

Investment in “Real Time” and “High Definition”: A Big Data Approach

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The Covid-19 crisis has reinforced the potential of Big Data tools for Economic Analysis and Policymaking

The high uncertainty triggered by the Covid-19 crisis has stressed the need to monitor the evolution of the economy in “real time”. These efforts have been materialized in several ways:

- **Focusing on timely, alternative indicators:** soft data surveys (particularly the Purchasing Manager Indexes, PMIs) and other high frequency indicators like electricity production or chain store sales released on daily or weekly basis.
- **Developing higher frequency models:** Some CBs have relied on this High Frequency indicators to develop weekly activity tracker models such as the FED´WEI (Lewis, 2020) and the Bundesbank WAI (Eraslan, S. and T. Götz, 2020).
- **Developing New Big Data Indicators*:** Focusing on daily aggregate information of banking transactions to track consumption, employment , turnover, mobility ([link to our BigData Project](#)).

* Some of the Recent literature on Big Data analysis Andersen, Hansen, Johannesen, & Sheridan (2020a), Andersen, Hansen, Johannesen, & Sheridan (2020b), Alexander & Karger (2020), Baker, Farrokhnia, Meyer, Pagel, & Yannelis (2020a), Baker, Farrokhnia, Meyer, Pagel, & Yannelis (2020b), Bounie, Camara, & Galbraith (2020), Chetty, Friedman, Hendren, & Stepner (2020), Chronopoulos, Lukas, & Wilson (2020), Cox, Ganong, Noel, Vavra, Wong, Farrell, & Greig (2020), Surico, Kanzig, & Hacıoglu (2020).

Through the analysis of the firm-to-firm transactions we extend our project of national accounts in real time & high definition to Investment

The investment spending is done mostly by companies and, to a lesser extent, by individuals

We track investment payments through



individual to firm transactions



firm to firm transactions

Firms are classified by their **NACE codes** to identify their **business activity** (in line with the European statistical classification of sectors)

We approximate investment demand in one type of asset taking into account the aggregate flows or transactions done from any firm or individual to the sector which produce the fixed assets

Total Investment

Machinery Investment*

Construction Investment

*Machinery & Equipment, Media & ICT, Agriculture & Animals, Forestry, Durable Goods, Retail Trade, Textile & Clothing, Transportation and Shipping.

The case of Turkey: Data and Representativeness

INVESTMENT DATA 2019: BBVA vs COMPANY ACCOUNTS (CENTRAL BANK & TURKSTAT)

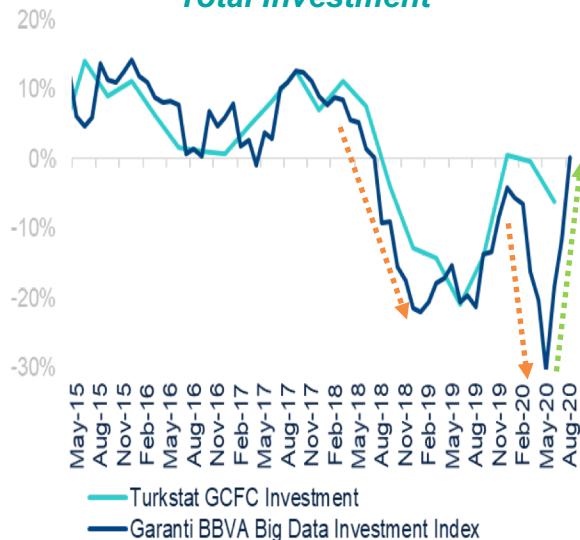
	BBVA Big Data			Turkey CBRT		
	Total	Machinery	Construction	Total	Machinery	Construction
Transactions (000s)	24.6	22.3	2.3			
Amount (US\$ bn)	308	280	28	440	257	183
Firms (000s)	179.7	156.5	23.2	730.2	614.4	115.8
Firms (% CBRT)	24.6%	25.5%	19.8%			

Validation I: The Big Data investment index shows a high correlation and co-movement with the official data

