Income | Turnover - Construction | Tax - Stamp Duty |
| | Tax - Total Tax Income | Tax - Income Tax | **EMP - Number of Employed** | IP - Machine and Equipment | GB BBVA Investment Index |
| | Tax - Stamp Duty | Credits - Mortgage | Tax - Stamp Duty | Tax - Income Tax | GB BBVA Const. Inv. Index |
| | Turnover - Construction | Credits - FX Adjusted Loans | Turnover - Construction | SURVEY - Manufacturing PMI | IP - Machine and Equipment |
| | IP - Machine and Equipment | **Credits - Commercial FX adj** | IP - Machine and Equipment | Credits - Mortgage | Turnover - Construction |
| | Tax - Income Tax | Credits - FX Adjusted Trend | Tax - Income Tax | Credits - FX Adjusted Loans | Tax - Income Tax |
| | SURVEY - Retail Trade Confidence | | SURVEY - Retail Trade Confidence | **Credits - Commercial FX adj** | GB BBVA Mach. Inv. Index |
| | SURVEY - Manufacturing PMI | | SURVEY - Manufacturing PMI | Credits - FX Adjusted Trend | Turnover - Energy |
| | Credits - Mortgage | | Credits - Mortgage | | SURVEY - Retail Trade Conf. |
| | Credits - FX Adjusted Loans | | **Credits - Consumer** | | **Credits - Commercial FX adj** |
| | **Credits - Commercial FX adj** | | SURVEY - Consumer Confidence | | Credits - FX Adjusted Trend |
| | | | Credits - FX Adjusted Loans | | |
| | | | **Credits - Commercial FX adj** | | |

| Common Factor Correlation with GDP | | | | | |
|---|---|---|---|---|---|
| **Core set** | 92.91% | 94.30% | 93.48% | 94.10% | 96.30% |
| **All set** | 94.49% | 96.31% | 95.18% | 96.04% | 98.40% |

Source: Garanti BBVA Research.

# Revised dataset: frequency, attributes & alternative small data set

## BENCHMARK MODEL VARIABLES

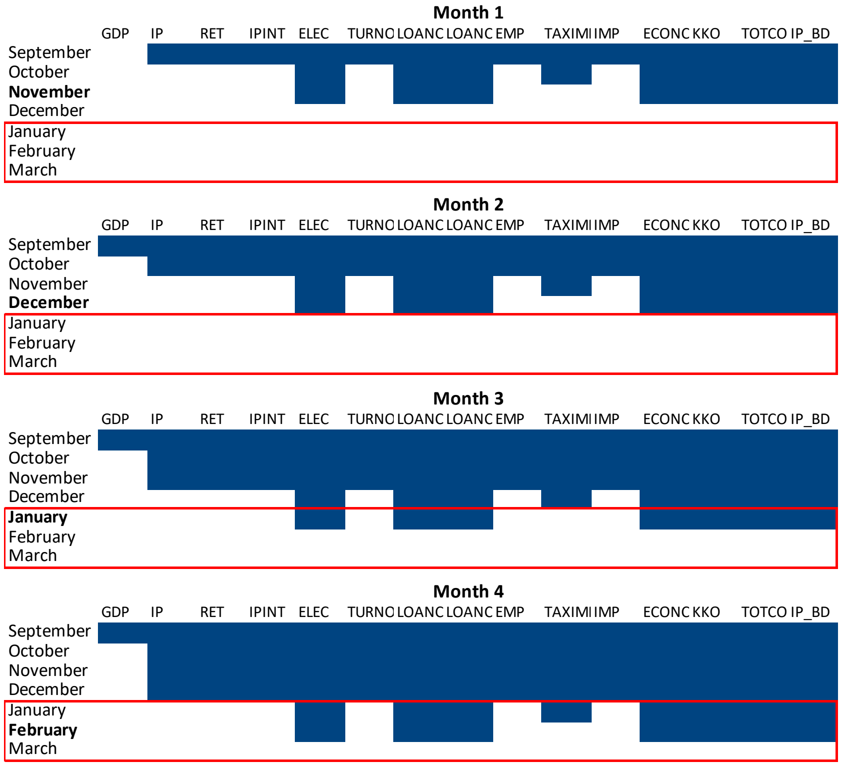
| BENCHMARK (MICA) | FREQUENCY |
|---|---|
| IP - Industrial Production | Monthly |
| IP - Non metalic minerals | Monthly |
| Electricity Production | Daily |
| Credits Fx adj (13w trend) | Weekly |
| EMP - Number of Employed | Monthly |
| EMP - Number of Unemployed | Monthly |
| SURVEY - Real Sector Confidence | Monthly |
| PMI | Monthly |
| AUTO - Sales | Monthly |
| AUTO - Imports | Monthly |
| AUTO - Exports | Monthly |
| Big Data Consumption | Daily |
| Big Data Investment | Daily |
| 13 variables | |

