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

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Abstract[1]

We introduce of novel set of Big Data indicators to mimic Investment in "Real Time" and "High Definition". We use the aggregate information of BBVA Big Data from firm-to-firm bank transactions and complement with individual-to-firm information to replicate the aggregate Investment. Particularly, we replicate the quarterly national accounts aggregate investment (gross fixed capital formation) and its bigger components (Machinery & Equipment and Construction) in real time for the case of Turkey. In addition, the high granularity and geo-localization of individual and firm-to-firm transactions data allow us to track the investment data in "high definition" from both a sectoral and geographical perspective. The results are successful and are validated through multiple robustness checks including cross-correlations with the official figures and higher frequency proxies of investment, as well as the improvement of the properties of a standard Dynamic Factor Model for Nowcasting including forecasting accuracy, anticipation and news contributions. We also extend part of our tests to other countries, such as Spain and Mexico, with positive results.

JEL Classification: C55, C81, E22

Keywords: Big Data, investment, national accounts, real time, nowcasting.

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1. Introduction

The economists normally use the information produced by National Statistical Agencies or Central Banks (GDP, industrial production, unemployment, etc.) to assess the state of the business cycle. While this information is consistently designed to track the business cycle, it also has some shortcomings. One of the important problems is that most of the key indicators are low frequency and released with some time lag. In the case of some countries, the lag in statistical releases can be considerable.

While there is some economic information available at high frequency – such as stock market prices, interest rates, etc. – it is normally related to financial conditions and expectations, which do not necessarily match the real conditions of the economy.

The need to react rapidly to the changing economic conditions after the COVID-19 crisis has enhanced efforts to follow the economy in "real time" in several lines of analysis:

- Focusing on alternative high frequency indicators: Some analysts have turned their attention to the more advanced released indicators such as the soft data surveys (i.e. Purchasing Manager Indexes or PMIs, Consumer confidence, etc.) and other high frequency indicators like electricity production, chain store sales released on a daily or weekly basis, respectively.
- Developing higher frequency models: Some Central Banks have relied on the use of traditional nowcasting methods but mixing quarterly or monthly variables with higher frequency indicators (i.e. weekly, daily) to better capture the real time component information. This has been the case of the Federal Reserve of New York weekly economic index or WEI (Lewis, Mertens & Stock, 2020) and the Bundesbank Weekly Activity Index or WAI (Eraslan, S. and T. Götz, 2020).
- Developing New Big Data Indicators: A new stream of work, including our previous work (Carvallo et al, 2020)2, has focused on the use of transaction data, company information or mobility indicators reflecting the economic activity in real time. In this sense, the COVID-19 pandemic of 2020 has acted as a major stimulus for movement in this direction, and in a short space of time an entire new literature has grown using these indices[3].

In this working paper, we make a step forward in the development of Big Data indicators by introducing a "real time" and "high definition" indicator of investment demand. This is relevant for several reasons, including methodological, empirical and policy reasons.

From the Big Data methodological point of view, we complement the individual-to-firm transactions (i.e. Aggregated Point of Sale information from credit and debit cards transactions) with firm-to-firm flows collected from Bank transactions.

While much of the effort or recent empirical literature has been devoted to the analysis of consumption in real time, it is difficult to find any empirical work on the evolution of investment. In this sense, this paper contributes to fill the gap between more structural literature that stresses the role of investments as a source of business cycle4 and the scarce empirical works on measurement investment in real time.

Finally, complementing consumption information with real time investment information has several advantages for analysts and policymakers. First, investment is more volatile than consumption and has leading indicator properties. Second, some parts of investment as residential investment can have systemic implications for the banking and financial systems, as the 2008-2009 crisis revealed, and having a real time assessment of the evolution of this component could be relevant. Therefore,

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[2] In our case, we track consumption and its segments in real time by aggregating, cleaning and parsing banking transactions at BBVA-operated Point of Sales (PoS) and transactions by BBVA-issued credit and debit cards. We update these real-time and high definition consumption indicators for six countries on a weekly basis in the following link.

[3] A selection of papers, besides the April 14, 2020 draft of this paper, includes 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, & Hacioglu (2020).

[4] The role of investment in the business cycle has been increasingly analyzed and there are numerous examples, such as those mentioning the role of liquidity constraints to explain the role of investment in the business cycle (Gertler and Gilchrist,1994), the impact of credit constraints on investment spending (Azzari, Hubbard, and Peterson 1988, Gertler and Hubbard 1988, Hoshi, Kashyap, and Scharfstein 1991, Whited 1992, Kashyap, Lamont, and Stein 1994), the empirical literature mentioning the prominent role of investment as evidence from the SVAR Models (Fisher, 2006, Canova, Lopez-Salido, and Michelacci, 2006)) and in general equilibrium analysts (Greenwood, Hercowitz, and Krusell, 2000, Justiniano, Primicieri and Tambalotti, 2010).

having a good and real-time assessment of the Investment cycle can provide an important advantage to policymakers and analysts.

The rest of the paper is organized as follows. First, we describe the Big Data methodology to compute investment for the case of Turkey. Particularly, we describe how to mimic the investment demand in national accounts from the firm-to-firm transactions included in BBVA Big Data. We estimate the demand of fixed assets by corporations on several fixed assets (machinery and transport and construction).

Second, and for robustness purposes, we validate the use of our Big Data indicator for Turkey from multiple perspectives. We test correlation from our indicator with national accounts' quarterly investment and its components. In addition, and as suggested by National Accounts manuals, we have checked the correlation of the indicators with alternative high frequency proxies (monthly) of investment. Beyond simple correlations, we check how the inclusion of the Big Data information complements and adds extra information to the traditional Nowcasting Dynamic Factor Models. Last, but not least, we describe how we can also obtain "high definition" investment in sectorial and geographical terms from our Big Data information.

We complete our analysis by introducing some preliminary results for other countries such as Spain, Mexico and Colombia to check for the potential extension of our indicators to other countries. Finally, we describe the conclusions.

2. Investment through a Banks' Big Data: The role of firm-to-firm transactions

The United Nations System of National Accounts (SNA) and European System of Accounts (ESA) define gross fixed capital formation as resident producers’ net acquisitions (acquisitions minus disposals) of fixed assets during a given period. The SNA and ESA refer to fixed assets as those used in production for more than one year, differentiating between: (1) dwellings; (2) other buildings and structures, including major improvements to land; (3) machinery and equipment, such as ships, cars and computers; (4) weapons systems; (5) cultivated biological resources, e.g. trees and livestock; (6) costs of ownership transfer on non-produced assets, like land, contracts, leases and licenses; (7) R&D, including the production of freely available R&D; (8) mineral exploration and evaluation; (9) computer software and databases and (10) entertainment, literary or artistic originals.

While the yearly SNA and ESA national accounts provide detailed information, the quarterly national accounts relied on estimations of the supply and demand of investment. Accordingly, "these estimates are derived mainly from surveys in which statistical agencies ask capital goods producers what they have produced and ask capital goods purchasers what they have purchased." They complement this information by using commodity flow methods, registration records, labor inputs, materials supplied, etc."

Given the reliance on indirect measures or proxies, the quarterly national account manuals highly recommend "Validation" as an essential part of the estimation of quarterly national accounts. According to national account manuals, a good validation process has three different dimensions: statistical, accounting and economic[5].

The accounting dimension guarantees consistency to the national accounts. Accounting identities guarantee, for example, that there is a single GDP figure (Production=Expenditure=Income). While this is an important property of national accounts, it is very complex to develop at Big Data levels. Given the difficulties in checking consistency with the Big Data information, our validation system is mainly statistical and economic, as we will cross-check the correlation with the quarterly investment and their monthly indicators and check the contribution in terms of forecast accuracy and the explanatory power of our Big Data indicators as explanatory variables in our nowcasting models.

The quarterly national accounts group the different ten categories into three big components. The first segment is Construction investment, which is divided into dwellings and other buildings and structures (i.e. Civil engineering and Public works). The machinery and equipment group includes machinery, transport equipment, ICT equipment (hardware), weapons systems, etc.

[5] Eurostat: Handbook on quarterly national accounts (2013 edition).

Finally, Investment in other assets includes computer software, databases, research and development, etc.[6] The latter includes highly differentiated information, which makes the replication exercise for which the conversion from Bank transactions to aggregate proxies more complicated. In this paper, we track the first two components, Constructions and Machinery and Transports, which in the case of Turkey, accounts for nearly 95% of total investment.

The use of Big Data to track economic activity has focused on consumption. The main source of information has been the use of transactions in operated Point of Sales (PoS) and transactions by credit and debit cards. This transaction data can be obtained from a Bank's individual database (Carvallo et al, 2020, Andersen et al, 2020) or from different sources compiled by some specific companies (Chetty et al, 2020).

While the consumption is basically carried out by households by way of individual-to-firm payment, an important share of investment spending is carried out by companies or firm-to-firm transactions. For example, a machinery investment expenditure basically entails a firm-to-firm transaction or a money transfer from one corporation (of any sector) to the corporations manufacturing the machines. In contrast, transactions such as the purchase of a house by households (individual-to-firm transactions) are considered an investment in dwellings in the national accounts.