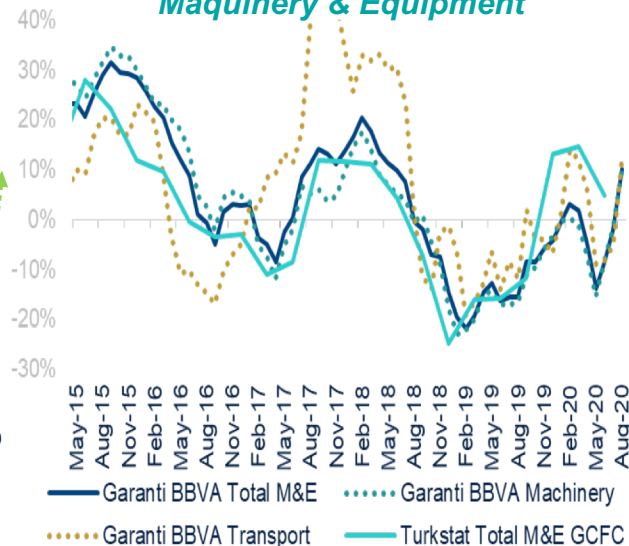
TURKEY: GBBVA BIG DATA INVESTMENT INDICES

(28-day cum. YoY real)

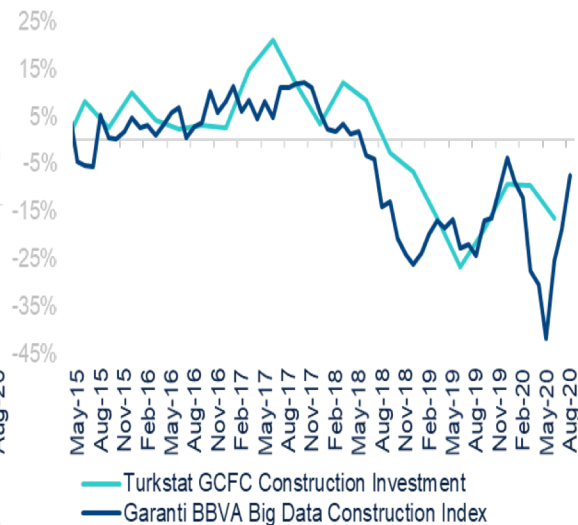
Total Investment



Maquinery & Equipment



Construction



Correlation coefficient: 0.88

Correlation coefficient: 0.84

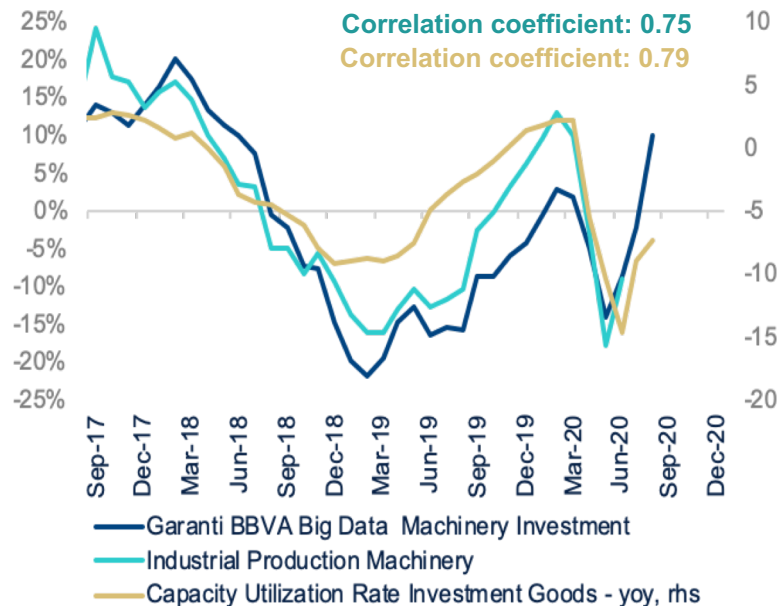
Correlation coefficient: 0.77

Validation II: The synchrony of BigData Investment with the Investment Cycle is validated by the high correlation coefficients with HF proxies