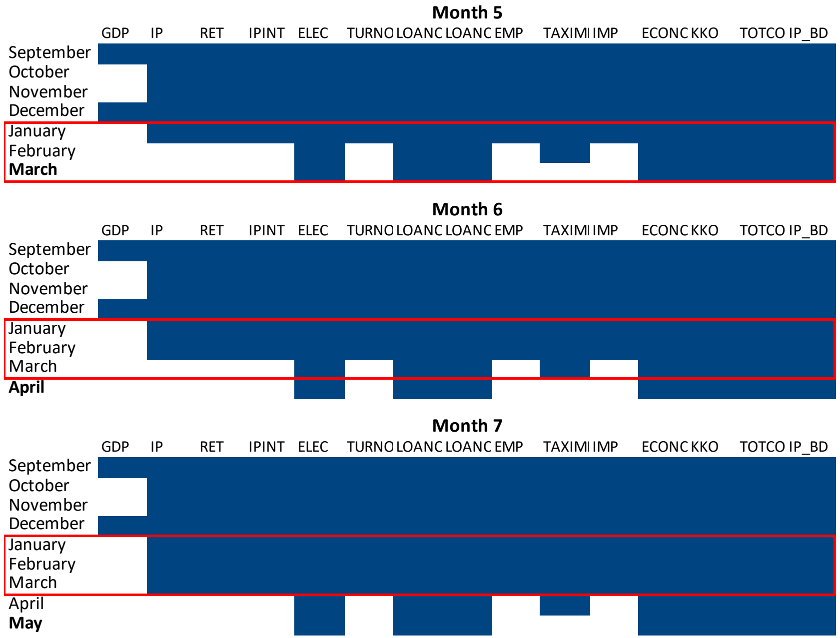
## SELECTED VARIABLE SETS TO BE USED

| LARGE SET | SMALL SET | FREQUENCY |
|---|---|---|
| IP - Industrial Production | IP - Industrial Production | Monthly |
| Retail Sales | Retail Sales | Monthly |
| IP - Intermediate Goods | | Monthly |
| Electricity Production | Electricity Production | Daily |
| Turn-over - Composite | | Monthly |
| Credits - Consumer | | Weekly |
| Credits - Commercial FX adj. | | Weekly |
| Number of Employed | | Monthly |
| VAT on Imports | | Monthly |
| Import Volume Index | | Monthly |
| Economic Confidence | | Monthly |
| Capacity Utilization Rate | Capacity Utilization Rate | Monthly |
| Big Data Consumption | | Daily |
| Big Data IP Proxy | Big Data IP Proxy | Daily |
| 14 variables | 5 variables | |

Source: Garanti BBVA Research.

# We specify the data lag structure in backtest exercises



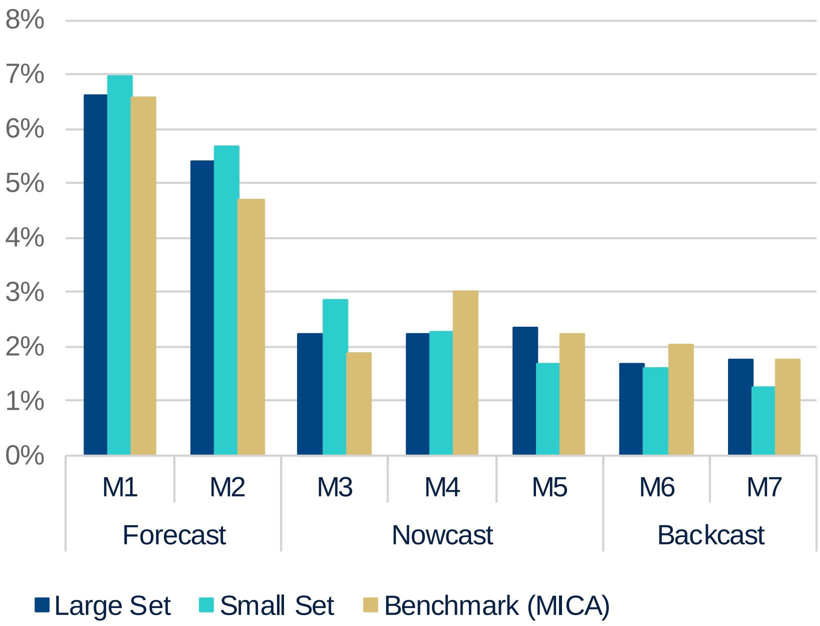




We specify three different periods, *forecast, nowcast and backcast*, depending on the timing of the forecast and availability of data releases at the time of the estimation

Source: Garanti BBVA Research.

# We obtained better results during nowcasting and backcasting

**RMSE Results (2017-2021)***




* Based on Dynamic Factor Nowcast Model backtests made with pseudo-real time data.
Source: Garanti BBVA Research.

- Relative performance on different horizons (forecast, nowcast & backcast).
- We improve upon our benchmark set both in the nowcasting & backcasting periods.
- Larger set marginally performs better in the nowcasting period.
- As we have more complete information in the backcasting period, signal/noise ratio works in favor of a smaller set.

| | Large Set | Small Set | MICA |
|---|---|---|---|
| Forecast | 5.99% | 6.33% | 5.63% |
| Nowcast | 2.26% | 2.27% | 2.36% |
| Backcast | 1.72% | 1.41% | 1.89% |

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# Extending Methods

# Different methods have different advantages & challenges*

## DFM

- More parsimonious specification than MFBVAR.
- Easy to handle missing observations on Kalman Filter.
- Heterogeneity in the data could not be handled easily.
- Generally requires data to be stationary.
- Generally better forecast performance in short run.
- Uncertainty on number of factors/lags and block structure.

## MFBVAR

- Balanced data required so that data could only contain missing observations at the end of the period.
- Heterogeneity in the data can be handled.
- Estimation could be done even for non-stationary data.
- Generally better forecast performance in longer run.
- Uncertainty on number of lags, number of factors and block structure could be handled.
- The curse of dimension is critical especially if the number of variables and lags get larger.

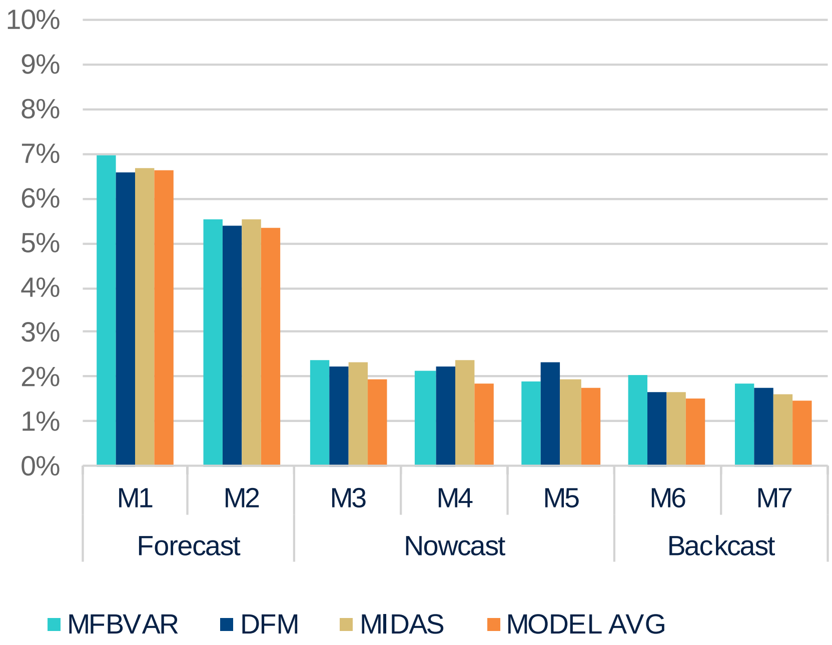
## Factor MIDAS

- More parsimonious specification than MFBVAR.
- Direct forecast approach and could be more robust to misspecification.
- Easy to handle missing observations on Kalman Filter.
- Heterogeneity in the data could not be handled easily.
- Better forecast performance in short run.
- Non-linear distributed lag function could be rigid.
- Uncertainty on number of factors and lags.