In the case of Turkey, we use the transactional database of BBVA, which includes all the monetary transactions between BBVA clients including individuals and firms. During the procedure, we first identify and filter out the transactions of the corporate clients of BBVA to capture the investment expenditures. For this, we identify the transactions or inflows by individuals and firms to the fixed investment assets manufacturing activities and we assume that these transfers are in exchange of these fixed assets. In BBVA Big Data, the firms are classified according to the corresponding NACE codes to identify their business activity sector classification. Through NACE, we can identify the firm-to-firm or individual-to-firm transactions with firms producing the different fixed investment assets according to national accounts.

The total number of firms to monitor for investment expenditures in BBVA Big Data was nearly 179.7k during the year 2019. This includes 23.2k or 13% in the Construction sector and 156.5K or 87% in the machinery group. The aggregate number of transactions identified is 24.6k (with 2.3k or 10% of the transactions in construction activities and 22.3k corresponding to machinery with a nominal value of 1.748 billion TL ($308 billion). The nominal value of the BBVA Big Data transactions is about 67% of the transactions of 2019 included in the recent corporate accounts database provided by the Central Bank of Turkey7. This database includes 2.613 billion TL ($440 billion) of tangible fixed assets of the firms included in the analysis (if amortization expenses were included). While the machinery investment would be relatively well represented in the BBVA Big Data Base, the share relative to this base dropped to 15% when we considered construction investment.

To aggregate the investment demand by group of assets, we calculate the firm or individual transactions with the firms producing the distinct fixed assets assigned to each group, according to the quarterly national accounts investment classification:

- Machinery investment and transport: We include transactions from firms concerning activities of Machinery & Equipment, Media & ICT, Agriculture & Animals, Forestry, Durable Goods, Retail Trade, Textile and Clothing. We include Transport vehicles and Shipping for the transport group.
- Construction investment: We include firm and individual transactions concerning investment in dwellings and public works.

In order to maintain the national representativeness, we maintain the historical shares of the activities in the official data. In this paper, we exclude the share of "Other Investments," representing 9% of the total investment.

Finally, once we estimate the nominal values for Machinery and Construction investment proxies, we deflate their annual growth rates with the Domestic Producer Price Index (D-PPI) to obtain the real growth rates. We also sought to deflate the series with the corresponding producer price deflators, but in the absence of a complete set of D-PPI individual deflators for all of the components and the fact that the results do not change significantly, we opted to use the general D-PPI for all of the components.

[6] More detailed metadata of the official GDP results for Turkey can be found at the following link.
[7] **Company Accounts Data 2009-2019.**

3. Aggregate Results and Validation

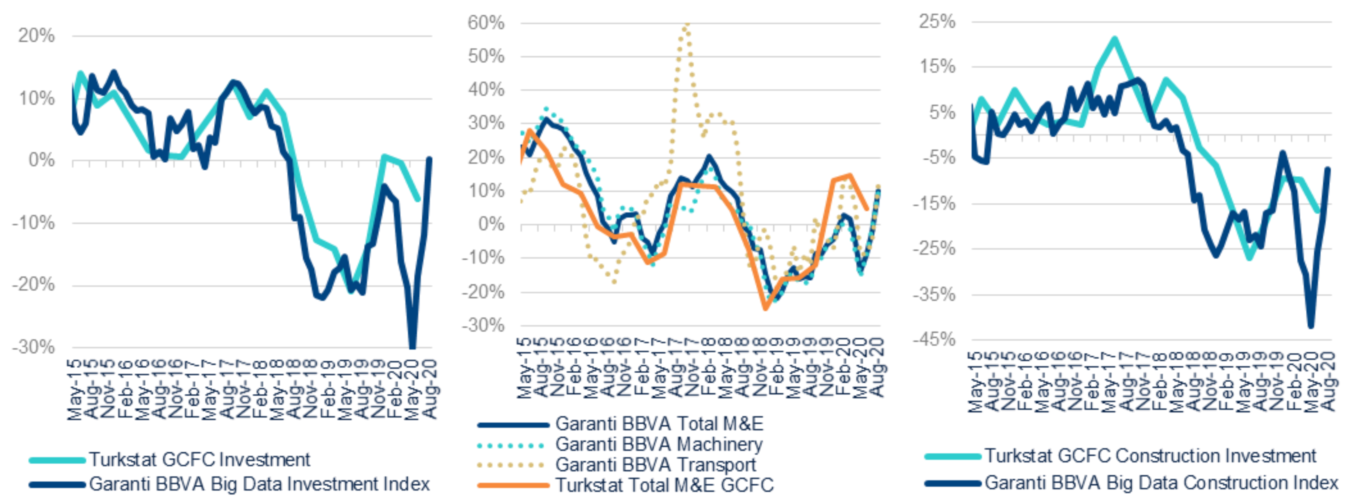
In this section, we show the results of the validation process. We first check how our Big Data Investment indexes correlate with the official investment. We also test the relation of our indexes with alternative higher frequency investment proxy indicators, as recommended by the national accounts manual. Finally, we check how the inclusion of the Big Data investment indexes improves the properties of a standard nowcasting dynamic factor model of GDP in terms of forecast accuracy, anticipation and contribution in terms of news.

3.1 Cross Correlations

Figure 1 below shows the estimated Big Data BBVA Investment Indices with the main components of Gross Fixed Capital Formation by the Turkish National Statistics Office. The graphs and the correlations table in the appendix show that the Big Data Investment indexes have a good fit with the official statistics and that the correlation coefficient from the last 5 years (March 2015 to March 2020) is high. The Pearson correlation coefficient is .84 for the Aggregate Investment, 0.81 for Machinery Investment and 0.78 construction investment. Given the strong fluctuations in investment during the financial crisis of summer 2018 and the recent COVID-19 crisis, we also computed the Spearman correlation coefficient. This reduces the positive bias in the correlation of these sharp investment movements. Spearman's correlations remain high for aggregate investment (0.83) and only slightly lower for investment in machinery and equipment (0.76) and construction investment (0.75).

Beyond the high correlation with the large investment components, the graph reveals an important advantage of the information coming from Big Data: getting the information in real time. In the case of Turkey, and other emerging countries, the advantage in terms of obtaining the information with respect to the publication of official data can reach three to four months.

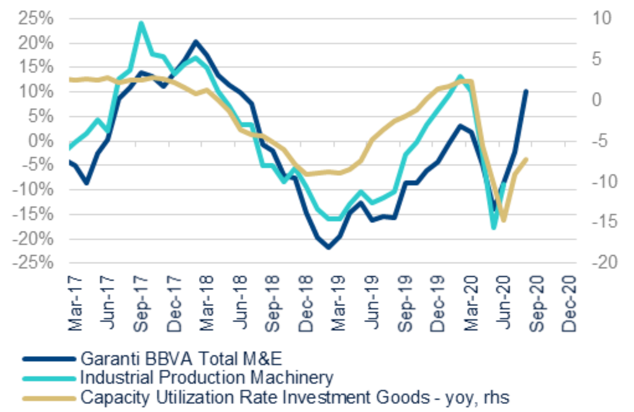
Figure 1. **TURKEY: BBVA BIG DATA INVESTMENT INDEX: TOTAL AND COMPONENTS**



Source: BBVA Research.

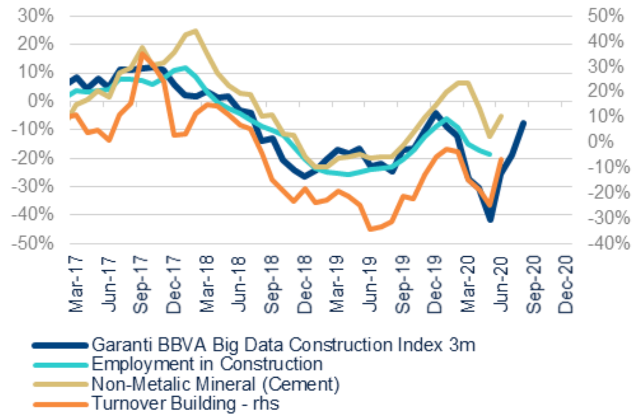
We also validate our Big Data indicators with higher frequency proxies of investment to check the co-movement our indicators with the investment cycle. Figure 2 shows the monthly evolution of the Big Data machinery index with machinery industrial production and the change in capacity utilization in investment goods. The graph shows a common pattern and the correlation coefficients are again high (0.75 with Industrial Production and 0.79 with the change in capacity utilization). In the case of construction investment (Figure 3), the validation exercise leads to similar results, showing a common and consistent pattern with employment in construction (0.85 correlation), production of non-metallic minerals mainly composed of cement (0.72 correlation) and the turnover of construction (0.90 correlation).

Figure 2. **BBVA BIG DATA MACHINERY INVESTMENT AND PROXIES** (YoY, 3m)



Source: BBVA Research.

Figure 3. **BBVA BIG DATA CONSTRUCTION INVESTMENT** (YoY, 3m)



Source: BBVA Research.

3.2 Does Big Data Investment improve Nowcasting models?

In the previous section, we have shown some of the advantages of the Big Data Investment indexes in terms of the correlation with both the official data and other high frequency proxies and their availability in real time. In this section, we analyze how the Big Data information can enhance or complement the results of the standard nowcasting models. Particularly, we evaluate how this source of information can improve or complement these models in terms of forecasting accuracy, anticipation and contributions in terms of news.