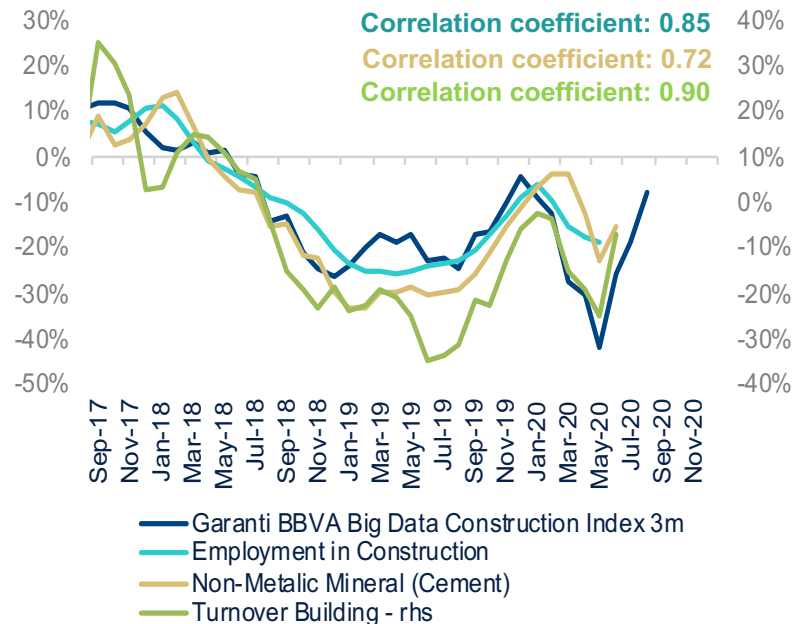
BBVA BIG DATA INVESTMENT & HIGH FREQUENCY PROXIES

(28-day cum. YoY real)

Maquinery & Equipment



Construction



Investment Big Data in an Nowcasting Model (DFM): The framework

A Dynamic factor Model (DFM)

$$y_t = \Lambda f_t + \epsilon_t,$$

$$f_t = A_1 f_{t-1} + A_2 f_{t-2} + \dots + A_p f_{t-p} + u_t,$$

$$u_t \sim \text{i.i.d. } \mathcal{N}(0, Q)$$

Expectation Maximization (EM) Algorithm

$$L(\theta, \theta(j)) = \mathbb{E}_{\theta(j)} [l(Y, F; \theta) | \Omega_T];$$

$$\theta(j+1) = \arg \max_{\theta} L(\theta, \theta(j)).$$

the conditional moments of the latent factors,
 $\mathbb{E}_{\theta(j)} [f_t | \Omega_T]$, $\mathbb{E}_{\theta(j)} [f_t f_t' | \Omega_T]$, $\mathbb{E}_{\theta(j)} [f_{t-1} f_{t-1}' | \Omega_T]$
 and $\mathbb{E}_{\theta(j)} [f_t f_{t-1}' | \Omega_T]$.

obtained through the Kalman smoother

for the state space representation:

$$y_t = \Lambda(j) f_t + \epsilon_t, \quad \epsilon_t \sim \text{i.i.d. } \mathcal{N}(0, R(j))$$

$$f_t = A(j) f_{t-1} + u_t, \quad u_t \sim \text{i.i.d. } \mathcal{N}(0, Q(j))$$

Outcomes

Nowcasting Accuracy

Nowcasting Anticipation

News Contribution

Investment Big Data in a Nowcasting Model (DFM): Variables & Releases

TURKEY: VARIABLES IN MONTHLY GDP DFM

	2020								
	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept
GDP									
Industrial Production									
Non-metal Mineral Production									
Auto Sales									
Number of Employed									
Number of Unemployed									
Auto Imports									
Auto Exports									
Electricity Production									
Manufacturing PMI									
Real Sector Confidence									
Total Loans growth 13-week									
Big Data Consumption									
Big Data Investment									