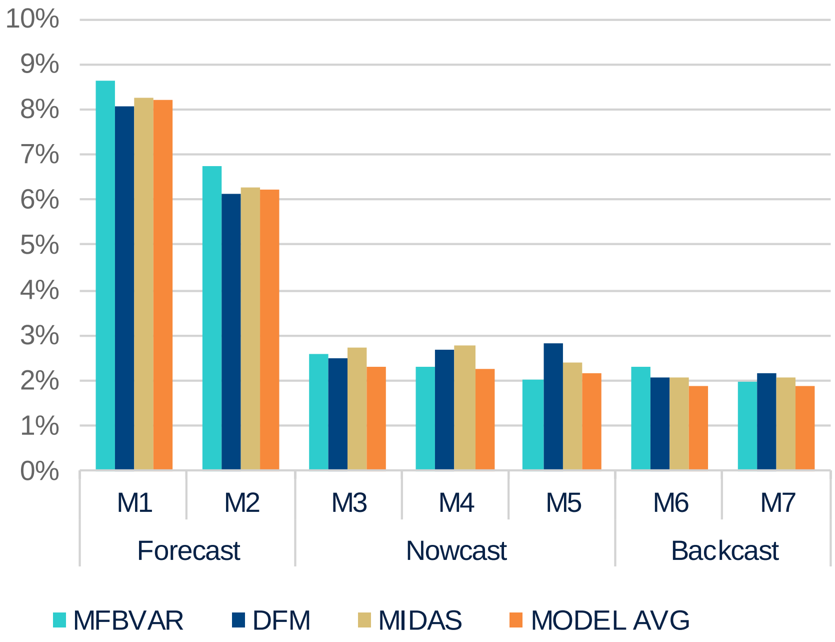
* Details of methods are described in the annex.
Source: Garanti BBVA Research.

# Average of model results provides smaller errors

## RMSE RESULTS
(2017-2021)




## RMSE RESULTS
(2019-2021)



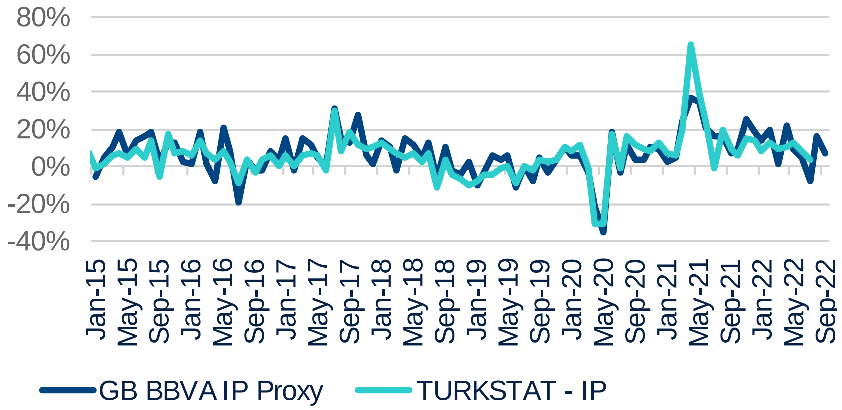

We benefit from the advantages of different models by making an average of model results

Source: Garanti BBVA Research.

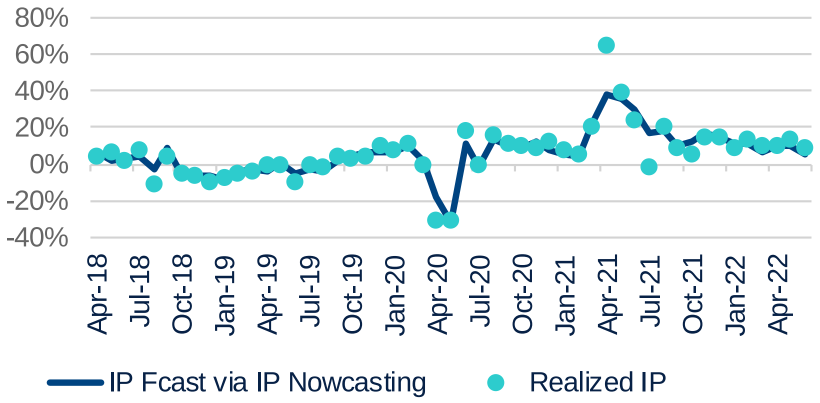
# We also check our results with our *in-house* IP forecast

- We take the advantage of our Big Data proxies to improve our model results
- We forecast IP on Capacity Utilization Rate (CUR), Electricity Production, Big Data IP Proxy, Big Data Retail Sales and Big Data Total Consumption by referring to both supply and demand driven factors
- Since IP has the most explanatory power in nowcasting exercises, introducing IP forecast in our models improve our results in general