As the benchmark nowcasting model, we use a standard monthly Dynamic Factor Models as in the Banbura & Modugno (2014)[8] and Modugno, Soybilgen & Yazgan (2016)[9]. With these models, we nowcast the yearly growth rates of GDP and its subcomponents (i.e. Consumption, Investment and Net Exports) for Turkey.

The reason we adopt this version is the implementation by these models of the factors as unobserved states. Particularly, this specification allows the Kalman filter to estimate the unobserved factors and missing observations. This is key to mixed Big Data information with traditional hard, soft and market data, as despite being high frequency information, this new source of information normally has a short history (in our case, since March 2015). The Expectation Maximization (EM) algorithm used in Banbura and Modugno (2014) to solve this model was precisely designed to work with general patterns of missing data, as the authors signaled "the framework allows to handle efficiently and in an automatic manner sets of indicators characterized by different publication delays, frequencies and sample lengths."

A general specification of a Dynamic Factor Model is as follows: Let $y_t = [y_{1,t}, y_{2,t}, \dots, y_{n,t}]$, $t = 1, \dots, T$ denotes a stationary n-dimensional vector process standardized to mean 0 and unit variance. We assume that y_t admits the following factor model representation:

$$y_t = \Delta f_t + \epsilon_t \tag{1}$$

$$f_{t=} A_1 f_{t-1} + A_2 f_{t-2} + \dots + A_p f_{t-p} + u_t \qquad where\ \ u_t \sim i.i.d\ N(0,Q) \tag{2}$$

where f_t is a $r \times 1$ vector of (unobserved) common factors and $\epsilon_t = [\epsilon_{1,t}, \epsilon_{2,t}, \dots, \epsilon_{n,t}]$ is the idiosyncratic component, uncorrelated with f_t at all leads and lags. The $n \times r$ matrix Δ contains factor loadings. $X_t = \Delta f_t$ is referred to as the common component. It is assumed that t is normally distributed and cross-sectionally uncorrelated. In our case, we assume that the

[8] Banbura, M. and M. Modugno (2014). Maximum Likelihood Estimation of Factor Models on Datasets with Arbitrary Pattern of Missing Data. Journal of Applied Econometrics 29 (1),133-160.
[9] Modugno, M., Soybilgen, B., & Yazgan, E. (2016). Nowcasting Turkish GDP and news decomposition. *International Journal of Forecasting*, *32*(4), 1369-1384.

dynamics of the idiosyncratic component is serially uncorrelated and follows an AR(1) process. Further, it is assumed that the common factors f_t follow a stationary VAR process of order p. In our case, the test selects only one factor, in line with many of the models developed to nowcast GDP models.

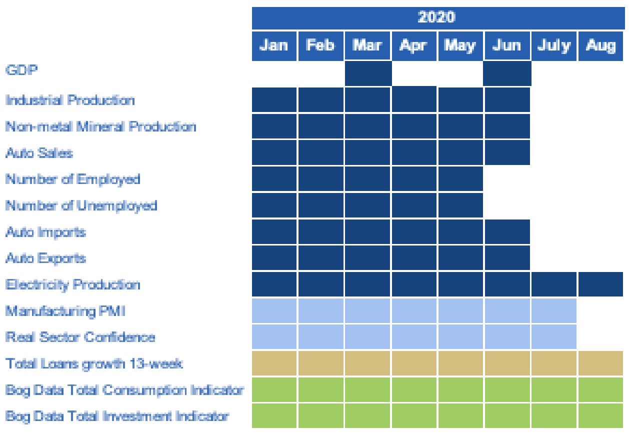
As f_t is unobserved, the maximum likelihood estimators of the parameters of model (1)-(2) are in general not available in closed form and the Expectation-Maximization (EM) algorithm is used. In our case, depending on the purpose of the application (and the pattern of missing data), these conditional expectations can be used for forecasts, back testing and interpolation from the Kalman filter[10].

We first test whether our aggregate Big Data Investment index improves the forecasting accuracy of our standard GDP and Investment Dynamic Factor Models, which include not only soft and hard data information but also Investment Big Data information as described below:

- The GDP Nowcasting model includes hard data variables such as the GDP itself (quarterly), industrial production (monthly), non-metallic minerals production under industrial production (monthly), electricity production (daily), automotive sales (monthly), employment growth (monthly), unemployment growth (monthly), automotive exports (monthly) and automotive imports (monthly). It also includes soft data such as manufacturing PMI (monthly) and real sector confidence (monthly). Finally, we include our own Big Data Indexes for Consumption (daily) and Investment (daily).
- The Investment Nowcasting model. This model includes hard data such as the gross fixed capital formation (quarterly), capital goods production (monthly), non-metallic mineral production under industrial production (monthly), capital goods import volume (monthly), and commercial vehicles sales (monthly). We also include soft data variables such as real sector confidence (monthly) and financial variables such as real corporate loan growth (monthly). Finally, the model is completed with our Big Data information for Investment.

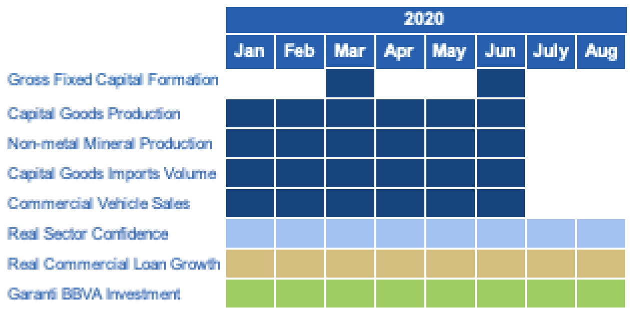
Tables 1 and 2 show the indicators included in our benchmark nowcasting models. The GDP nowcasting model includes fourteen variables including their own GDP. Besides the GDP, 8 out of the 14 variables are hard data indicators available at a monthly frequency level but with a lag relative to the current period of two or three months. Only daily electricity production is released on a daily basis and updated in real time. The second group of indicators corresponds to soft data survey indicators, which are released at the end of the current month and normally lead the information in the traditional nowcasting models. We also include financial variables as the weekly credit releases, which are only two weeks lagged over the current day. Finally, we complement the real time information with our Big Data indicators. In the case of the GDP model, we also include our real time consumption indicator (Carvallho et al, 2020) which we complement with our Big Data index. Therefore, adding real-time information to the actual models will complement the set of our high frequency, surveys and financial indicators but will also increase the amount of real-time information in our models.

Table 1. **MONTHLY GDP DFM NOWCAST MODEL** (VARIABLES & LAG STRUCTURE)



Source: BBVA Research.

Table 2. **MONTHLY INVESTMENT DFM NOWCAST MODEL** (VARIABLES & LAG STRUCTURE)



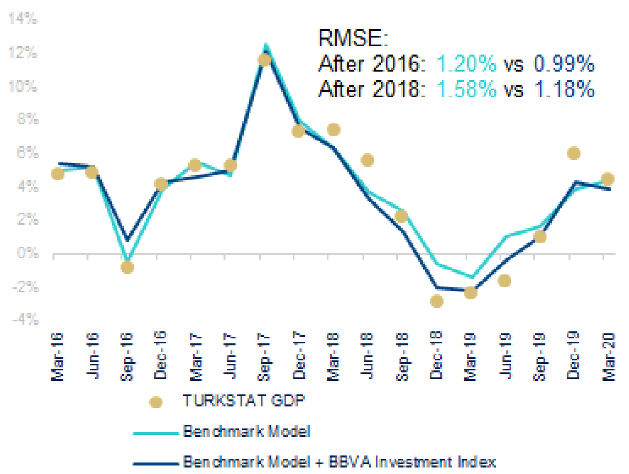
Source: BBVA Research.

[10] A detailed description of the estimation process is described in Banbura and Modugno (2014).

To test the forecasting accuracy, we compute the Root Mean Squared Forecast Error (RMSE) of the models from the first quarter of 2016 and the first quarter of 2018 until the first quarter of 2020. We select two periods in order to account for a more volatile period including the financial crisis and post-recession (August 2018 to 2020) and a longer sample (from Q1 2016) to focus on more stable periods. We choose a recursive estimation process to maintain the size of the sample. We recursively compute the errors and we compare the RMSE of the alternative samples of the models: the standard models excluding the Big Data information (Ω_1) and the one including our Big Data information (Ω_2). One key advantage of using Big Data information in the backtest exercises lies in the release lag structure relative to our hard and soft data alternative indicators. Obviously, including reliable and useful real-time information should improve the relevance of our real time Big Data indices if they prove to be efficient estimators of investment.