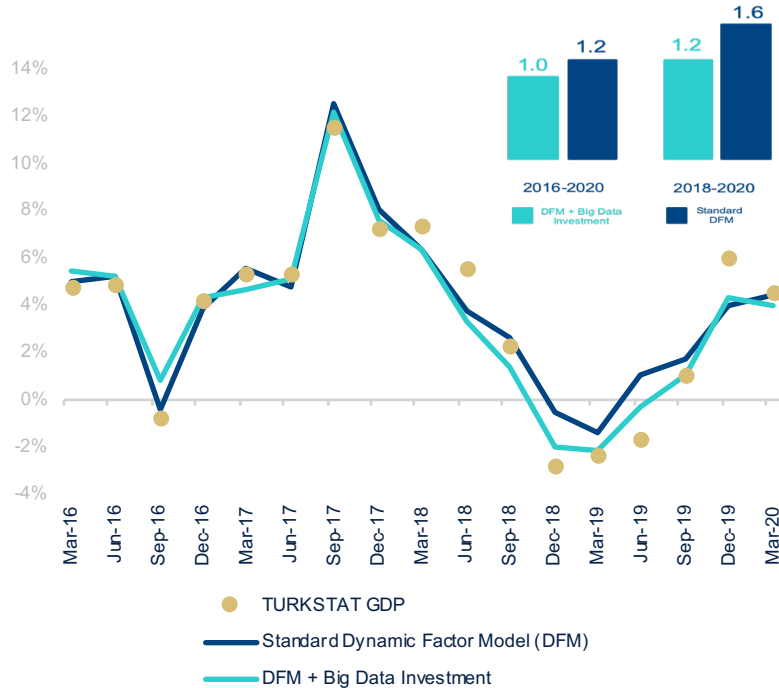
Hard Data (M & D)
 Soft (M)
 Fin (W)
 Big Data (D)

TURKEY: VARIABLES IN MONTHLY INVESTMENT DFM

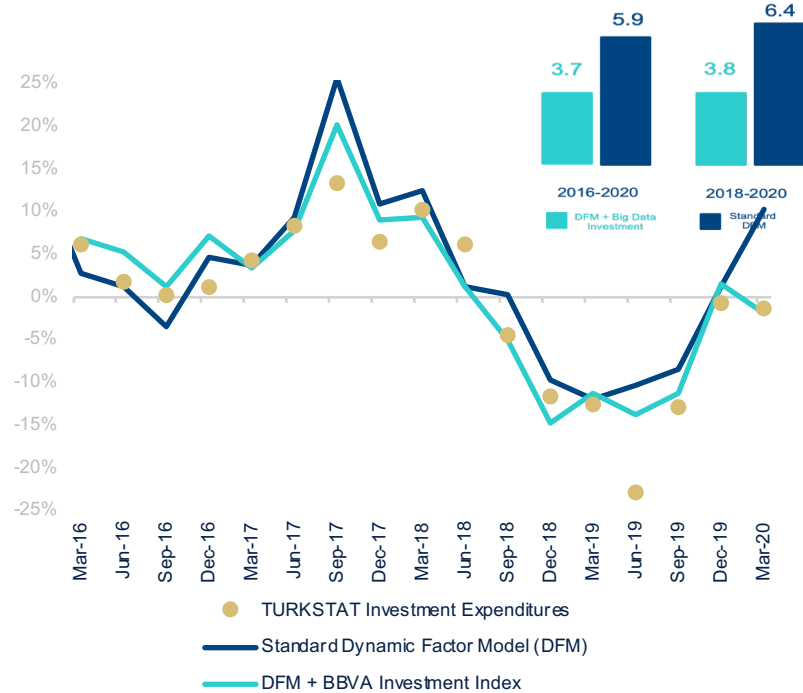
	2020								
	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep
GFCF									
Capital Goods Production									
Non-metal M. Production									
Capital Goods Imports									
Commercial Vehicle Sales									
Real Sector Confidence									
Corporate Lonas									
Big Data Investment									