**IP & IP PROXY**
(YOY GROWTH)



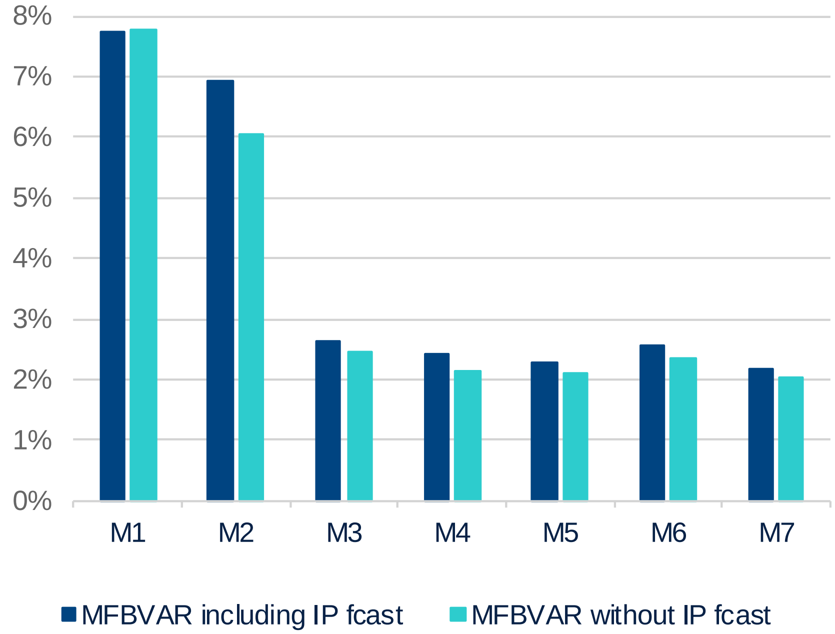

**IP & IP FORECASTS**
(YOY GROWTH)



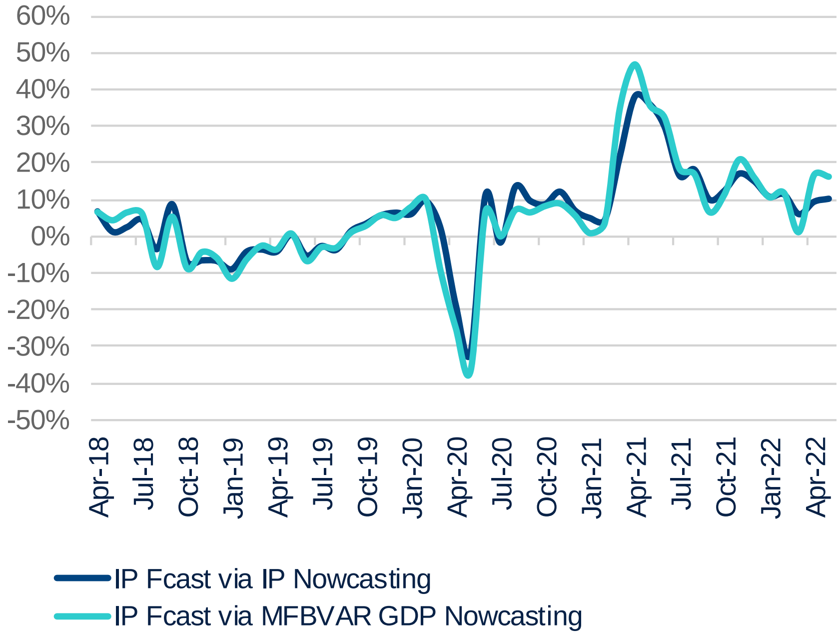

Source: Garanti BBVA Research.

# MFBVAR results don't change much if we introduce our IP forecast

## RMSE RESULTS
(2018Q3-2021Q4)



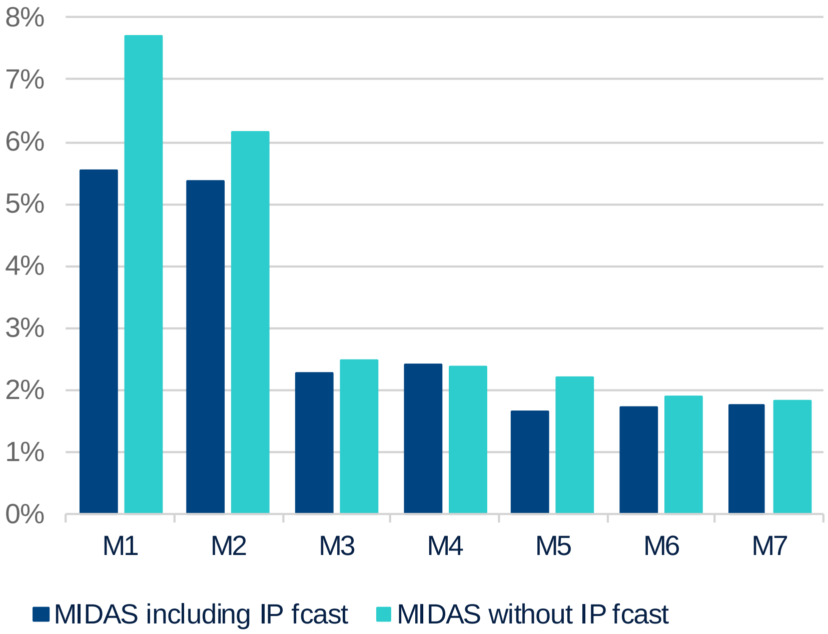

## IP FORECASTS
(YOY)



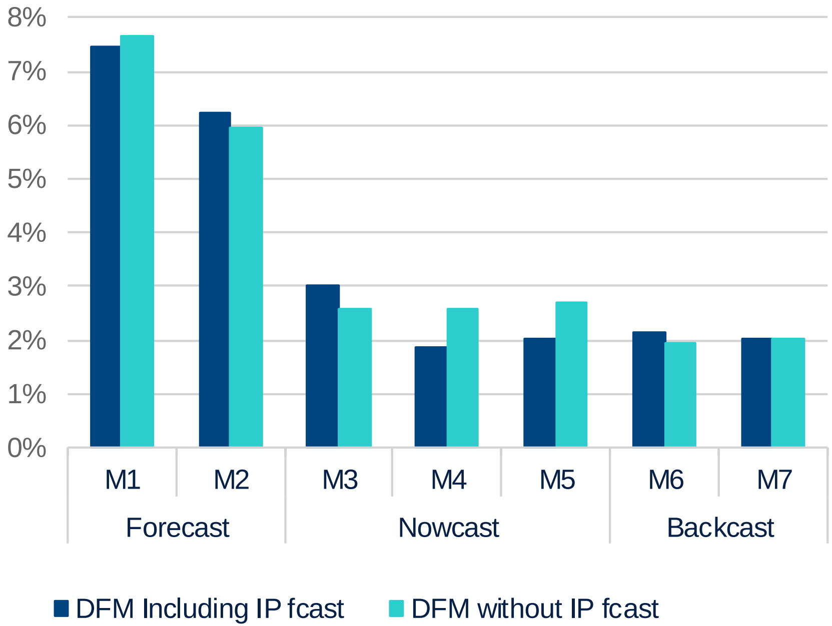

Source: Garanti BBVA Research.