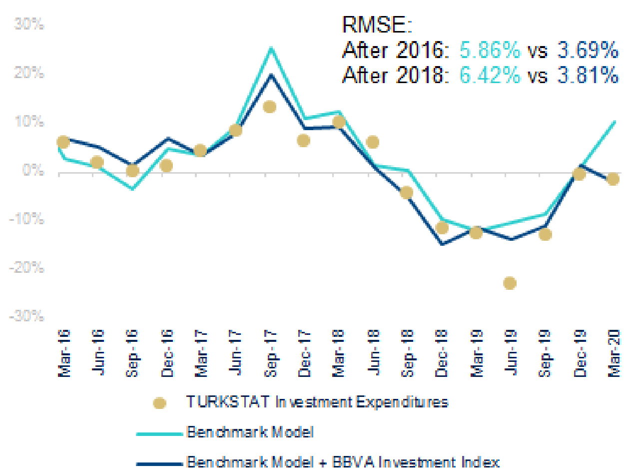
The results confirm the improvement of the forecast accuracy when we use the Big Data Investment information. Figures 4 and 5 present the results of our backtest exercise. For each quarter-end starting from 2016, we have run our nowcast models – for benchmark and alternative – with only available data as of that date according to the release lag structure. For both GDP and Investment nowcasting models, inclusion of the Investment Index in the alternative model significantly improves the real-time nowcasting performance with lower Root Mean Squared Errors. The RMSE of the sample including the Big Data information is reduced more than two percentage points (37% from 5.9% to 3.7%) and remains significant after the Turkish financial crisis, where the error is also reduced (nearly 40% from 6.4% to 3.8%). The reduction in terms of the GDP model is obviously lower as investments have a lower share than other components like consumption in the GDP. However, it continues to be significant in both samples, the long sample (nearly 16% from 1.20% to 0.99%) and the more recent one after the financial crisis (nearly 25% from 1.58% to 1.18%).

Figure 4. **BACKTESTS FOR GDP NOWCAST**
(BENCHMARK & ALTERNATIVE MODEL, YoY)



Source: BBVA Research.

Figure 5. **BACKTESTS FOR INVESTMENT NOWCAST**
(BENCHMARK & ALTERNATIVE MODEL, YoY)



Source: BBVA Research.

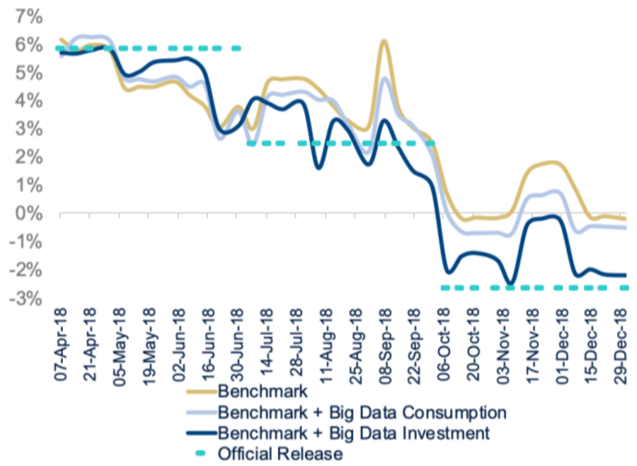
In addition to check the size of the out-of-sample error we analyze to what extent the introduction of the Big Data Investment index (and consumption) help a benchmark model to anticipate sharp changes in the performance of economic activity. The case of Turkey offers two recent crises that can help us to solve this question: The financial crisis of August-September 2018 and the recent Covid-19 crisis in March 2020.

For both periods we track the evolution of the nowcasting of a benchmark model (which does not include Big Data) and another one including the Big Data investment index. The results shown in figure 6 and 7 are the following:

- The Big Data Investment index played an important role in anticipating the effects of the crisis in the summer of 2018. Figure 6 shows how, since the end of August, the model including Big Data investment data rapidly diverge from the benchmark model that does not include this type of information. The difference in the gap is more than one percentage point which is due exclusively to one variable in a model of fourteen variables. The difference begins to be evident from the beginning of September.

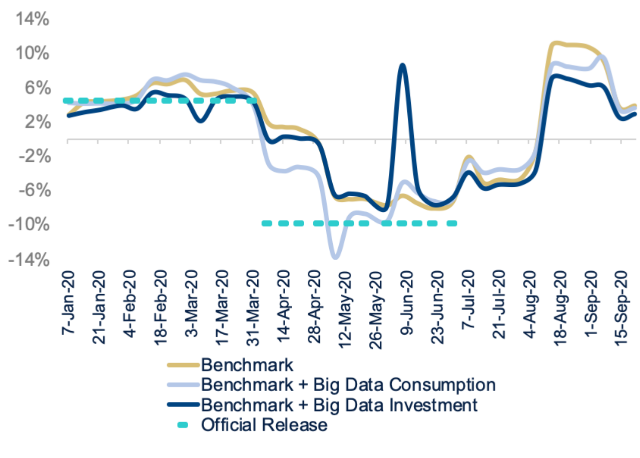
- The anticipation role of the Big Data inversion index during the Covid-19 Crisis has been less important but replaced by the anticipation role of the Big Data consumption index. Figure 7 shows how the difference between the benchmark model and the one that includes the Big Data investment index is not significant. However, the model including the Big data Consumption index began to collapse almost a month earlier, at the end of March while the benchmark model began to adjust strongly at the end of April.

Figure 6. **GDP NOWCAST & BIG DATA 2018 CRISIS (BENCHMARK & ALTERNATIVE MODEL, YoY)**



Source: BBVA Research.

Figure 7. **GDP NOWCAST & BIG DATA 2020 COVID (BENCHMARK & ALTERNATIVE MODEL, YoY)**



Source: BBVA Research.

The use of the EM algorithm also allows the Kalman filter to analyze the contribution of any variables (or groups of variables) included in the model to revisions at any moment. This is an important feature, as nowcasting faces a continuous inflow of information as new data are released at different periods of time with different degrees of delay. Intuitively, only the news or the "unexpected" component from released data should revise the forecast. This would allow the nowcast revisions to be divided by the contribution of individuals variables or a group of them to be grouped as real variables, financial, soft information in surveys or our big data information (see Banbura and Modugno (2014) for a general application and Modugno, Soybilgen & Yazgan (2016) also for the case of Turkey).

We apply this exercise for our GDP and Investment. From 2017-Q1, the model delivers four-period-ahead forecasts at the end of each month, starting from the first month of 2017-Q1. The model generates forecasts not only for the target variable (GDP or Investment) but the rest of the variables included in the dataset. Given that only the "unexpected" component from the new released data or a change in the parameters resulting from any re-estimation can modify the nowcasts of the target variable (GDP or Investment), we can divide the change in the Nowcasts into the contribution of changes in information in the variables (i.e. News) and changes in the model parameters due to the re-estimation. Although we can estimate the individual contribution of any of the variables included in the model, we group the variables into four categories: real economy variables (Real), soft information obtained from surveys (Survey), financial variables (Financial) and Big Data information (Big Data) while Re-estimation denotes the impact of model re-estimation (ReEst).

We can describe it formally by denoting Ω_{v+1} and Ω_v as two consecutive datasets collected one month apart and x_t as the newly released data which is included in Ω_{v+1} but not in Ω_v. Defining the nowcast of quarterly x_t as an orthogonal projection of itself on the available dataset, the nowcast can be shown as follows:

$$E\left[\frac{x_t^Q}{\Omega_{v+1}}\right] = E\left[\frac{x_t^Q}{\Omega_v}\right] - E\left[\frac{x_t^Q}{I_{v+1}}\right]$$

where $E\left[\frac{x_t^Q}{\Omega_{v+1}}\right]$ and $E\left[\frac{x_t^Q}{\Omega_v}\right]$are new and old nowcasts and $E\left[\frac{x_t^Q}{I_{v+1}}\right]$ is the revision in the two consecutive nowcasts. The unexpected part of the release with respect to the model, which denotes news, is shown as $I_{v+1} = x - E\left[\frac{x_t^Q}{\Omega_v}\right]$. The equation above shows that GDP nowcasts between successive months change only if values of newly released variables and the DFM's predictions of those variables based on Ω_v differ or the effect of parameter re-estimation on nowcasts with each dataset expansion is taken into account. The relative impact of the contribution of i news (or a model re-estimation) for the reference quarter r at the nowcast horizon h as $C(i,r,h)$ can be defined as:

$$Relative\ impact_{i,r,h} = \frac{|C_{i,r,h}|}{\sum_{i=1}^{S}|C_{i,r,h}|}$$

Figure 8 shows a graph plotting the relative contribution of the group of news (hard data, surveys, financial and Big data) for the reference quarter at different horizons for both the GDP and Investment nowcasting models. The X-axis includes the reference nowcast sample starting from the first quarter of 2017 to the first quarter of 2020. The Y-axis shows the successive nowcasts (h) for every quarter and the Z-axis shows the relative contribution of different data groups i (real, survey, financial and Big data, including also changes coming from parameter re-estimation).