Investment Big Data in a Nowcasting Model (DFM): Forecasting Accuracy

TURKEY: OUT-OF-SAMPLE ERROR GDP MODEL



TURKEY: OUT-OF-SAMPLE ERROR INVESTMENT MODEL

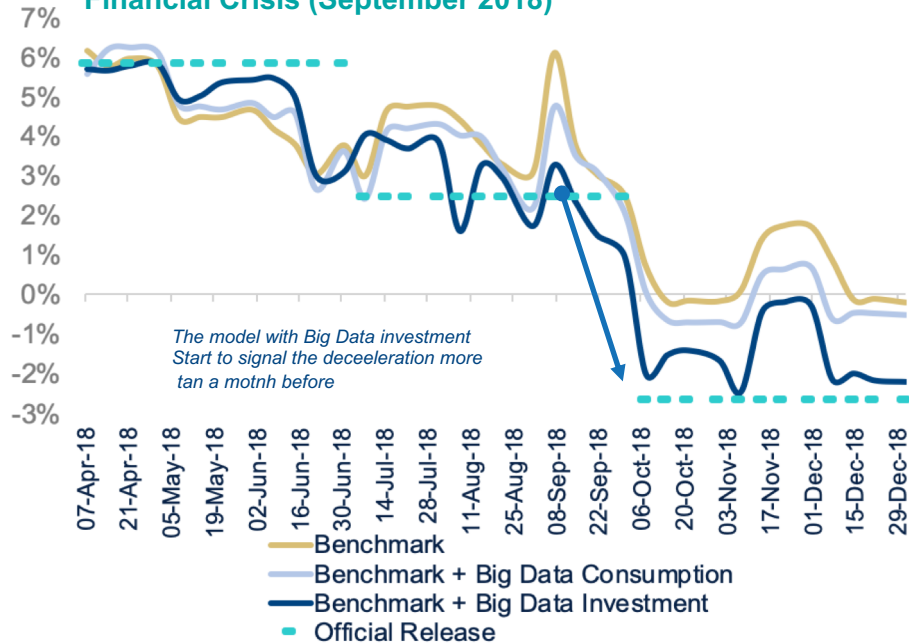


Investment Big Data in a Nowcasting Model (DFM): Anticipation

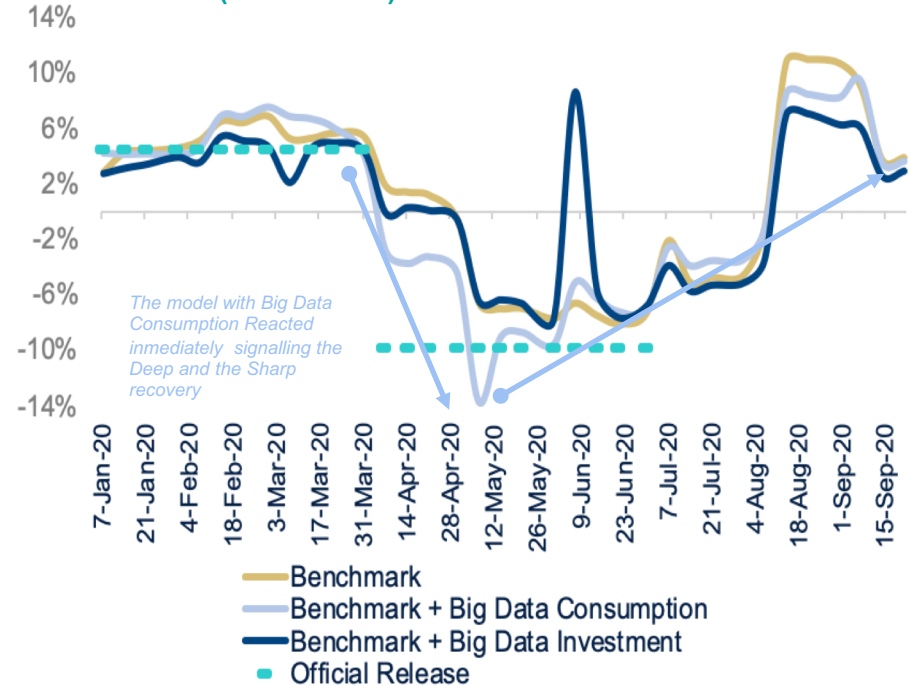
TURKEY: NOWCASTING FINANCIAL CRISIS (SEPT 2018) & COVID CRISIS (MAR 2020)

(quasi real time nowcasting with and without Big Data Indexes vs Benchmark)**

Financial Crisis (September 2018)