# However, MIDAS & DFM results improve with our IP forecast

## RMSE RESULTS WITH MIDAS
(2018Q3-2021Q4)



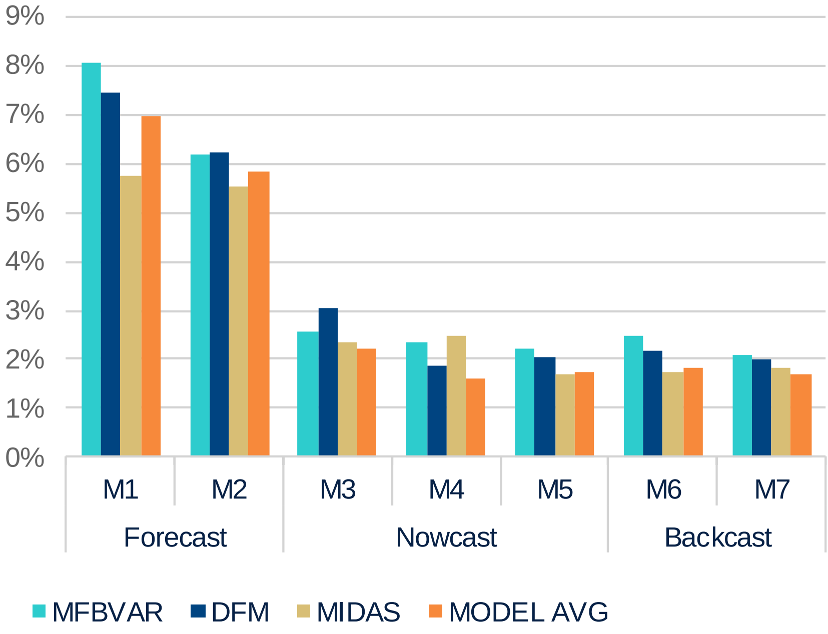

## RMSE RESULTS WITH DFM
(2018Q3-2021Q4)



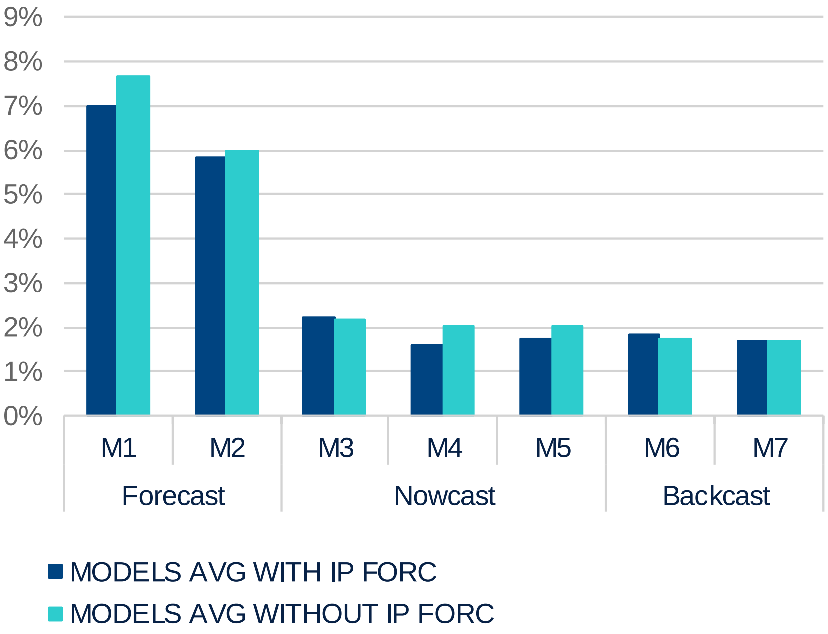

Source: Garanti BBVA Research.

# Not surprisingly, average of model results also gives lower errors

## RMSE RESULTS WITH MIDAS INC. IP FCAST
(2018Q3-2021Q4)




## RMSE RESULTS
(2018Q3-2021Q4)



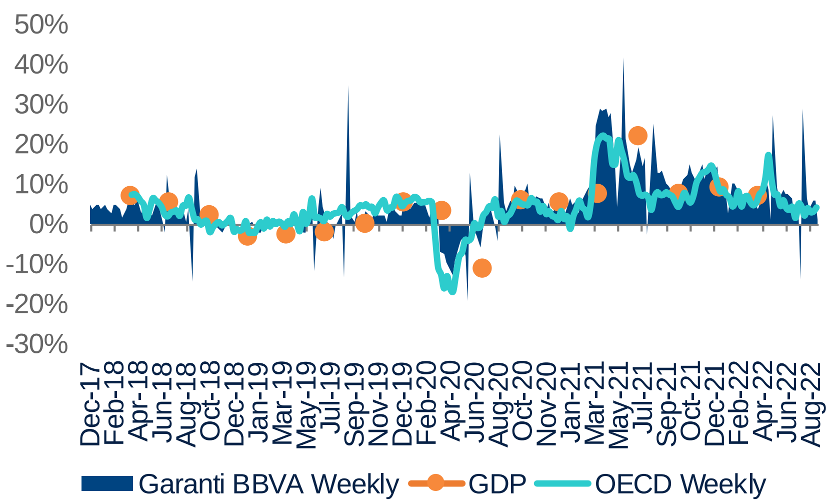

Source: Garanti BBVA Research.

# We introduce a weekly GDP model with the best available data

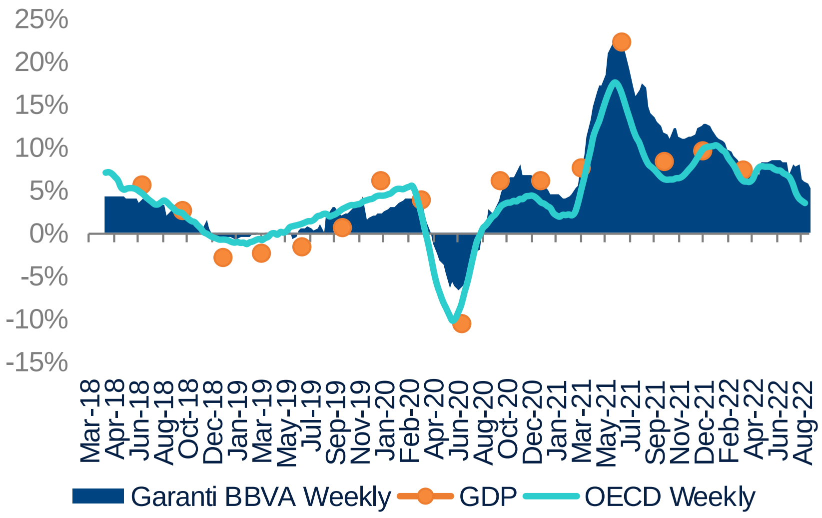
- We take the advantage of Daily & Weekly available data to construct weekly factors:
  - Big Data IP Proxy (BBVA, Daily, 2015-present)
  - Total Card Consumption (CBRT, Weekly, 2015-present)
  - Electricity Consumption (TEİAŞ, Daily, 2010-present)
  - FX-adjusted Total Loan Growth (BRSA, Weekly, 2006-present)
- We calculate the interaction with the official GDP series by weighting the weeks during the quarter
- We benefit from the weekly tracker to observe the responses to several impulses happening frequently
- Main challenge is dealing with «partial» calendar day effects of our Big Data series in annual comparisons
- We plan to extend our Daily series with new Big Data activity proxies