While some of the results confirm the main findings of the literature[11] of Modugno, Soybilgen & Yazgan (2016), the results of the exercise add some new insights from the contribution of news coming from the Big Data indexes:

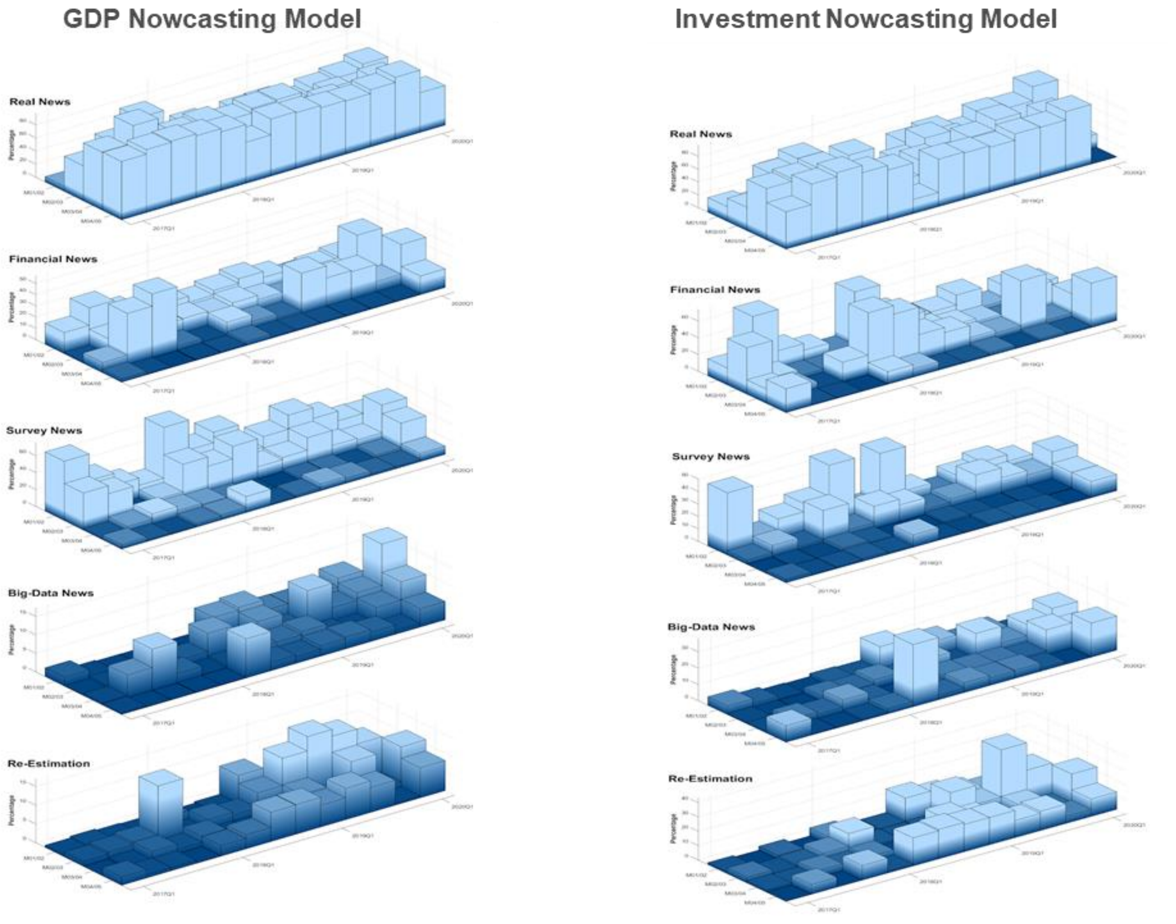
- In line with other empirical works, the contribution of the news from the real variables' hard data (9 out of 14 variables or 64% of information the model) increases over time when most of the hard data is released. The contribution of news is lower than its representation in the model during the first sequences of nowcasts, increasing later to nearly 60%.
- The contribution from soft data or Surveys (14% of the variables in the model) becomes more relevant during the first releases of the quarter when the information from the real news is not available. The contribution to the total reaches nearly 20%, above its representation in the model of 14%.
- The contribution from the financial variable (Credit growth trend, 1 out of 14 variables or 7% of the information) is uniform and near the representation in the model, with a higher contribution during the periods of high credit growth such as 2017, when the Government applied the Credit Guarantee Fund (CGF) Program to stimulate the economy.
- The contribution from Big Data news (2 out of 14 variables or 14%) is more relevant at the beginning of the quarter when availability of releases of real variables is low, as in the case of the survey news. More importantly, these results show the increasing contribution of our news from Big Data indices to nowcast revisions for GDP.

This is important, given that the shorter sample used by the Big Data information relative to the rest of the variables is somehow penalizing the contribution due to a prevalence bias. The reason lies in the Kalman filter procedure, that whenever there is a missing value, the blanks will be filled with the weights of the variable and the correlation with the common factor. In this sense given that information from Big Data is only available from 2013, the news provided in later periods will be more similar to the common factors, as from prior to 2013 the influence of the common factor will be higher while the idiosyncratic providing the information content could be penalized.

In order to correct for information prevalence bias, we re-estimate the contribution of the individual variables in the model, restricting the information of any individual variables to the sample used for the Investment Big Data but maintaining the rest at the original sample. We repeat this "fair conditions" exercise for all the individual variables in 13 re-estimations, cropping the information from prior to 2013 for any of the alternative variables.

[11] see Banbura and Modugno (2014) and Modugno, Soybilgen & Yazgan (2016)

Figure 8. **CONTRIBUTION OF BIG DATA NEWS TO GDP AND INVESTMENT NOWCASTING MODELS**

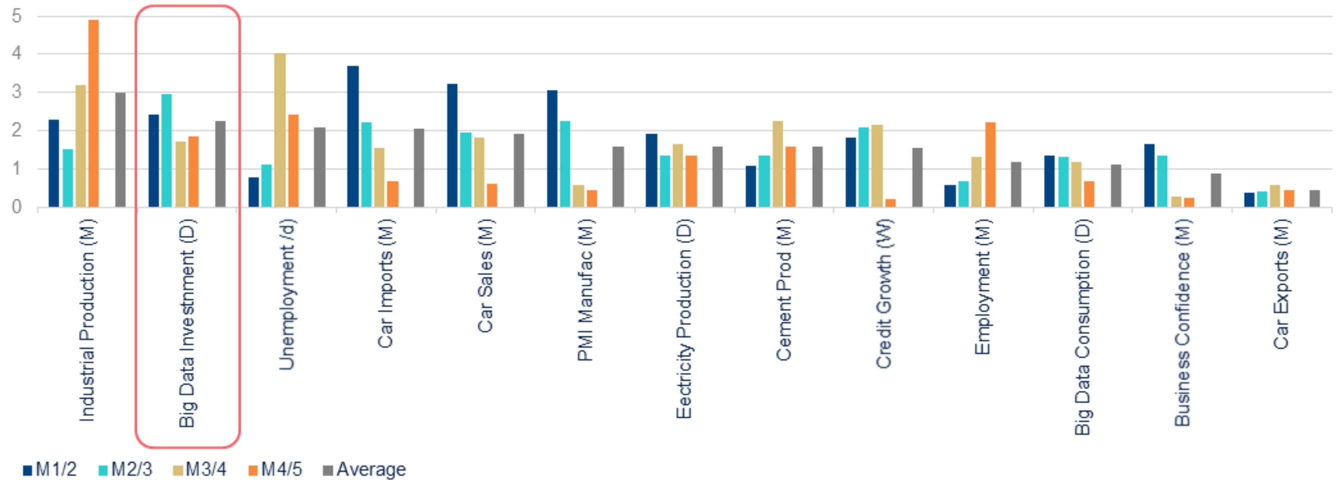


Source: Own calculations.

Figure 9 shows the news contribution from all of the variables in similar conditions. The graph also shows the subsequent h horizons according to the order of releases in blue colors (darker colors for advanced releases and lighter colors for the most lagged) and the average of the four information updates in gray. The results confirmed the previous results in the literature, mainly that the real variables information news is important but there is some useful information in using soft data information and surveys and financial or credit news.

More importantly, the unbiased news contribution of Big Data Investment indicators increases in terms of relevance and only the Industrial Production looks to have information superior to that of Big Data Investment. There are two additional advantages for using the Big Data Investment. First, the relevance of its news is relatively constant, but more important in the first update of the model during the quarter, when uncertainty is higher. Second, this information can be obtained on a daily basis, which is only possible for some real variables such as electricity production and Big Data consumption.

Figure 9. **CONTRIBUTION OF THE BIG DATA INVESTMENT NEWS USING SAME SAMPLE FOR THE REST OF THE VARIABLES**



Source: Own calculations.

In sum, the analysis of the contribution from Big Data news to the Nowcasting models leads to some important results. First, the inclusion of a Big Data investment increases the nowcast accuracy of the models in terms of reduction of the out-of-sample root mean square error. Secondly, the contribution of Surveys to the information included in Big Data news is more relevant at the beginning of the quarter, when the uncertainty about the results of the quarter is higher. Third, the importance of Big Data in the Nowcasting models has been increasing during the last years. In addition, the analysis of the relevance in similar sample conditions shows that the Big Data investment leads in relevance, followed only by industrial productions, which are released with significant lags. Last but not least, the relevance of Big Data is especially important during the crisis and turning points, making it an important tool to anticipate the crisis for analysts and policymakers to react rapidly to changing conditions.