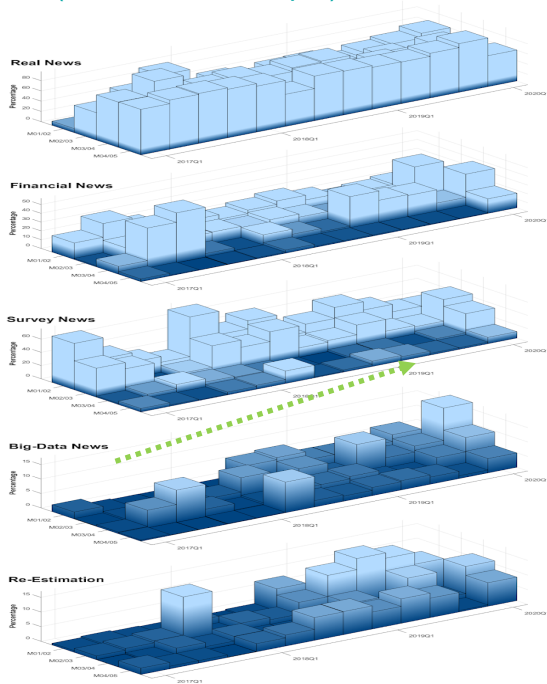


COVID-19 (March 2020)



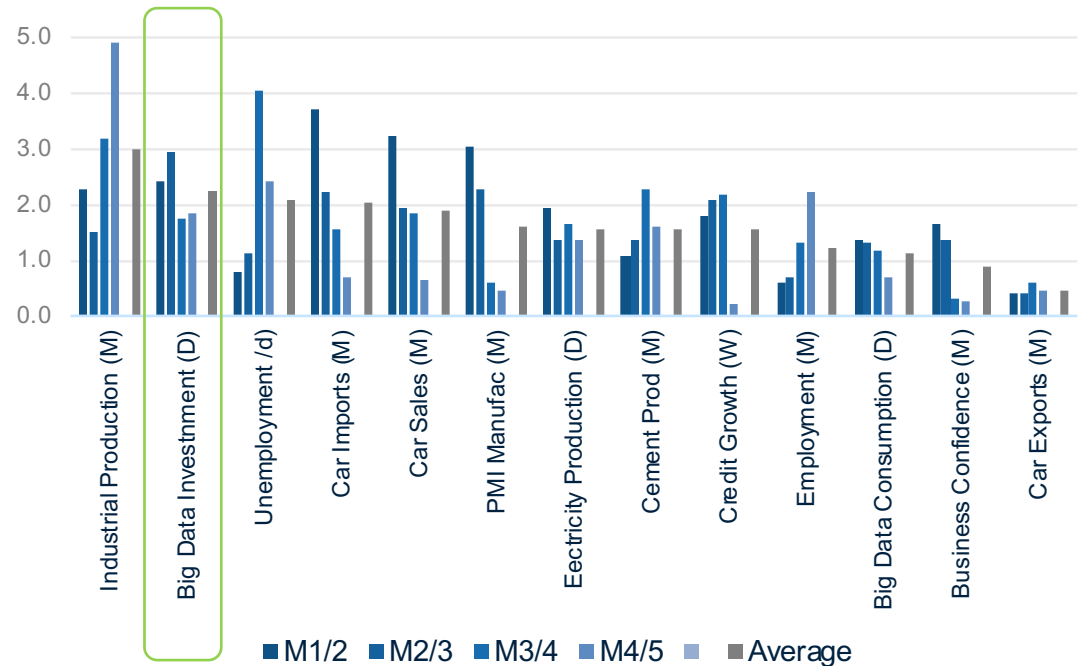
Investment Big Data in a Nowcasting Model (DFM): News & Prevalence Bias

DFM News Contributions (Unbalanced Sample)



Source: Own Estimations

DFM News Contributions correcting Prevalence Bias (Maintaining individually all the variables for the sample of Big data information)



