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Big data financial transactions and GDP nowcasting: The case of Turkey

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Abstract

We use aggregated information from individual-to-firm and firm-to-firm transactions from the Garanti BBVA Bank to simulate domestic private demand and estimate aggregate consumption and investment for Turkey's quarterly national accounts in real time. We show that these big data variables successfully nowcast official consumption and investment flows. To further validate the usefulness of these indicators, we include both indicators among others which are generally used in gross domestic product (GDP) nowcasting and evaluate their contribution to nowcasting power of Turkish GDP by combining both linear and nonlinear models. The results are successful and confirm the usefulness of consumption and investment banking transactions for nowcasting purposes. These big data are valuable, especially at the beginning of the nowcasting process, when the traditional hard data are scarce. Accordingly, this information is especially relevant for countries with longer statistical release lags, such as emerging markets.

KEYWORDS

Bayesian vector autoregressive model, big data, dynamic factor model, machine learning, nowcasting

1 | INTRODUCTION

Economists normally use information produced by national statistical agencies or central banks (gross domestic product [GDP], industrial production, unemployment, etc.) to assess the state of the business cycle. Although this information is designed to track the business cycle, it has some shortcomings. One important problem is that most of the key indicators are low frequency and released with a time lag. For some countries, this lag can be considerable.

Although some economic information is available at high frequency (e.g., stock market prices and interest rates), it is normally related to financial conditions and expectations, which do not necessarily match the real condition of the economy. In the wake of the Covid-19 crisis, the need to react rapidly to changing economic conditions 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 sophisticated ones such as soft data from surveys (e.g., purchasing manager indexes [PMIs] and consumer confidence surveys) and hard high-frequency indicators such as daily electricity production and weekly chain store sales data.
- Developing higher-frequency models: Central banks have used traditional nowcasting methods combining quarterly or monthly variables with higher-frequency

- indicators (e.g., weekly or daily data) to better capture real-time information. Examples include the Federal Reserve of New York's weekly economic index (Lewis et al., 2020), the Bundesbank Weekly Activity Index (Eraslan & Götz, 2020), and the Central Bank of Portugal's daily economic index (Lourenco & Rua, 2020), among others.
- Developing new big data indicators: A new stream of work (Barlas et al., 2020; Carvalho et al., 2021; Chetty et al., 2020) uses transaction data, company information, and Google trends (Woloszko, 2020) to capture economic activity in real time. The Covid-19 pandemic of 2020 has been a major stimulus for movement in this direction, and an entirely new literature has rapidly developed using these indexes.

This paper makes several contributions. We extend the increasing literature on electronic payments to an emerging economy, Turkey. We use information on individual-to-firm and firm-to-firm transactions from the Garanti BBVA Bank[1] to replicate aggregate consumption and investment in quarterly national accounts. One of our main contributions to the existing literature is to extend the use of bank transactions to create high-frequency proxies for investment and consumption. To do this, we combine firm-to-firm transactions and the traditionally used individual-to-firm information from credit and debit cards, as a high-frequency proxy for consumption. Although the literature on use of bank transactions to replicate consumption is growing rapidly, we are not aware of any empirical work using financial transactions to capture investment flows. To the best of our knowledge, this paper is the first to attempt.[2]

As we do for consumption and investment, we also investigate the usefulness of this big data financial transaction information for nowcasting GDP, the most aggregated measure of total economic activity. Since data on GDP are released with significant lags, nowcasting GDP is always considered important to obtain timely information on economic activity. The usage of high-frequency proxies of investment and consumption may contribute the accuracy of GDP nowcasts. To nowcast GDP, we combine our big data proxies of investment and consumption with other traditional variables that are frequently used in GDP nowcasting and test their significance in improving nowcast accuracy.[3] Because these results may be sensitive to the choice of model used in nowcasting, we also check their robustness to different nowcasting models. In particular, we use dynamic factor models (DFMs) and Bayesian vector autoregression models to test the out-of-sample accuracy of our nowcasts with and without our big data proxies. Moreover, following the recent papers by Babii et al. (2021) and Soybilgen and Yazgan (2021), we also include machine learning models such as random forests (RF) and gradient boosting-based models.

After presenting the evidence on significant contribution to the predictive performance from all variables that are employed in nowcasting, we focus solely on the contribution of our high-frequency investment and consumption proxies among other variables. We show that our big data proxies provide an additional accuracy to nowcasting performance. These data appear to make a greater contribution at the beginning of the nowcasting process, when traditional hard data are relatively scarce.

The increasing availability of electronic payment data has spurred the recent literature on real-time economic activity. However most recent empirical studies focus on developed economies. For the United States, Barnett et al. (2016) derive an indicator-optimized augmented aggregator function for monetary and credit card services using credit card transaction volumes. This new indicator, inserted in a multivariate state-space model, nowcasts GDP more accurately than a benchmark model. Verbaan et al. (2017) analyze whether the use of debit card payment data improves the accuracy of nowcasting and one quarter ahead forecasting of Dutch private household consumption. Baker et al. (2020a) and Olafsson and Pagel (2018) use transaction level data from financial apps to track household spending and income. Galbraith and Tkacz (2015) nowcast Canadian GDP and retail sales using electronic payment data, including both debit card transaction and checks clearing through the banking system. Duarte et al. (2017) produce nowcasts and one step ahead forecasts of Portuguese private consumption by combining data from ATM and point-of-sale (POS) terminals. Aprigliano et al. (2019) use payment data to nowcast investments (and other GDP's components) and show that models including retail payment flows generally outperform a model based on standard short-term indicators. For Spain, Bodas et al. (2019) replicate a retail sales index through POS transaction data.

The Covid-19 pandemic of 2020 has acted as a major stimulus in this direction, and in a short space of time, a new literature has grown that uses indexes derived from transaction data to track the impacts of the virus's spread and of lockdowns. Again, most papers in this literature focus on developed economies. Andersen et al. (2020) present evidence from Denmark of a sharp reduction of total card spending during the early phase of the crisis. Alexander and Karger (2020), Baker et al. (2020b), Chetty et al. (2020), and Cox et al. (2020) focus on the effect of Covid mobility restrictions on card transactions in the USA. Bounie et al. (2020) track the effect on consumer transactions in France. Chronopoulos et al. (2020) and Hacioglu et al. (2020) analyze the response in the UK, and Chapman and Desai (2021) demonstrate how payments systems data that capture a variety of economic transactions can be used to estimate the state of the economy in real time using Canadian data. Only a few studies have extended this empirical work to emerging economies. Carvalho et al. (2021) use credit and debit card information to proxy consumption in Turkey, Mexico, Colombia, Peru, and Argentina, and Chen et al. (2021) utilize offline financial transaction data to track consumption in China during the Covid crisis.