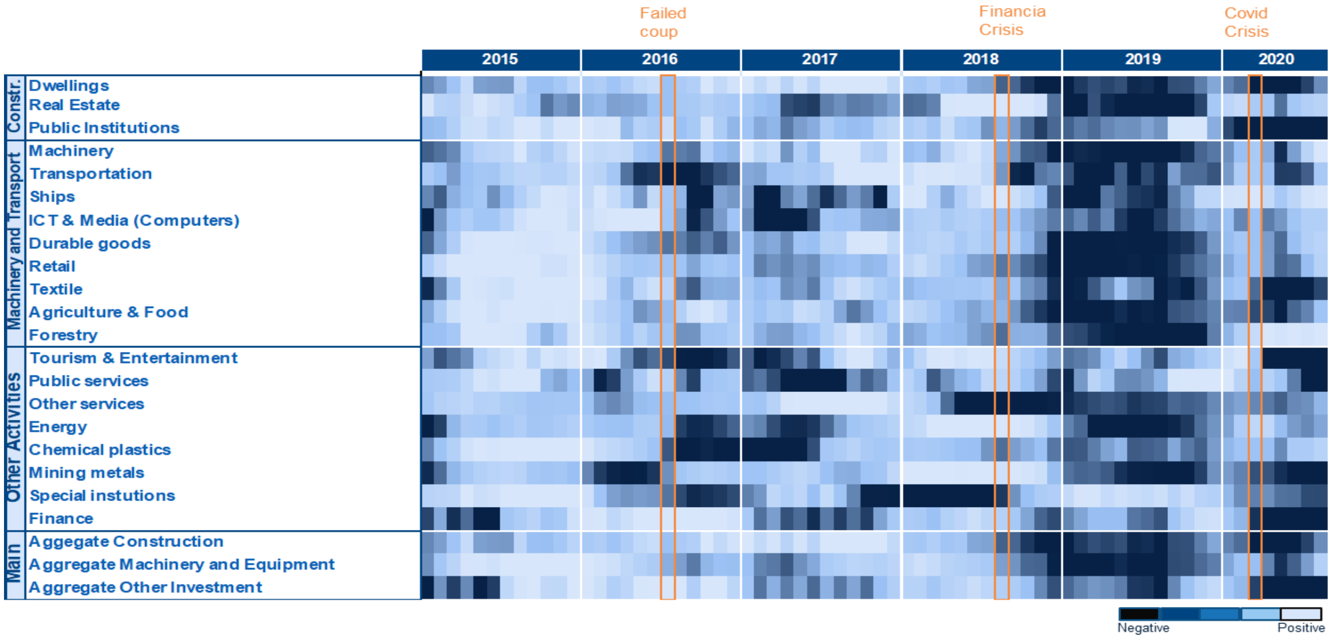
4. Big Data Investment in high definition: Sectorial and geography

Besides the advantages of providing information of the investment cycle in real time, the Big Data Investment Indicators developed in this working paper present additional advantages. An important one is the ability of this information to be registered not only in real time but also in high definition. As the information is registered at a very granular level in the BBVA Big Data, the analysis of the investment data can be traced by sectoral activities and geographically, also in real time.

Figure 10 shows the evolution of the Big Data investment flows by different activities grouped by those included in the three big aggregates: construction, machinery and transport and other investments. The heat map shows the evolution of the yearly growth rate (three-month moving averages) from 2015 to 2020. The darker blue colors stand for the lowest 10th percentile while the lighter blue colors represent the higher growth rates of the 90th percentile.

The different nature of shocks hitting the Turkish economy during this period (2015 to 2020) makes Turkey an interesting case of study to assess the impact of these shocks on investment and its diffusion over time and on sectoral activities. In this period, three important and different shocks hit the economy (marked in orange): the failed coup of July of 2016, the financial crisis during the summer of 2018 and the recent COVID-19 shock.

Figure 10. **SECTORIAL BIG DATA INVESTMENT 2015-2020** (YoY 3-MONTH MOVING AVERAGES)



Source: Own calculations.

The response of the investment to these events has been somewhat different, as they were of different natures:

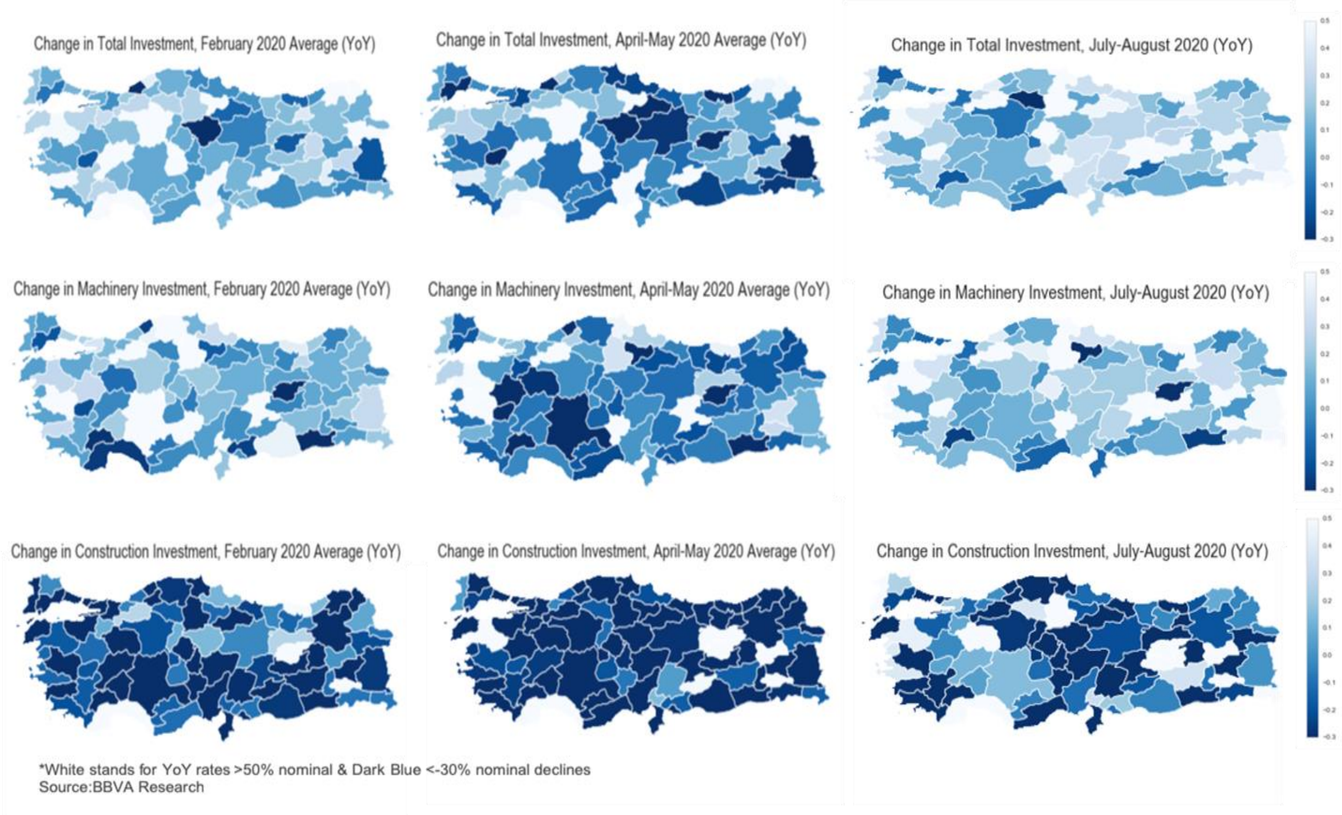
- The response to the failed coup (political uncertainty shock) was short-lived and concentrated on some specific activities (darker colors), as shown in the non-homogeneous dark colors in the diffusion map. The negative impact was mainly observed in transportation, while construction and machinery equipment was not specifically affected and recovered very rapidly once the initial political shock died out. The impact on tourism was longer, but this was also related to the round of terrorist attacks in the big cities of Turkey.
- The response to the summer 2018 financial crisis (currency shock) was more intense and homogeneous. After the sharp depreciation of the Turkish lira (nearly 40%), the capital flows suddenly stopped and credits declined rapidly for most activities. The shock to investment started just after the financial crisis across the board for most of the sectors until the end of 2019 when credits started to grow after one-and-a-half years of rapid and deep de-leveraging of the sector.
- The response to COVID-19 (pandemic shock) has been somewhat in the middle of the previous two shocks in terms of intensity, homogeneity and length. One special point to mention is the temporary shock to investment in Turkish sectors highly integrated in global value chains such as Textile and Automobiles (i.e. transportation), which could have been affected by the shut-down of external markets. Specifically affected by mobility restrictions, the tourism and entertainment sectors suffered the most. Contrary to the previous crisis, public investment did not play the traditional anti-cyclical role, as public finances were more constrained this time.

Another important advantage of the Big Data information from BBVA is that the information is geolocalized. This allows the inflows on investment activities to be tracked not only by sector, but also on a regional basis. This will help the research of interesting questions, such as how investment is being allocated and how the different regions of a country react to an investment shock.