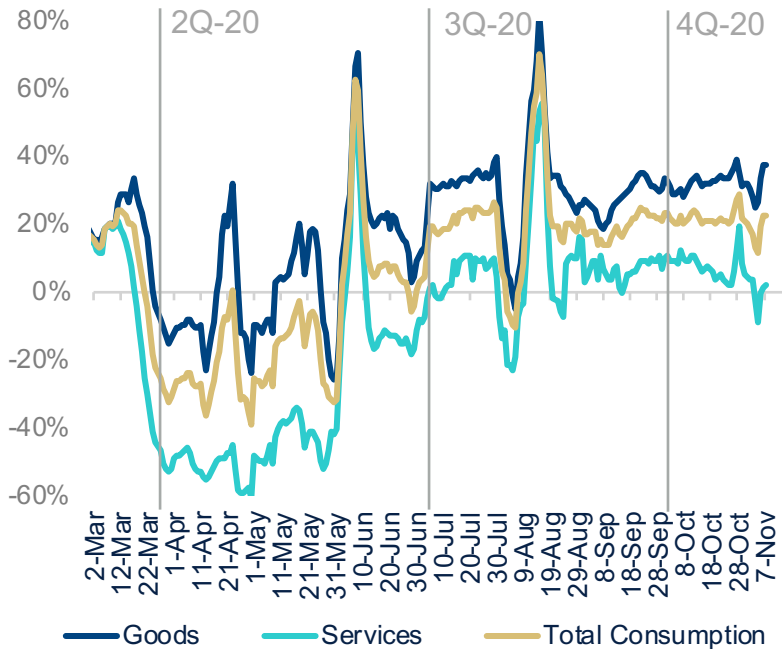
Source: Own Elaboration

Results: Investment in Real Time will help policy makers to react faster

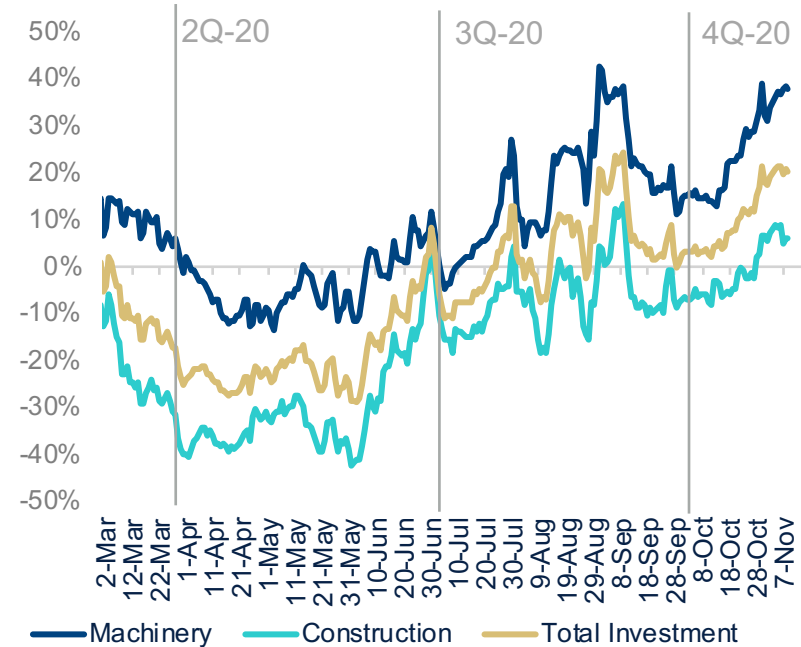
TURKEY: BIG DATA CONSUMPTION & INVESTMENT

(7-day cum. YoY nominal in Cons., 28-day cum. YoY nominal in Invest.)