Our paper contributes to this literature not only by expanding nowcasting practices by including investment flows but also by extending the consumption oriented literature to an emerging market, deriving big data proxies for both consumption and investment flows and demonstrating their usefulness in nowcasting.

The remainder of this paper is organized as follows. Section 2 describes the big data methodology for computing private domestic demand in Turkey. In particular, we describe how we simulate consumption and investment in national accounts from individual-to-firm and firm-to-firm transactions in big data from the Garanti BBVA. After the indicators are developed, we describe their performance in mimicking consumption and investment flows of national accounts. Sections 3 and 4 present our methodology for nowcasting GDP using these variables in traditional and more recent machine learning nowcasting models. We also check how the inclusion of big data complements improves the nowcasting performance relative to the other traditional variables generally used in nowcasting. The last section concludes the study.

2 | CONSUMPTION AND INVESTMENT THROUGH A BANK'S BIG DATA: THE ROLE OF INDIVIDUAL-TO-FIRM AND FIRM-TO-FIRM TRANSACTIONS

The recent literature on using banking transactions to replicate GDP focuses on analyzing credit and debit card data to proxy consumption. These transaction data can be obtained from anonymized bank data (Andersen et al., 2020; Carvalho et al., 2021) or from sources compiled by some companies (Chetty et al., 2020). Most studies estimate individuals' consumption through individual-to-firm card transactions (whether through a POS or online) for purchases of goods and services. More recently, Carvalho et al. (2021) have extended the transactions used to include those for consumption of goods and services normally paid for through direct money transfers, such as utilities, telephone costs, and other bills.

We extend investment demand expenditure by including firm-to-firm transactions featuring firms that produce fixed assets, as explained by Barlas et al. (2020). We assume that firm-to-firm money transfers going to firms that manufacture fixed assets are payments for investment goods. In the case of dwellings investments, we also include individual-to-firm transactions reflecting house purchases.

The definition of gross fixed capital formation provided by the System of National Accounts (SNA) is "the resident producers' net acquisitions (acquisitions minus disposals) of fixed assets used in production for more than 1 year." The concept differentiates between the following: (1) dwellings; (2) other buildings and structures, including major improvements to land; (3) machinery and equipment; (4) weapons systems; (5) cultivated biological resources, for example, trees and livestock; (6) costs of ownership transfer on nonproduced assets, such as land, contracts, leases, and licenses; (7) R&D; (8) mineral exploration and evaluation; (9) computer software and databases; and (10) entertainment, literary, or artistic originals. Finally, these categories are grouped into three components: (1) construction investment, (2) machinery and equipment, and (3) other investment, including computer software, databases, and research and development. We track the first two components, construction and machinery and equipment. In Turkey, these two categories account for nearly 90% of the total investment expenditure.

In this paper, we use the transactions database of the Garanti BBVA, which includes all monetary transactions featuring the Garanti BBVA clients, including individuals and firms. To simulate consumption, we identify individuals' credit and debit card transactions. To simulate investment, we identify inflows from individuals and firms to firms that produce fixed investment assets related to construction or machinery and equipment (nearly 90% of the total investment in the Turkish economy) and assume that these transfers represent investment in fixed capital formation.

2.1 | Estimating consumption through individual-to-firm transactions

Nontraditional financial transactions including electronic payments have been increasingly used. Baker and Kueng (2022) summarize well the evolution in the use of financial transaction data that has occurred in recent years in three broad groups:

- Some researchers began to exploit data from the accounts of stock market intermediaries or "Brokers" to understand how investors make their decisions. Among the results, they found gender differences or how investors made systematic errors that penalized the rate of return on investments.

- From the early 2010s, the economic research exploiting detailed transaction data from bank accounts increased. These data are provided by individual banks, online banks, or associations of banks. As banks offer a wide range of services to customers (current accounts, debit and credit cards, mortgages, consumer loans...), these data offer the possibility to explore spending and income flows, as well as different type of assets, lending behavior, and other demographic information.
- A more limited option has been to obtain access to transaction data directly from credit card companies (Einav et al., 2021) or from credit card issuers (Quispe-Torreblanca et al., 2019). The rise of payment apps, such as Apple Pay, Venmo, and Alipay, has created new avenues for directly observing household spending transactions across large segments of the population in many countries.
- Finally, behavioral economics analysis has benefited from the pioneering work of an emerging ecosystem of FinTech products and apps. Among the data provided by these startups are those that aggregate and track a customer's various financial accounts and those that focus more on a specific end goal, such as increasing savings rates or helping to pay down debt.

Various research projects had already highlighted the growing importance of high-frequency financial data, but it was the Covid-19 pandemic that truly showcased its advantages. The crisis triggered a sudden recession, unprecedented in terms of magnitude and speed of spread. Given the uncertainty of the event, the traditional data that had been used on previous occasions failed to provide a quick and accurate picture of what was happening.

Most of this work focused on card transaction data to develop real-time monitoring of the magnitude of the crisis. The response was relatively quick, and some working papers were published only a couple of months after the outbreak of Covid-19. Most of these papers focused on developed countries such as Andersen et al. (2020) for Denmark and Sweden, Chetty et al. (2020) and Cox et al. (2020) for the United States, Chen et al. (2021) for China, Carvalho et al. (2021) and Aspachs et al. (2022) for Spain, Chronopoulos et al. (2020) and Hacioglu et al. (2020) for the United Kingdom, and Bounie et al. (2020) in the case of France. Only a couple of studies have extended this empirical work to emerging economies, such as Carvalho et al. (2021) who used credit and debit card information as a proxy for consumption in Turkey, Mexico, Colombia, Peru, and Argentina or Chen et al. (2021) who used online consumption data for China.