# Weekly Model - unadjusted from calendar day effects

## WEEKLY GDP NOWCASTING, YOY




## WEEKLY GDP NOWCASTING, 13-WEEK YOY

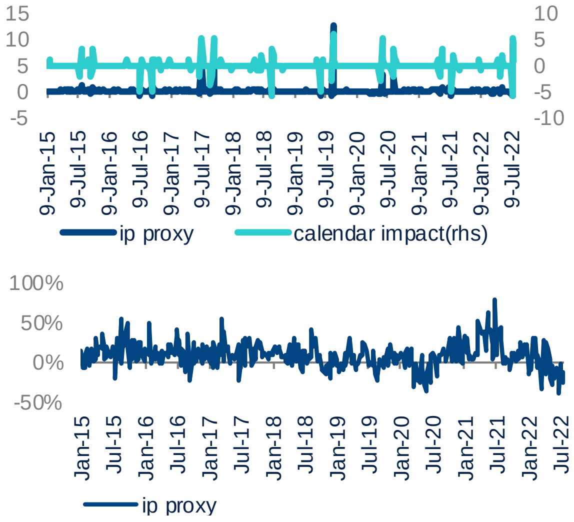



Source: Garanti BBVA Research.

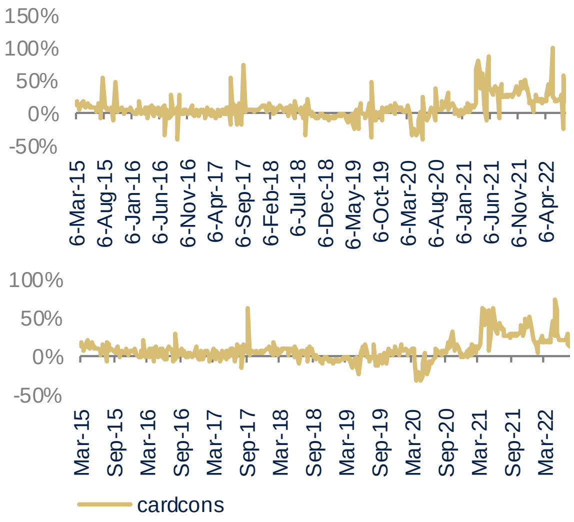
Long holidays in Türkiye, mostly religious, result in significant weekly shifts in annual comparisons
Bridge day effects: merging holidays and working days before and after the official holiday date

# We deal with calendar day effects and smooth the data

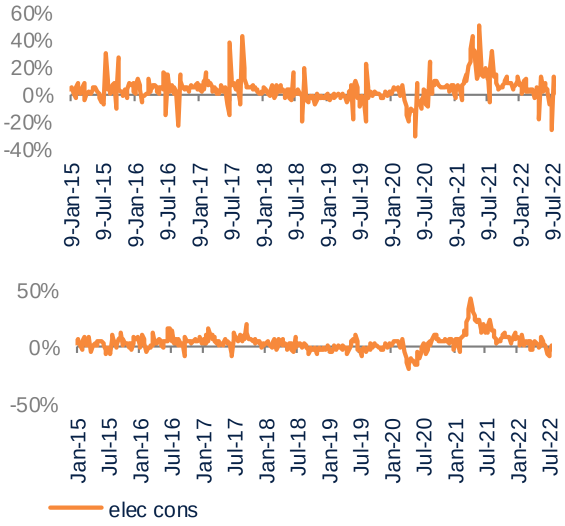
## IP PROXY GROWTH, YOY ADJ. & UNADJ.




## CARD CONS. GROWTH, YOY ADJ. & UNADJ.




## ELEC. CONS. GROWTH, YOY ADJ. & UNADJ.

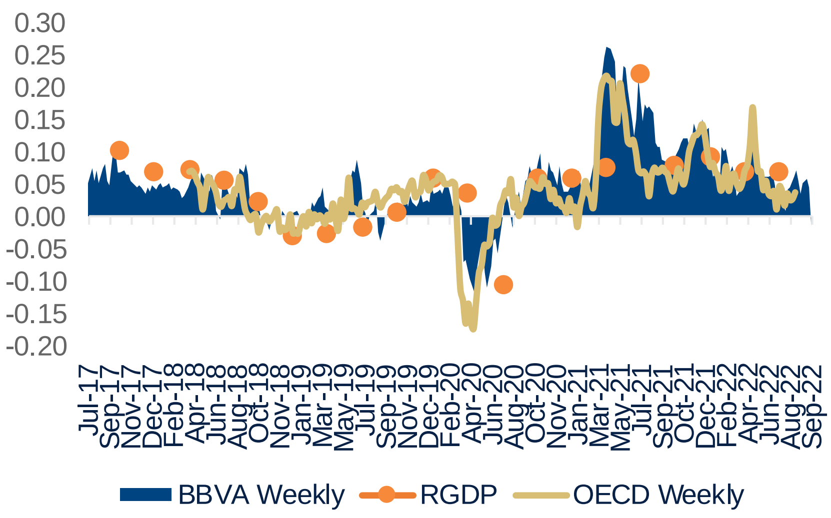



Source: Garanti BBVA Research.