BIG DATA CONSUMPTION

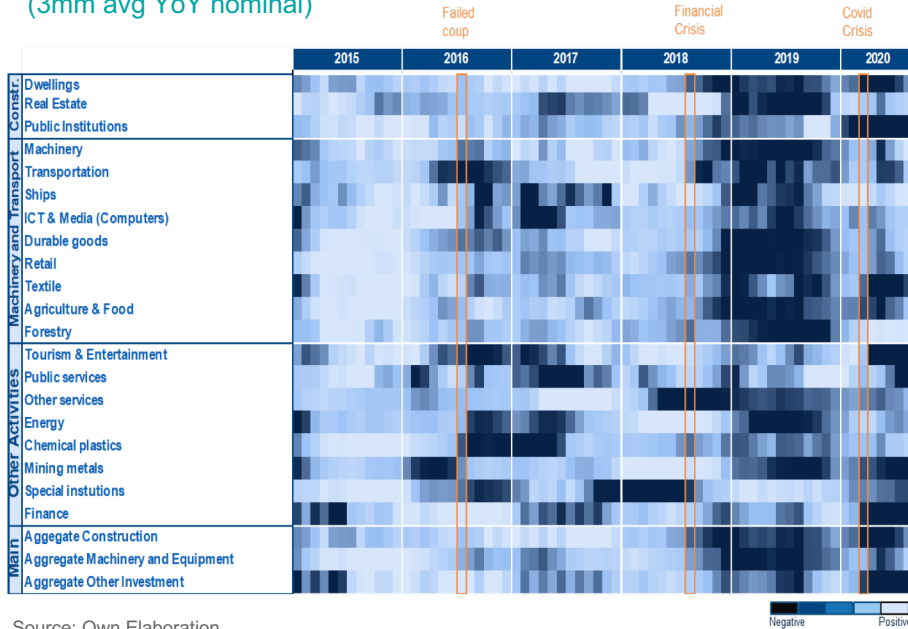


BIG DATA INVESTMENT

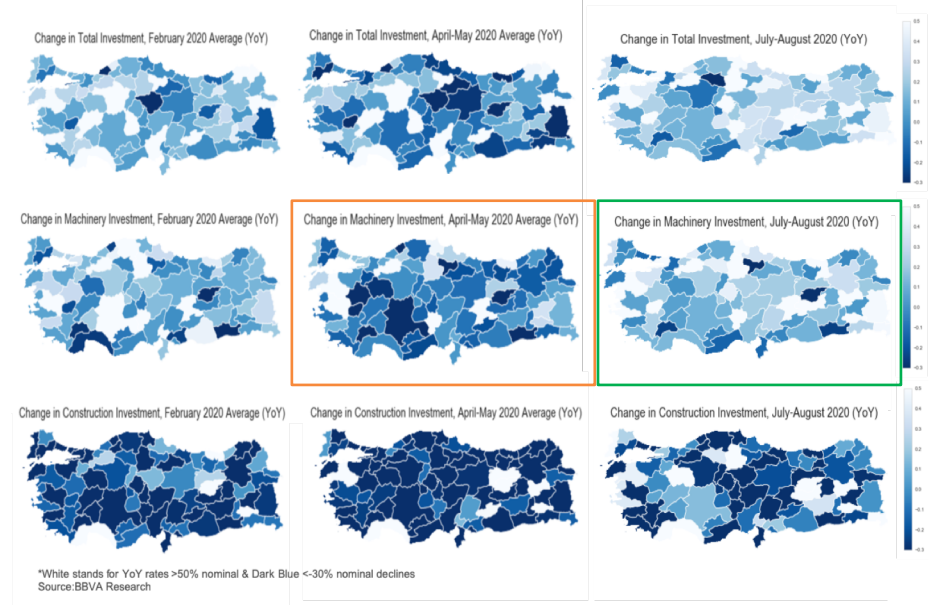


Results: The "High Definition" dimension will allow policymakers to differentiate shocks and design more targeted policies

TURKEY:GB-BBVA BIG DATA INVESTMENT HEAT MAP (3mm avg YoY nominal)



TURKEY:GB-BBVA BIG DATA INVESTMENTS GEO-MAPS RECOV (Change in YoY investment before, during and after the lockdowns by Covid)



20 Activities & **81** Province in Real Time & High Definition

Conclusions & further Research

- We present a **novel approach to estimate Investment in “Real Time & High Definition”** from the analysis of a Bank’s Big Data (BBVA)
- **We cross validate the results** through the high correlations **with national accounts and high frequency proxies** for Turkey and other countries.
- **The Investment index improves the properties of a Standard Nowcasting Model** in terms of forecasting accuracy, anticipation and news.
- **The “High Definition” dimension can help to design targeted policies**
- The **characteristics of Big data** Information (detailed but short history) advocates for the **use of non linear and/or regularization techniques (Further Research)**

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