To estimate consumption flows from our big data, we follow a similar procedure to Carvalho et al. (2021), who use individual financial transactions from credit and debit cards in the Garanti BBVA financial transactions database. In 2021, the number of credit and debit cards in Turkey's financial system was 212.2 million cards, and the Garanti BBVA clients accounted for 27 million cards (12.7% of the total). Given that the consumption surveys performed by the official agency of statistics sample 15,000 individuals, we can consider our much larger number of credit and debit cards as representative of Turkish consumers. To develop our big data consumption index, we apply the following rules:

- We rely on daily individual-to-firm transactions paid by credit and debit cards. These transactions include (i) physical transactions occurring at POS, (ii) online e-commerce transactions, and (iii) mail/telephone orders.[4]
- We restrict the dataset to transactions in Turkey's national territory. The information is geo-localized and includes at least one transaction from every city in Turkey.
- We include only residents' credit cards to avoid nonresident transactions, which should be accounted as exports of goods or services.
- The data are grouped by their merchant category codes (MCCs) and classified according to corresponding sectors (goods or services) and subsectors (airlines, restaurants, tourism, etc.).
- After the information is extracted, the data are filtered to correct for outliers and noisy transaction data.
- After extracting and processing the data, we aggregate the detailed information to compute (i) the total volumes of sales transaction for goods and (ii) the total volume of sales transactions for services. For both series, we compute year-on-year growth rates.
- We deflate goods transactions with the retail sales deflator and deflate services transactions using subitems from the consumer price index (CPI). Both deflators are provided by the Turkish National Statistical Office (TURKSTAT).
- In order to limit sample bias in the total aggregate consumption index, we reweight both the goods and services consumption indexes with their respective time-varying shares in TURKSTAT.

The dataset obtained after applying the above rules to bank data for 2020 comprises 395.7 million individual-to-firm transactions and 1.67 million firm-to-firm transactions from around Turkey, which will be used for developing investment index discussed in the following subsection. The aggregate nominal value of the transactions is 299.9 billion Turkish lira (6% of Turkish GDP).[5]

Figure 1 compares our big data proxies with actual total aggregate consumption and the main components of consumption of goods and services. The trends of the proxies and actual data are very similar, showing that our proxies achieve a good fit. The correlation is high not only for the end of the sample period, which includes the Covid crisis, but also for the rest of the sample period.

2.2 | Using firm-to-firm transactions to track investment

Our main assumption used in building an investment indicator from big data financial transactions is that the purpose of individual and firm money transfers or inflows to firms producing investment assets is mainly to purchase investment goods.[6] Furthermore, we need to include firm-to-firm transactions in our database to capture all monetary transactions representing purchases of real investment assets by individuals and firms.[7] The points considered when constructing the data are summarized as follows:

1. The data include only daily money transfers (planned installment payments, one-off payments, and regular daily purchases) in which the counter-party is not the firm issuing the payment (i.e., the transaction is not an internal transfer of funds).
2. We include only transactions fulfilling the following rules. (i) The firm must be an active entity, that is, firms that went out of business are automatically excluded. (ii) We include only transactions where the paying firm is identified with its NACE (Statistical Classification of Economic Activities in the European Community) sector (agriculture, machinery, construction, etc.).
3. We exclude individual and firm transactions to non-residents, which should be considered imports rather than investment flows. Like for consumption, the information is geo-localized and includes at least one transaction from every city in Turkey.
4. In order to identify transaction flows related to fixed tangible investments, firms are classified by NACE Rev. 2 classifications to identify sectors that produce investment goods. These sectors are selected based on the sectoral distribution of Gross Fixed Capital Formation in the Use Table (2012) released by TURKSTAT and the mapping between Capital Goods and NACE codes in the Main Industrial Groupings classification.
5. After firms have been classified by NACE categories, the firm-to-firm and individual-to-firm transactions with firms that produce real fixed investment assets are classified based on national accounts subgroups of machinery and transport investment and construction investment:
   - For machinery investment, we include transactions with firms whose activities are classified as machinery and equipment, media and ICT, agriculture and animals, forestry, durable goods, retail trade, textiles, and clothing. For transport investment, we include transport vehicles and shipping firms.
   - For construction investment, we include firms classified as investment in dwellings and public works.
6. We aggregate transactions in these two investment groups to compute aggregate nominal values and estimate yearly nominal growth rates.
7. We maintain the historical time-varying shares of these aggregate investment activities in total gross fixed capital, excluding other investment types (e.g., intangible investments are not included in this work).
8. Finally, we deflate yearly growth rates with the Domestic Producer Price Index (D-PPI) to obtain real growth rates, given the absence of a complete set of D-PPI individual deflators for all components.

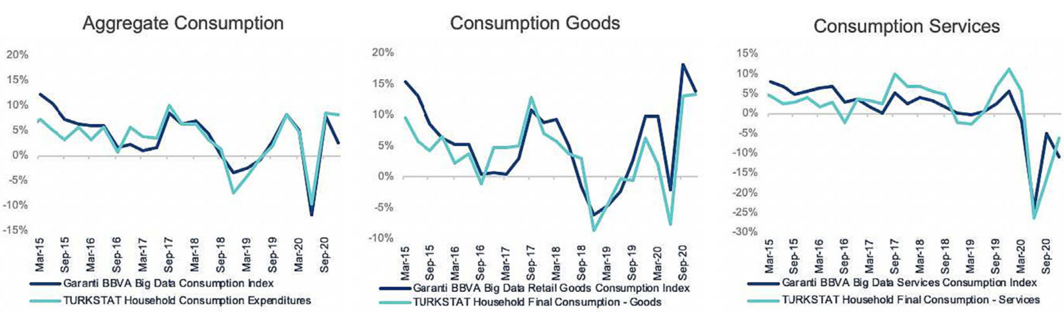

FIGURE 1 Consumption: Big data proxies versus national accounts: 2015–2021. (March 2015 to March 2021, % year-on-year [YoY]). *Source*: Own elaboration and TURKSTAT.

The total number of firms included in the Garanti BBVA big data sample for investment assets expenditure was nearly 179,700 in 2020. This constitutes almost 20.9% of the 860,400 firms producing real assets in Turkey included in the TURKSTAT National Company Accounts Statistics. The aggregate value of investment transactions for real tangible assets in the Garanti BBVA database was USD 308 billion (nearly 21% of the turnover of the National Company Accounts).[8]

Table 1 compares firms producing real construction assets and machinery and equipment in the Garanti BBVA and TURKSTAT, National Company Accounts databases. As shown, the representative bias for the construction sector is higher than for the machinery and equipment sector. Whereas the construction activities firms included in the Garanti BBVA data total 23,200 (18.2% of the TURKSTAT total), the machinery and equipment firms total 156,500 (21.3% of the TURKSTAT total).[9]

Figure 2 shows the estimated the Garanti BBVA big data investment indexes vis-a-vis the main components of gross fixed capital formation provided by TURKSTAT.