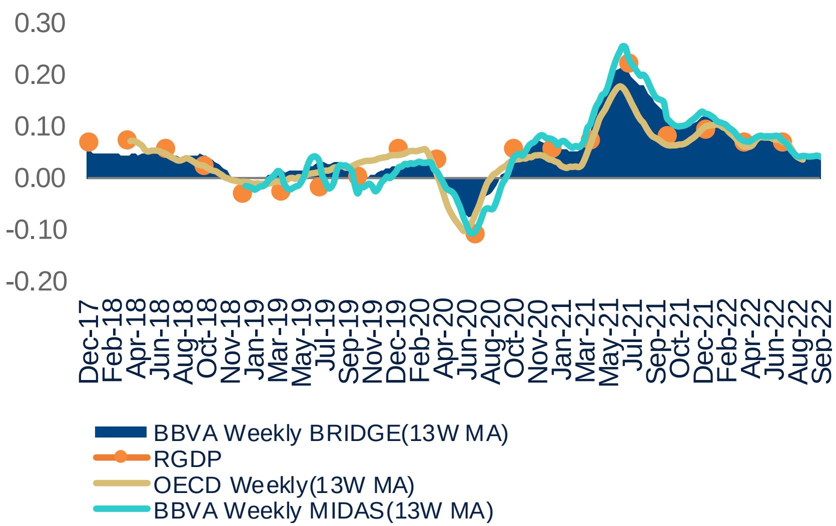
We smooth flow variables: IP Proxy, card consumption and electricity consumption. Credit growth, which is a stock variable, is taken as raw data

# Nowcasting Performance - Adjusted Weekly Model

## WEEKLY GDP NOWCASTING, YOY




## WEEKLY GDP NOWCASTING, 13-WEEK YOY




Source: Garanti BBVA Research.

We specify calendar day effects during the officially pre-announced holidays and smooth the data by filling missing days with the previous and week-after non-holiday daily averages

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# 03

# Conclusion

# Main Results

We enhance our dataset and make it available to routine updates with new potential variables or dropping old ones

We differentiate small and large data sets, which generate benefits from the relative advantages arising from the timing of the nowcast exercise

We reduce forecast errors by averaging alternative model results relative to single model results

We develop a «Weekly GDP Tracker» in order to maximize data releases and better assess policy implications

# Potential future steps

QoQ models taking into account seasonal adjustment complications (particularly daily big data)

Much larger data set so that we can decompose contributions to GDP by different categories

Sectorial GDP nowcasting to have both weekly & monthly activity indicators in sectors

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# 04

# Annex

# Description of Models – Dynamic Factor Model (DFM)

## MODEL FEATURES

- Monthly dynamic common factors drive the comovement among macroeconomic data series.

$$x_{t_m} = \Lambda f_{t_m} + \epsilon_{t_m};$$

$$\epsilon_{t_m} = \alpha \epsilon_{t_m - 1} + v_{t_m}; \quad v_{t_m} \sim i.i.d.\,\mathcal{N}(0, \sigma^2)$$

$$f_{t_m} = \varphi(L) f_{t_m - 1} + \eta_{t_m}; \quad \eta_{t_m} \sim i.i.d.\,\mathcal{N}(0, R)$$

- Dealing with mixed frequency data: YoY quarterly GDP figures are associated with monthly factors via transformation used in Giannone (2013).

- Dealing with unbalanced data (data lags, missing data): We follow expectation maximization (EM) algorithm through Kalman filter for maximum likelihood estimation.

$$\begin{aligned} x_{i,t}^{QY} &= X_{i,t}^{Q} - X_{i,t-12}^{Q} \\ &= (1 - L^{12}) X_{i,t}^{Q} \\ &\approx (1 - L^{12})(1 + L + L^2) X_{i,t}^{M} \\ &= (1 + L + L^2) x_{i,t}^{UM} \\ &= x_{i,t}^{UM} + x_{i,t-1}^{UM} + x_{i,t-2}^{UM}; \end{aligned}$$

# Description of Models - MFBVAR

- $x_t$ is defined as nx1 monhtly process and decomposed as follows

$$x_t = (x_m^T, x_q^T)^T$$

where $n_m$ monthly variables and $n_q$ dimensional latent process for quarterly variables

- Let $y_t = (y_m^T, y_q^T)^T$ denote observations then $y_{m,t} = x_{m,t}$ defined as monthly part is always observed

- We used intra-quarterly averaging aggregations (Schorfheide and Song (2015)) since we used annual change

$$y_{q,t} = \begin{cases} \frac{1}{3}(x_{q,t} + x_{q,t-1} + x_{q,t-2}), & t \in \{\text{Mar}, \text{Jun}, \text{Sep}, \text{Dec}\} \\ \varnothing, & \text{otherwise}, \end{cases}$$

- Define a VAR($p$) as

$$x_t = \phi + \Phi_1 x_{t-1} + \cdots + \Phi_p x_{t-p} + \epsilon_t, \quad \epsilon_t \sim \mathrm{N}(0, \Sigma)$$

- Let $z_t = (x_t^T, x_{t-1}^T, \ldots, x_{t-p+1}^T)^T$ the companion form for Var($p$) would be as follows:

$$z_t = \pi + \Pi z_{t-1} + u_t, \quad u_t \sim \mathrm{N}(0, \Omega)$$

- Then observation equation could be defined as follows

$$y_t = M_t \Lambda z_t$$

where $M_t$ deterministic selection matrix and $\Lambda$ weighting scheme

- We used Minnesota prior distribution for regression parameters and common stochastic volatility prior for error covariance (Carriero et al. (2016))

# Description of Models - Factor MIDAS

## 1 FIRST STEP

- Monthly factors from monthly variables obtained

$$\mathrm{X}_t = \mathrm{Cf}_t + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, \mathrm{R})$$
$$\mathrm{f}_t = \mathrm{Af}_{t-1} + \mathrm{u}_t, \qquad u_t \sim \mathcal{N}(0, \mathrm{Q})$$

- Two-step factors and quasi maximum likelihood (QML) estimators calculated on *Doz, Gianone and Rechlin (2011, 2012)*

## 2 SECOND STEP

- Estimate Factor MIDAS

$h_q$ quarters with $h_q = h_m/3$ is

$$y_{t_q+h_q} = y_{t_m+h_m} = \beta_0 + \beta_1 b(L_m, \boldsymbol{\theta})\widehat{f}_{t_m}^{(3)} + \varepsilon_{t_m+h_m},$$