As an example, one interesting and special case has been how the COVID-19 shock has been transmitted geographically. Figure 11 shows how the COVID-19 shock has affected the different investment aggregates (Total, Machinery & Equipment and Construction) on a geographical basis. The maps show, for these sectors, the yearly growth rates immediately before the mobility restriction measures were imposed and most of the countries shut down borders (February 2020), the period including most of the mobility restrictions (April-May 2020) and the ease of mobility restrictions and recovery (July-August 2020). The maps confirm some of the observations from the sectoral analysis and also describe the geographical response:

- The first important pattern is that the negative effects on investment by the COVID-19 shock have not been as homogeneous as the 2018 financial shock neither, in sectorial nor in geographical terms. The key reason for this is that machinery investment response has been more differentiated and dispersed.
- The response of machinery investment shows a rapid recovery after the COVID-19 shock and the dispersion of the shock is heterogeneous. An important result is that big cities such as Istanbul or Ankara were not specially affected compared to other regions. Meanwhile, as we move from the east to the west of the country, we observe darker blues representative of contractions. This is not strange at all, as it is precisely where the manufacturing industry is mainly located (see Akcigit et al, 2019) and is consistent with the well-known regional east-west dualism in Turkey (Gezici, Walsh and Kacar, 2017). Besides, the export-oriented industries are located in these provinces. The maps also suggest that provinces specialized in products such as metal and electrical equipment (Central-West), mostly related to the automotive and durable consumer goods industries in the Global Value Chain (GVC), experienced the sharpest temporal declines compared to the textile industry in the GVC, which has an important presence also in the central-south of the country. The fact that the shock has been less permanent after COVID-19 is also relevant in geographical spillovers, as these GVCs are important sources of spillovers to other industries.
- The response of construction investment has been more homogeneous, but it is also recovering faster so far than the 2018 financial crisis. Facing a more negative performance than the machinery segment in the pre-COVID-19 period (as the construction sector was experiencing some de-leveraging led by the previous financial crisis), the initial response was homogeneous and amplified the already weak situation. However, the situation from June onward started to improve, at least in the big cities and the coast, but with some dark blue areas in the middle of the country. Whether this is the result of different allocation of credit or a different response of the macroprudential policies implemented by policymakers during COVID-19 is beyond this research.

Figure 11. **GEOGRAPHICAL RESPONSE OF BIG DATA INVESTMENT IN BIG AGGREGATES TO THE COVID SHOCK** (PRE COVID: FEBRUARY 2020, COVID: APRIL-MAY 2020, POST COVID: JULY-AUGUST 2020)



Source: Own calculations.

5. Big Data and Investment in other countries

In this section, we show the results of our Big Data Investment Indicators for Spain and Mexico, comparing the evolution of the obtained indicators with the official figures from National Accounts statistics and other monthly indicators, which could be used as a proxy of investment as tested in the case of Turkey. We test the robustness of our estimated BBVA Big Data Total Investment indicators for these three countries, measured as the Gross Fixed Capital formation, as well as some of their components like machinery and equipment (including transportation) and construction.

Tables 3 and 4 and Figures 12 and 13 show the BBVA Big Data Investment Indices estimated with the methodology of the official quarterly Gross Fixed Capital Formation (GFCF) or Investment series from the National Statistics Office of each country. Results show that the BBVA estimated indicators fairly reflect the pattern of the official figures, with the advantage of having the data in real time, covering the time lag in the publication of the official figures, which are released on quarterly basis.

Table 3. **CORRELATION OF BBVA BIG DATA INVESTMENT INDEX AND NATIONAL ACCOUNTS**

	Correlation with National Accounts		
Turkey (Mar 15 - Mar 20)	Total	M&E	Construction
BBVA Real Big Data Investment indicators	0.88	0.84	0.77
BBVA Nominal Big Data Investment indicators	0.83	0.73	0.79
Spain (Mar 18 - Mar 20)			
BBVA Real Big Data Investment indicators	0.78	0.58	0.73
BBVA Nominal Big Data Investment indicators	0.82	0.63	0.75
Mexico (Jul 18 - May 20)			
BBVA Real Big Data Investment indicators	0.84	0.7	0.76
BBVA Nominal Big Data Investment indicators	0.9	0.65	0.78

Source: BBVA Research.

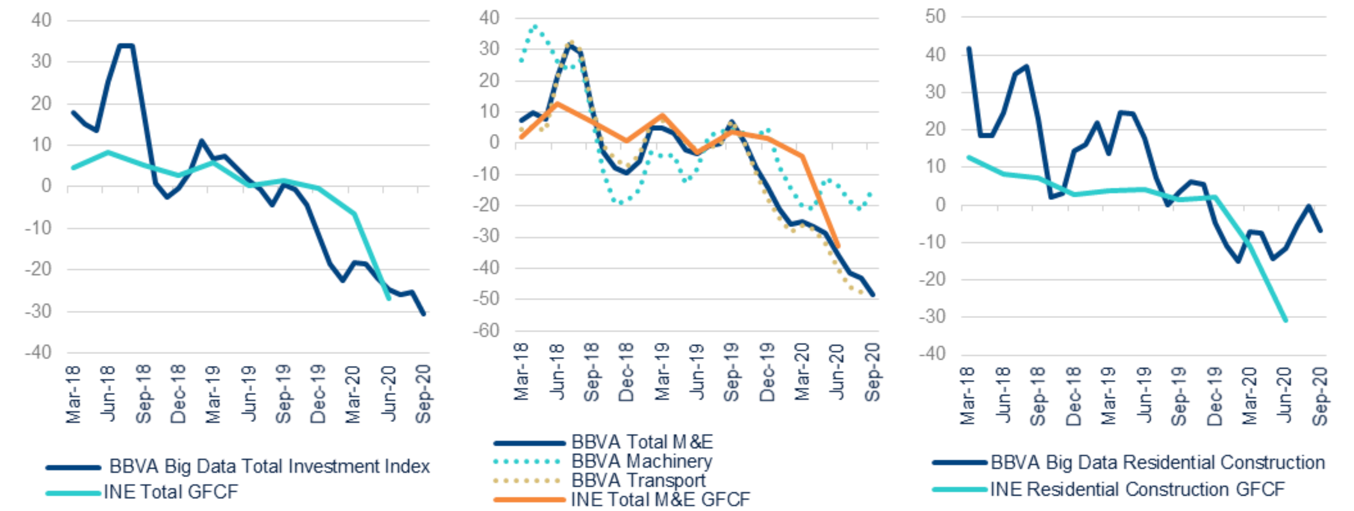
Table 4. **CORRELATION OF BBVA BIG DATA INVESTMENT INDEX AND INVESTMENT PROXIES**

	Correlation with National Accounts	Correlation with BBVA Real Big Data Investment indicators	Correlation with BBVA Nominal Big Data Investment indicators
Turkey (Mar 15 - Mar 20)			
M&E			
Industrial production	0.78	0.75	0.55
Capacity Utilization	0.78	0.79	0.30
Construction			
Employment	0.87	0.85	0.58
Non-Metalic Mineral (e.g. Cement)	0.71	0.72	0.46
Turnover Building	0.77	0.90	0.56
Spain (Mar 18 - Mar 20)			
M&E			
Industrial production	0.72	0.63	0.66
Industrial confidence capital goods	0.72	0.66	0.7
Turnover	0.68	0.61	0.63
Construction			
Employment	0.84	0.72	0.76
Non-Metalic Mineral (e.g. Cement)	0.79	0.74	0.76
Turnover	0.89	0.6	0.64
Mexico (Jul 18 - May 20)			
M&E			
Industrial production	0.82	0.72	0.75
Capacity Utilization	0.8	0.62	0.63
Construction			
Employment	0.86	0.85	0.87
Industrial production	0.99	0.68	0.72

Source: BBVA Research.

In the case of Spain (Figure 12 and Table 3), the Pearson correlation coefficient for the last 2 years (March 2018 to March 2020) of the BBVA Big Data Total Investment Index and the official data provided by the Spanish National Institute of Statistics (INE) is 0.78, with the advantage of having the data 3 months in advance compared to the official figures. By components, the correlation with National account figures is 58% for machinery Investment and 73% for construction investment. In addition, Spearman correlation coefficients maintained high values, reflecting that the correlation coefficient has not be influenced by the COVID shock.

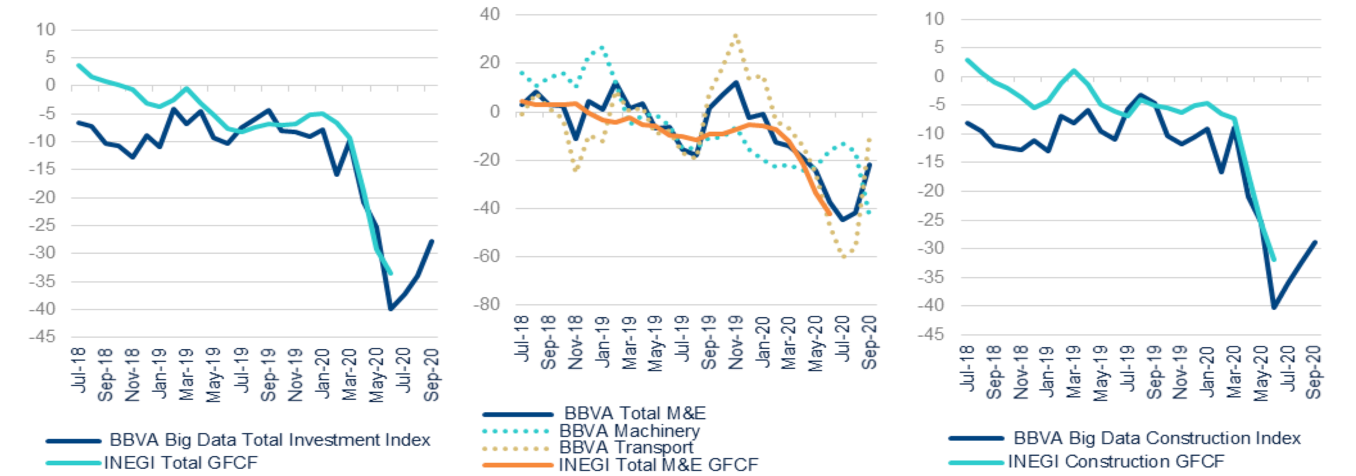
Figure 12. **SPAIN: BBVA BIG DATA INVESTMENT INDEX: TOTAL AND COMPONENTS**



Source: BBVA Research.