The graphs show that our big data investment indexes have a good fit with the official statistics, and the correlation coefficient between our indexes and the official series from the 5-year pre-Covid (March 2015 to March 2020) is high (the Pearson correlation coefficient is 0.84 for aggregate investment, 0.81 for machinery investment, and 0.78 for construction investment).

Figure 3 shows the evolution of the big data investment asset classes, excluding those listed under "other investment" (intangible assets). The investment assets are grouped by two high-level aggregates: machinery and transport and construction. The heat map shows the evolution of yearly growth rates (3-month moving averages) from 2015 to May 2021. The darkest blue indicates growth rates in the lowest 10th percentile and the lightest blue growth rates above the 90th percentile.

2.2.1 | A recent historical analysis using big data investment flows

During the period 2015–2021, various shocks with different natures hit the Turkish economy. Three important shocks can be identified (marked in orange in Figure 3): the failed coup of July 2016, the Turkish currency crisis in the summer of 2018, and the Covid-19 pandemic. The effects of these events on investment have been somewhat different.

The response to the failed coup in the summer of 2016 (a political uncertainty shock) was short lived and concentrated on some specific activities (darker colors), as shown in the nonhomogeneous darker colors in Figure 3. The negative impact was mild and mainly affected motor vehicles and transportation fixed assets, whereas construction and machinery equipment were

TABLE 1 Investment firms data, 2020: Garanti BBVA versus TURKSTAT, National Company Accounts.

	Garanti BBVA			TURKSTAT		
Variable	**Tot.**	**Machinery**	**Constr.**	**Tot.**	**Machinery**	**Constr.**
Transactions (000s)	24.6	22.3	2.3	—	—	—
Amount (US Bn)	308	280	28	1428	1235	193
Firms (000s)	179.7	156.5	23.2	860.4	733.3	127.1
Firms (% TURKSTAT)	20.9	21.3	18.3	—	—	—

Source: Garanti BBVA Bank, TURKSTAT, National Company Accounts. Data refer to companies producing real tangible assets in construction and machinery and equipment activities. Nontangible investment is not included.

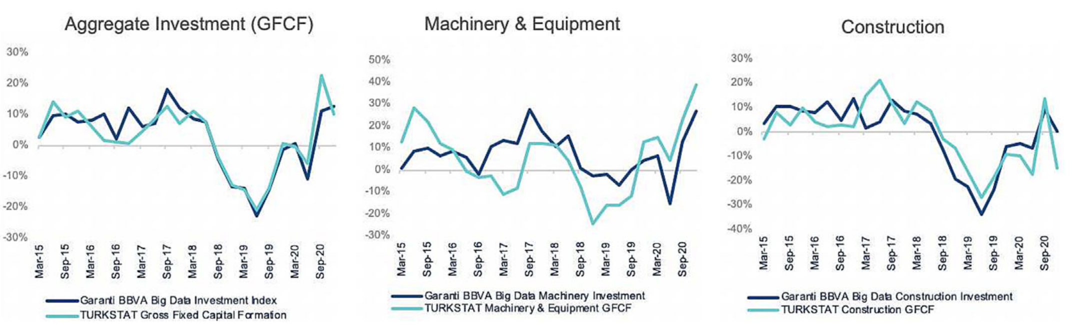

FIGURE 2 Investment: Big data and national accounts 2015–2021 aggregates. (March 2015 to March 2021, % year-on-year [YoY] nominal). *Source*: Own elaboration and TURKSTAT.

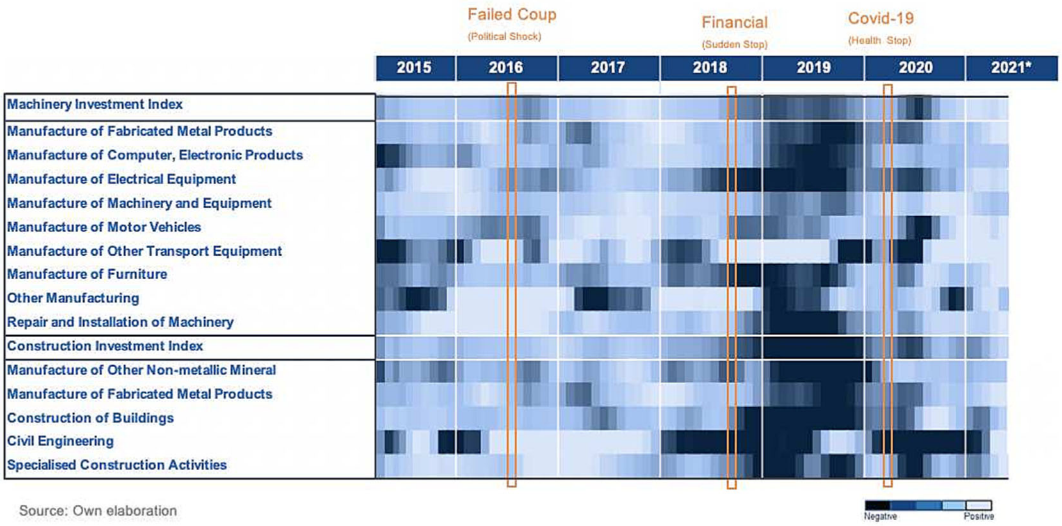

FIGURE 3 Big data investment by asset heat map 2015–2021. (% year-on-year [YoY]; light colors indicate positive growth rates, and dark colors indicate negative rates). *Source*: Own elaboration. The darkest blue color denotes growth rates in the lowest 10th percentile, and the lightest blue color denotes growth rates above the 90th percentile.

only mildly affected and recovered very rapidly after the initial political shock passed.

The response to the 2018 Turkish currency crisis (a full blown currency shock) was more intense and homogeneous. After the sharp depreciation of the Turkish lira (nearly 40%), capital flows suddenly stopped and credits declined rapidly for most activities. The shock to investment began just after the financial crisis and affected most sectors until the end of 2019, when, after one and a half years of deep and rapid deleveraging, credits resumed growth.

The response to the Covid-19 pandemic shock has been somewhere between the responses to the previous two shocks, in terms of intensity, homogeneity, and duration. It is relevant that the temporary shock to investment appears to be related to disruption to global value chains (GVCs), in which Turkey is more active in metals and automobiles (i.e., transportation). The bigger and longer-lasting effects are concentrated in investment in civil engineering projects, which may be more strongly affected by the uncertainty of the pandemic.