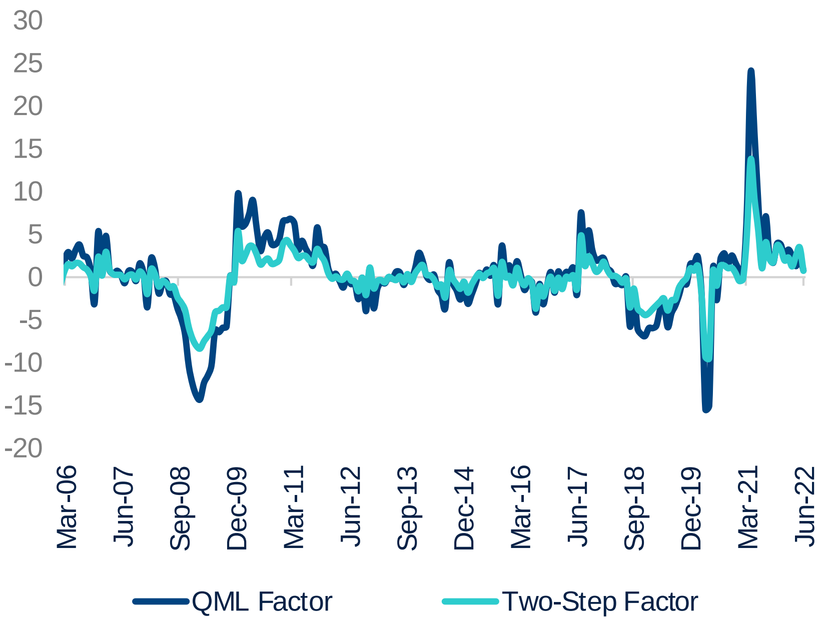
where the polynomial $b(L_m, \boldsymbol{\theta})$ is the exponential Almon lag with

$$b(L_m, \theta) = \sum_{k=0}^{K} c(k, \boldsymbol{\theta}) L_m^k, \quad c(k, \boldsymbol{\theta}) = \frac{\exp(\theta_1 k + \theta_2 k^2)}{\sum_{k=0}^{K} \exp(\theta_1 k + \theta_2 k^2)}.$$

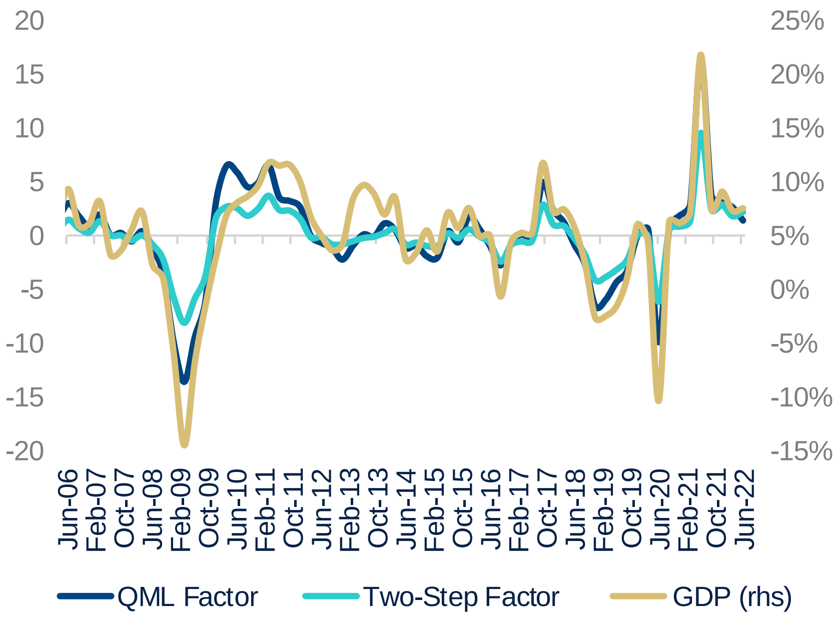
- Estimate Factor MIDAS with AR terms on *Clements and Galvao* (*2008*)

# QML Factors estimated by MIDAS help to improve goodness of fit

## FACTORS, MONTHLY



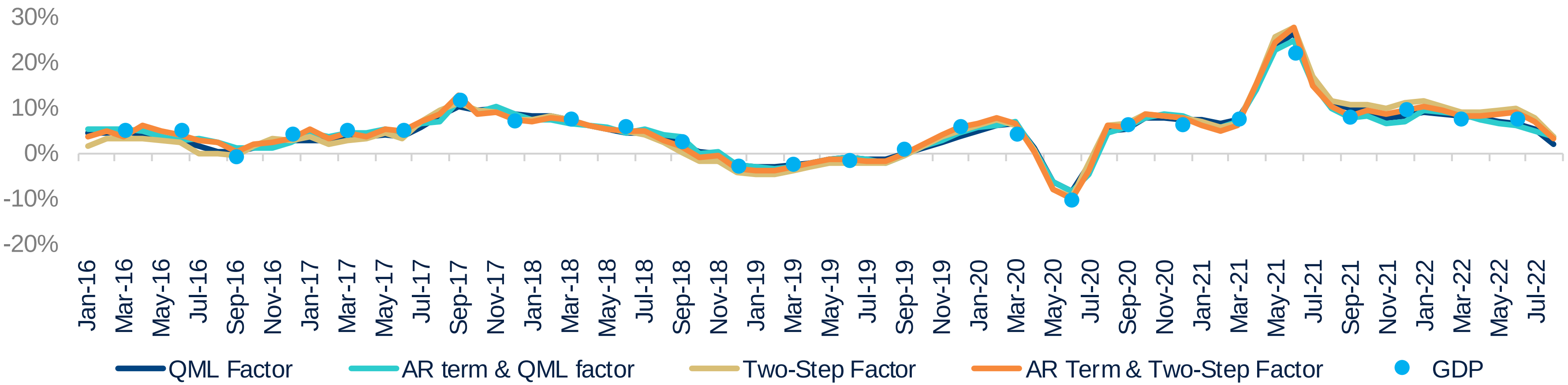

## GDP (YOY) VS FACTORS (3-MONTH AVG.)




Source: Garanti BBVA Research.

# Nowcasting Performance – Factor MIDAS

## MONTHLY GDP NOWCAST (RECURSIVE MIDAS, 3M YOY)




## RMSE RESULTS

| | QML Factor | AR Term & QML Factor | Two-Step Factor | AR Term & Two-Step Factor | AVG of Factor Models with AR |
|---|---|---|---|---|---|
| 2016Q1-2018Q4 | 1.2% | 1.3% | 1.6% | 0.9% | 0.9% |
| 2019Q1-2022Q1 | 1.8% | 1.7% | 2.0% | 1.7% | 1.6% |
| 2016Q1-2022Q1 | 1.6% | 1.5% | 1.8% | 1.4% | 1.3% |

Source: Garanti BBVA Research.

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October 2022

Creating Opportunities