In the case of Mexico (Figure 13 and Table 3), the correlation between the constructed estimates for Investment and the official figures is even higher. Particularly, for the last two years (July 2018 to May 2020), the correlation coefficient of the BBVA Big Data Total Investment Index and the official data of GFCF provided by the National Institute of Statistic and Geography (INEGI) is 0.84. In the case of machinery investment, it is 0.7 and 0.76 for construction investment. The high frequency of our indicators is especially relevant to monitor a period of high uncertainty at the current moment given the COVID-19 crisis. The Spearman correlation coefficients are not significantly lower.

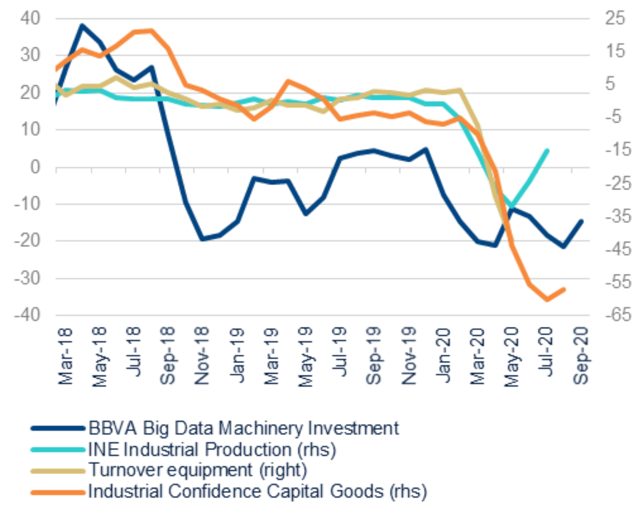
Figure 13. **MEXICO: BBVA BIG DATA INVESTMENT INDEX: TOTAL AND COMPONENTS**



Source: BBVA Research.

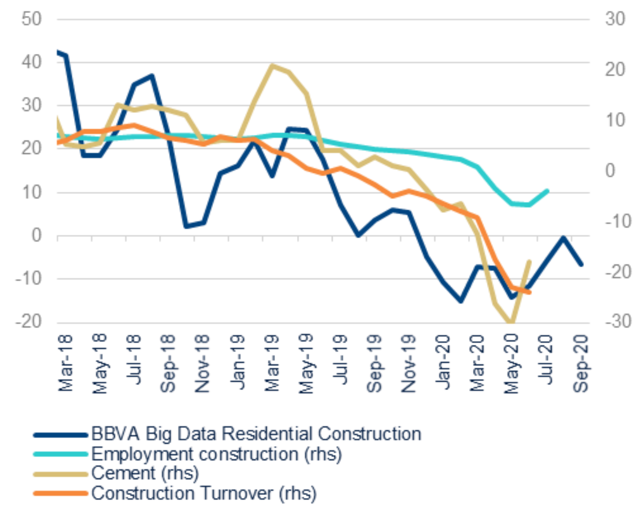
For validation purposes as in the Turkish case, we compare our estimated indicators with higher frequency (monthly) proxy investment variables. In the case of Spain (Figures 12 , 14 and 15 and Table 4), the correlation between the BBVA Big Data Machinery Investment Index and industrial confidence on capital goods is 0.66. It also correlates well with industrial production (0.63) and equipment turnover (0.61). This high correlation also keeps for construction, where our Big Data Construction Investment indicator correlates well with cement demand (0.74), employment in construction (0.72) and construction turnover (0.60).

Figure 14. **SPAIN: BBVA BIG DATA MACHINERY INVESTMENT AND PROXIES** (YoY, 3m)



Source: BBVA Research.

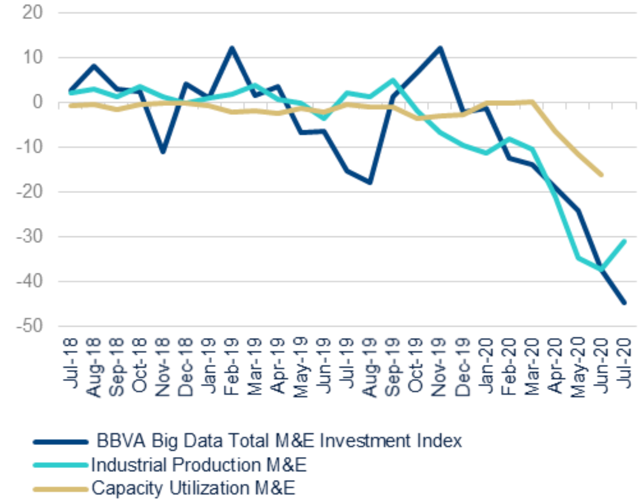
Figure 15. **SPAIN: BBVA BIG DATA CONSTRUCTION INVESTMENT AND PROXIES** (YoY, 3m)



Source: BBVA Research.

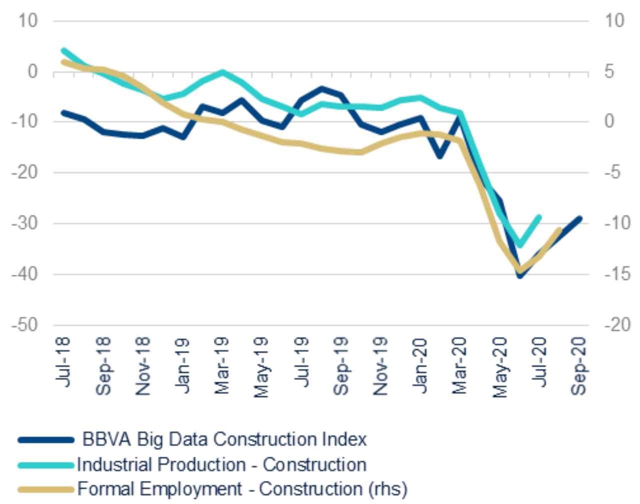
We repeat the exercise for Mexico (Figures 13, 16 and 17 and Table 4) and results remain positive. The correlation coefficient of the BBVA Big Data Machinery Investment with the industrial production of machinery is 0.72 and slightly lower but significant (0.62) with capacity utilization. For construction, the good fit is maintained, as can be observed in the graphs. Hence, BBVA Big Data Construction Index mimics the evolution of industrial production for construction (0.85) and, to a lesser extent, employment in construction (0.68).

Figure 16. **MEXICO: BBVA BIG DATA MACHINERY INVESTMENT AND PROXIES** (YoY, 3m)



Source: BBVA Research.

Figure 17. **MEXICO: BBVA BIG DATA CONSTRUCTION INVESTMENT AND PROXIES** (YoY, 3m)



Source: BBVA Research.

6. Conclusion

Big Data held by private companies and banks provide an unprecedented opportunity to measure economic activity in real time and high definition (i.e. at a granular level). These data have an enormous potential for policymakers, central banks and private corporations to react rapidly to the incoming news, particularly in uncertain environments such as the COVID-19 pandemic.

In this paper, we present a novel contribution for the analysis of information in real time and high definition by introducing a new Big Data indicator for Investment (GFCF). Thus, we extend our previous set of real-time consumption indicators (Carvallo et al, 2020) to include not only individual-to-firm transactions (point of sales transaction through credit and debit cards) but also adding firm-to-firm transactions.

By aggregating both individual-to-firm and firm-firm transactions to the sectors manufacturing the fixed assets, we successfully replicate the quarterly national accounts for Investment and its main subcomponents (Machinery Equipment and Construction) in real time and high definition for the case of Turkey.

We validate our results for Turkey through multiple perspectives, including correlations to national accounts investment, with higher frequency alternative proxies of investment and the validity of our indicators in order to improve the nowcasting accuracy (by reducing the out-of-sample error), anticipation and enhancing the properties of a standard Nowcasting Dynamic Factor Model. We also show how Big Data Information is increasingly important, especially if the information becomes feasible for longer periods of time.

The latter result could be an indication that alternative modelling techniques addressing the problem of very small samples relative to the number of variables (i.e. regularization methods such as Ridge, Lasso, Elastic, etc.), could improve the properties of the Big Data indicators for nowcasting, but we leave this as further research.

The high definition information of investment obtained through the Big Data information (i.e. sectoral and geographical basis) has also proved to be an important tool for economists and policymakers. In this working paper, we show how different the propagation of investment has been during three different shocks to investment (political, financial and health shocks) and, more recently, how the COVID-19 shock has propagated across the Turkish geography in different aggregates of investment.

Finally, we extend our results to other developed and emerging countries such as Spain and Mexico with similar correlation results in these countries. The correlation is high for both the aggregate investment indicators and machinery and construction and their proxies, and invite us to extend their ability to nowcast investment.

In sum, we confirm the results showing the usefulness of Big Data information for economic analysis and policymaking for the analysis of consumption (individual-to-firm transactions), extending to transactions between corporations in the case of investment by also including firm-to-firm transactions.

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