Another important advantage of the big data on financial transactions is that all the transactions are geolocalized. This allows us to track investment activities not only by asset type but also geographically.

The postpandemic shock to GVCs is a good example of how this information can help us to identify different types of shocks. Figure 4 shows how the Covid-19 shock affected different investment assets (total investment assets, machinery and equipment, and construction) on a geographical basis. The heat maps show the yearly growth rates immediately before mobility restrictions began to be imposed in Europe (February 2020), the period during which most mobility restrictions were in force (April–May 2020), and the period of easing of mobility restrictions and recovery (July–August 2020).

The maps confirm some of our observations from the evolution of fixed assets' performance (Figure 3), showing that the negative effects on investment of the Covid-19 shock were not as homogeneous as those of the 2018 Turkish currency and debt crisis, in either sectoral or geographical terms. The key reason for this is that the response in machinery investment was more differentiated and short lived after the Covid-19 shock.

An important finding is that big cities such as Istanbul and Ankara were not especially affected compared to other regions. As we move from the east to the west of the country, we observe darker blues, representative of contraction. This is unsurprising because the west is where the manufacturing industry is mainly located (Akcigit et al., 2019), and the pattern is consistent with the well-established east-west regional dualism in Turkey (Gezici et al., 2017). The maps also suggest that provinces that specialize in products such as metal and electrical equipment (the central-western region), mostly related to the automotive and durable consumer goods industries in the GVC, experienced sharper temporal declines than those specializing in the textile industry in the GVC (central-south region). The fact that the Covid-19 shock has been less permanent than the 2018 Turkish currency crisis shock is also relevant to geographical spillovers, possibly because these GVCs are important sources of spillovers to other industries.

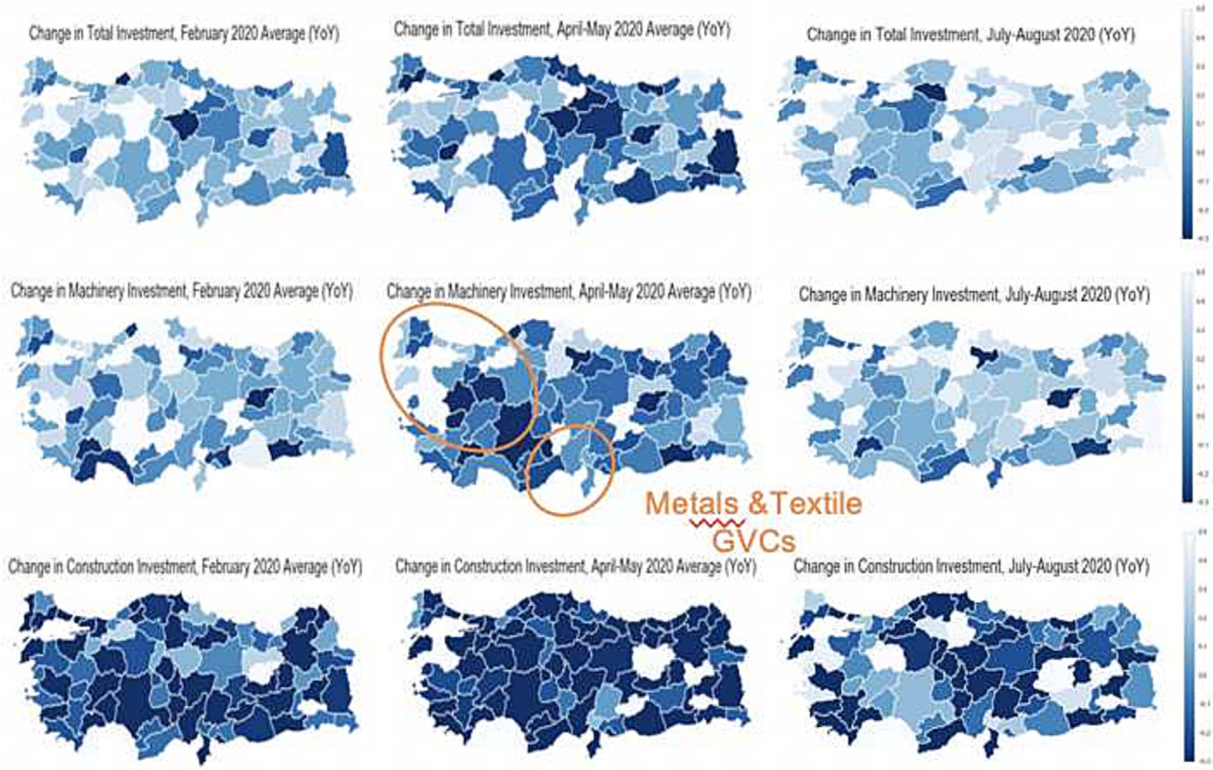

FIGURE 4 Big data regional investment maps (*). (% year-on-year [YoY]). *Source*: Own elaboration. The darkest blue color denotes growth rates in the lowest 10th percentile, and the lightest blue color denotes growth rates above the 90th percentile.

The response of construction investment has been more homogeneous, but (at time of writing) it is also recovering faster than it did in response to the 2018 crisis. The sector's performance in the pre-Covid-19 period was more negative than the machinery sector (because the construction sector was experiencing deleveraging, attributable to the previous financial crisis), and its initial response to the Covid-19 shock was homogeneous and amplified the already weak situation. However, from June 2020 onward, the situation started to improve, at least in the big cities and coastal regions, but with some dark blue areas in the middle of the country. Whether this is the result of different allocations of credit or different responses to the macro-prudential policies implemented by policymakers during Covid-19 is beyond the remit of this research.

3 | DATA AND METHODOLOGY FOR NOWCASTING TURKISH GDP USING BIG DATA PROXIES FOR CONSUMPTION AND INVESTMENT

Section 2 described how we developed our big data consumption and investment indexes using the Garanti BBVA bank transaction data. We then demonstrated how well these indexes capture their actual official counterparts. We also presented a historical analysis of the effects of recent shocks on sectoral categories of investment and their geographical distributions, using our high-frequency big data proxy for investment.

Having demonstrated the good fit of our high-frequency big data proxies, now we nowcast GDP using our newly developed high-frequency proxies of investment and consumption, together with other variables traditionally used in GDP nowcasting. In this section, we present our data and models used in nowcasting. In the next section (Section 4), after showing the gain in the prediction power by all these variables across different models, our final aim is to assess our big data proxies' contribution for the prediction accuracy when nowcasting GDP.

3.1 | Data included in nowcasting

The dataset used in our analysis includes several variables with different frequencies. We use the quarterly chain-linked GDP series from TURKSTAT, transformed into year-on-year growth rates, as the main target variable in our nowcasting exercises. In terms of explanatory variables, we employ a total of 13 series representing

TABLE 2 Variables included in the nowcasting models.

Variable	Type	Frequency	StartDate	Transformation	Release lag (months)
GDP	Hard	Quarterly	2003	YoY growth	2–3
Industrial production	Hard	Monthly	2006	YoY growth	2
Auto imports	Hard	Monthly	2006	YoY growth	2
Auto sales	Hard	Monthly	2003	YoY growth	2
Auto exports	Hard	Monthly	2006	YoY growth	2
Nonmetallic minerals	Hard	Monthly	2006	YoY growth	2
Electricity production	Hard	Daily	2003	YoY growth	0
Number of employed	Hard	Monthly	2006	YoY growth	3
Number of unemployed	Hard	Monthly	2006	YoY growth	3
PMI	Soft	Monthly	2006	Level	1
Real sector confidence	Soft	Monthly	2003	Level	0
Loans (credit)	Hard	Weekly	2006	Annualized 13-week growth	1
Big data consumption	Hard	Daily	2015	YoY growth	0
Big data investment	Hard	Daily	2015	YoY growth	0

Abbreviations: GDP, gross domestic product; PMI, purchasing manager index; YoY, year-on-year.
Source: Own elaboration.

broad categories of Turkish economic activity, including hard data on the labor market, manufacturing, and international trade, combined with financial data, soft data from corporate surveys, and our big data activity indexes including consumption and investment.

Table 2 lists the series used together with their publication lags, frequencies, and the transformations applied. Because our main interest is to nowcast the year-on-year GDP growth rate, for all variables, we utilize the raw form of the series, not seasonally or calendar adjusted data. All series comprise real-form data except (nominal) total loan growth, which is deflated by the headline CPI index published by TURKSTAT.

The dataset used in the nowcasting exercise is unbalanced in terms of different lengths of the time series and different release lag structures. This is addressed by the use of different techniques appropriate to the models we employ in the following sections. All variables except for our big data information are publicly available.

3.2 | Nowcasting methodology

We illustrate our nowcasting methodology by presenting the different models employed in nowcasting. We use linear and nonlinear bridge equation models, DFMs, and a Bayesian vector autoregressive model (BVARM) to nowcast year-on-year (YoY) GDP growth rates. To build linear and nonlinear bridge equation models, we follow a similar approach to Soybilgen and Yazgan (2021). The major difference between our approach and Soybilgen and Yazgan (2021) is that whereas Soybilgen and Yazgan (2021) use estimated dynamic factors in bridge equations, we directly use the variables themselves rather than their dynamic factors. DFMs are estimated following Modugno et al. (2016) and Bańbura and Modugno (2014), and the BVARM is estimated following Ankargren and Yang (2019).

The DFM used in this study can also perform in the presence of the missing values; in other worlds, it can handle unbalanced datasets. However, we need to have a balanced data to estimate bridge equation models and BVARM. We follow the MissForest algorithm of Stekhoven and Bühlmann (2012) to fill out the missing data at the beginning of the dataset.[10] We can outline the methodology of Stekhoven and Bühlmann (2012) as follows:

Let us define X be $t \times n$ data matrix and let γ be the stopping criterion of the MissForest algorithm. Then, sort the variables $s = 1, \ldots, n$ according to the number of missing values starting with the lowest number and store as $X^{(s)}$.

1. Make an initial value for missing values.
2. Let k be a vector of sorted indices of columns in x_{t_m} with increasing number of missing values.
3. While γ is above the target number:

    (a) Store previously imputed matrix as X_{old}^{imp}

    (b) For each i in k:
        i. Fit a RF as $y_{obs}^{(i)} = f(x_{obs}^{(i)})$ where $y_{obs}^{(i)}$ denotes observed rows of variable i and $x_{obs}^{(i)}$ is the corresponding rows of other variable;

ii. Predict $y_{mis}^{(s)}$ using $\hat{f}(x_{mis}^{(s)})$ where $y_{mis}^{(i)}$ is the missing rows of variable i and $x_{mis}^{(i)}$ is the corresponding rows of other variable;
iii. Update imputed matrix using $\hat{y}_{mis}^{(s)}$ as X_{new}^{imp}

(c) Update γ

If there is any observation missing at the end of the dataset, we fill missing observations using an auxiliary model for bridge equation models.[11] BVARM can produce predictions for missing observations on its own based on the past data without needing an auxiliary equation.

3.2.1 | Bridge equations

Let $x_{t_m} = (x_{1,t_m}, x_{2,t_m}, \ldots, x_{n,t_m})', t_m = 1,2,\ldots,T_m$ denote n monthly standardized explanatory variables. To construct bridge equations, we convert monthly explanatory variables to quarterly variables, $x_{t_q} = \left(x_{1,t_q}, x_{2,t_q}, \ldots, x_{n,t_q}\right)', t_q = 1,2, \ldots, T_q$, by taking simple averages of x_{t_m}. Then, quarterly explanatory variables and quarterly GDP growth rates are linked as follows:

$$y_{t_q} = g\left(x_{t_q}\right) + \varepsilon_{t_q}, \tag{1}$$

where $g()$ defines a linear or nonlinear functional form. We estimate Equation (1) using ordinary least squares (OLS), RF, and GBM.

RF, proposed by Breiman (2001), is an ensemble machine learning model based on bagging (bootstrap aggregating) of decision trees. In RF, we first obtain B bootstrapped training sets from original data and then fit a decision tree to each bootstrapped training set while allowing only a random sample of variables to be considered in each variable/split point for each terminal node of a decision tree. Let $b = 1,\ldots,B$ denote the number of bootstrap iterations. Then following Hastie et al. (2009), we predict quarter-on-quarter (QoQ) GDP growth rates using RF as follows:

1. Obtain the bootstrapped data from the original data;
2. Using the bootstrapped data obtained in the previous step, estimate a regression tree, $\hat{g}_{RF}^{(b)}$, by considering just a fraction of variables, p, at random from n variables when determining the best variable/split point for each terminal node of a decision tree;
3. Repeat steps 1 and 2 B times;
4. Obtain predictions of GDP growth rates as $\frac{1}{B}\sum_{b=1}^{B} \hat{g}_{RF}^{(b)}\left(x_{t_q+h_q}\right)$.

GBM is another decision tree-based ensemble machine learning model. The difference between GBM and RF is that GBM turns weak learners into strong learners in a sequential way, instead of separately as in RF. After an initial estimate, each tree is fitted to the pseudo-residual, the gradient of the cost function, of the previous estimate, and this fitted tree is then used to update the current estimate according to different learning rates for each region of a decision tree. Let us define $m = 1,\ldots,M$ as the number of boosting iterations, λ as the learning parameter, and $L()$ as the loss function. Then, following Friedman (2002) and Hastie et al. (2009), we predict QoQ GDP growth rates using GBM as follows:

1. Initialize $g_{GBM}^{(0)}(\boldsymbol{x}) = \underset{\gamma}{\operatorname{argmin}} \sum_{t_q=1}^{T_q} L(y_{t_q}, \gamma)$;
2. Compute the gradient of the cost function, $r_{t_q,m} = \left[\frac{\partial L\left(y_{t_q}, g_{GBM}^{(m-1)}\left(x_{t_q}\right)\right)}{\partial g_{GBM}^{(m-1)}\left(x_{t_q}\right)}\right]$;
3. Fit a decision tree to $r_{t_q,m}$ giving terminal regions of the decision tree, $R_{j,m}, j = 1,2,\ldots,J_m$;
4. For $j = 1,2,\ldots,J_m$, compute $\gamma_{j,m} = \underset{\gamma}{\operatorname{argmin}} \sum_{g_{t_q} \in R_{j,m}} L\left(y_{t_q}, g_{GBM}^{(m-1)}\left(x_{t_q}\right) + \gamma\right)$;
5. Update $g_{GBM}^{(m)}(\boldsymbol{x}) = g_{GBM}^{(m-1)}(\boldsymbol{x}) + \lambda \sum_{j=1}^{J_m} \gamma_{j,m} \mathbb{I}(\boldsymbol{x} \in R_m)$;
6. Repeat steps 2–5 M times;
7. Derive the final model $g_{GBM}(\boldsymbol{x}) = g_{GBM}^{(M)}(\boldsymbol{x})$;
8. Obtain predictions of GDP growth rates as $g_{GBM}\left(x_{t_q+h_q}\right)$.

For the LBEM, we obtain predictions of GDP growth rates as $\hat{c} + \hat{\beta} x_{t_q+h_q}$ where $\hat{c}$ and $\hat{\beta}$ are estimated OLS coefficients of Equation (1).

3.2.2 | DFMs

We model the DFM whose idiosyncratic components, $\epsilon_{i,t}$, follow an AR(1) process as follows:

$$x_{t_m} = \Lambda f_{t_m} + \epsilon_{t_m}; \tag{2}$$

$$\epsilon_{t_m} = \alpha \epsilon_{t_m-1} + \nu_{t_m}; \; \nu_{t_m} \sim i.i.d. \; \mathcal{N}\left(0, \sigma^2\right), \tag{3}$$

where Λ is a n x r vector containing factor loadings and f_t is a r x1 vector of unobserved common factors and is modeled as a stationary vector autoregression process as follows:

$$f_{t_m} = \varphi(L) f_{t_m-1} + \eta_{t_m};\ \eta_{t_m} \sim i.i.d.\ \mathcal{N}(0,R), \tag{4}$$

where $\varphi(L)$ is a r x r lag polynomial matrix and η_{t_m} is a r x1 vector of innovations.

To include quarterly GDP growth rates into the model, we use the approximation of Giannone et al. (2013) and impose restrictions on the factor loadings as follows:

$$y_{t_m}^{MY} = \Lambda^Q f_t + \epsilon_{t_m}^Q; \tag{5}$$

$$\epsilon_{t_m}^Q = \alpha^Q \epsilon_{t_m-1}^Q + v_{t_m}^Q;\ v_{t_m}^Q \sim i.i.d.\ \mathcal{N}\left(0,\sigma^2\right), \tag{6}$$

where $y_{t_m}^{MY}$ denote the unobserved monthly YoY GDP growth rates. $y_{t_m}^{MY}$ can be linked to a partially observed (at every third month of the quarter) quarterly YoY rate as $y_{t_m}^{QY} = y_{t_m}^{MY} + y_{t_m-1}^{MY} + y_{t_m-2}^{MY}$.

We estimate the DFM by following the procedure proposed by Bańbura and Modugno (2014), which is a modified version of the expectation–maximization (EM) algorithm for maximum likelihood estimation. After casting Equations (2)–(6) as state-space form, Kalman filter and smoother allow us to extract the common factors and generate projections for all of the variables in the model.

3.2.3 | Bayesian vector AR model

Let us assume that $x_{t_m}^{QM} = \left(x_{t_m}, x_{t_m}^Q\right)$ represents both observed monthly variables, x_{t_m}, and unobserved monthly counterparts of GDP growth rates, $x_{t_m}^Q$ and $X_{t_m}^{QM} = \left(x_{t_m}, y_{t_m}^Q\right)$, represent observations. Similar to the previous section, $y_{t_m}^Q$ denotes a partially observed monthly counterpart of GDP growth rates that can only be observed in the third month of the quarter and is linked to its unobserved monthly counterparts as follows:

$$y_{t_m}^Q = \frac{1}{3}\left(x_{t_m}^Q + x_{t_m-1}^Q + x_{t_m-2}^Q\right). \tag{7}$$

We assume that $x_{t_m}^{QM}$ follows a VAR(p) process as follows:

$$x_{t_m} = \varphi(L) x_{t_m-1} + u_{t_m};\ u_{t_m} \sim i.i.d.\ \mathcal{N}(0,\Sigma). \tag{8}$$

Following Schorfheide and Song (2015), Sebastian et al. (2020), and Ankargren and Yang (2019), BVARM's state-space form transition equation, which is the companion form of the VAR(p) process, and the measurement equation are shown as, respectively:

$$z_{t_m} = \pi + \Pi z_{t_m-1} + \zeta_{t_m};\ \zeta_{t_m} \sim i.i.d.\ \mathcal{N}(0,\Omega); \tag{9}$$

$$X_{t_m} = M_t \alpha z_{t_m} \tag{10}$$

where $z_{t_m} = \left(x'_{t_m}, x'_{t_m-1}, x'_{t_m-p+1}\right)'$; π and Π are the corresponding companion form matrices, M_t is a deterministic selection matrix, and α is an aggregation matrix.

We use the Minnesota prior for the AR coefficients and an inverse Wishart prior for the error-covariance. Using a Gibbs sampler, we generate draws from the posterior distributions and simulate future trajectories of X_t and calculate point forecasts of all variables. Using Ankargren and Yang (2019), BVARM is estimated using Markov Chain Monte Carlo (MCMC) and Gibbs sampling.

4 | PREDICTION PERFORMANCE OF NOWCASTING MODELS AND IMPACT OF BIG DATA PROXIES FOR CONSUMPTION AND INVESTMENT

In this section, we first illustrate the prediction power obtained in nowcasting by using all the variables described in Table 2 across different models discussed in Section 3.2. Although our final aim is to evaluate the impact of our big data proxies on the prediction performance of GDP nowcasting among others, we first want to establish the prediction of power of different models against a benchmark AR model that does not include any of these variables. We also try to determine whether any of those models consistently outperforms the others. While searching for a best performer model has an apparent value for practitioners, it can also be served as the model upon which we measure the impact of big data consumption and investment proxies on prediction performance among other variables.

4.1 | Prediction performance against AR

We estimate our models for each month from January 2016 to December 2020 using an expanding estimation window.[12] We assume that each prediction is computed at the end of the month and adjusts the announcement lag for each variable accordingly, as shown in Table 2. Vintage data for Turkish macro variables are not readily available from any statistical agencies, so we use a pseudo-real-time dataset that ignores historical data revisions.[13]

For each month, we produce predictions for the current quarter. We also predict the previous quarter if GDP for the previous quarter has not yet been announced. Turkish GDP is announced with a delay of more than 2 months, so we produce five predictions for each reference quarter.[14] For example, from January to March 2016, we produce three nowcasts for 2016Q1 (current quarter). From April to May 2016, we produce two nowcasts (backcast) for 2016Q1 (previous quarter) and two nowcasts 2016Q2 (current quarter), which provides five nowcasts for 2016Q1 and two nowcasts for 2016Q2. In June 2016, 2016Q1 GDP is announced, so we stop nowcasting 2016Q1 but continue nowcasting 2016Q2 (current quarter). Similarly, we produce two further nowcasts for 2016Q2 in July and August to obtain five nowcasts in total, and we also compute two nowcasts for 2016Q3. In September, we stop nowcasting 2016Q2 because official data are released. We continue in the same manner until we obtain five nowcasts for each quarter from 2016Q1 to 2020Q3.

We use mean absolute errors, $\mathrm{MAE}^{(i)}$, and root mean squared errors, $\mathrm{RMSE}^{(i)}$, to evaluate the accuracy of the ith nowcast produced by each model between 2016Q1 and 2020Q3 as follows:

$$\mathrm{MAE}^{(i)} = (1/n)\sum_{t_q=2016Q1}^{2020Q3}\left|y_{t_q}-\hat{y}_{t_q}^{(i)}\right|;\ i=1,2,\dots,5; \tag{11}$$

$$\mathrm{RMSE}^{(i)} = \sqrt{(1/n)\sum_{t_q=2016Q1}^{2020Q3}\left(y_{t_q}-\hat{y}_{t_q}^{(i)}\right)^2};\ i=1,2,\dots,5, \tag{12}$$

where $\hat{y}_{t_q}^{(i)}$ denotes the ith nowcast of a model and y_{t_q} represents the actual GDP growth rate.

Tables 3 and 4 present MAEs and RMSEs for linear and nonlinear bridge equations and the BVARM, DFM, and benchmark AR model. We also perform modified Diebold–Mariano (DM) tests, proposed by Harvey et al. (1997), to evaluate the significance of the difference in prediction accuracy between the benchmark AR model and the other competing models. The null hypothesis is that the two models compared have equal predictive accuracy.

As shown by Tables 3 and 4, all models have much lower MAEs and RMSEs than those of benchmark AR model in all periods, indicating that there is strong evidence that including the series in Table 2 makes an improvement in predictive performance. In both Tables 3 and 4, loss measures fluctuate around one-half of that of AR when these data are included. According to DM tests, this improvement in predictive performance appears to be statistically significant in many cases despite small forecast sample sizes. In Tables 2 and 3, where rejections of the null of equal forecast loss versus AR are indicated with "*"s at 1%, 5%, and 10% significance levels, in fourth and fifth nowcasts, all models statistically perform better than AR for both loss measures. The results in Table 3 indicate that there is at least one model that has statistically lower MAE than that of AR for all nowcast periods; for RMSEs (Table 4), first and second nowcasts constitute exceptions in this sense.[15] Among the loss measures, we consider here the MAE RMSE that gives a relatively high weight to large errors. Turkey experienced several important economic and political downturns during our nowcasting period: the failed coup in 2016, the currency shock in 2018, and the Covid-19 shock in 2020, and models that cannot anticipate the volatility of these periods will be penalized more heavily by the RMSE than the MAE.

Among the methods using the additional data (DFM, BVARM, LBEM, RFBEM, GDBEM), there is no single model which seems to dominate remarkably over any

TABLE 3 MAEs of the models for successive nowcasting horizons between 2016Q1 and 2020Q3 and modified DM test results.

	AR	DFM	BVARM	LBEM	RFBEM	GDBEM
First nowcast	3.71	2.31	1.77*	1.86	1.64**	2.10**
Second nowcast	3.71	2.08*	2.29	2.30	1.94*	2.13
Third nowcast	3.80	1.70**	1.52**	1.73**	1.56**	1.86*
Fourth nowcast	3.80	1.75**	1.45***	1.37**	1.68**	1.69*
Fifth nowcast	3.80	1.63**	1.64***	1.43**	1.64**	1.55**

Abbreviations: AR, autoregressive model; BVARM, Bayesian vector autoregressive model; DFM, dynamic factor model; DM, Diebold–Mariano; GDBEM, gradient tree boosted bridge equation model; LBEM, linear bridge equation model; MAE, mean absolute error; RFBEM, random forest-based bridge equation model.
*Significance level for modified Diebold–Mariano test: $p < 0.10$.
**Significance level for modified Diebold–Mariano test: $p < 0.05$.
***Significance level for modified Diebold–Mariano test: $p < 0.01$.

TABLE 4 RMSEs of the models for successive nowcasting horizons between 2016Q1 and 2020Q3 and modified DM test results.

	AR	DFM	BVARM	LBEM	RFBEM	GDBEM
First nowcast	5.76	2.85	2.23	2.29	2.49	2.75
Second nowcast	5.76	2.58	2.57	2.78	2.43	2.63
Third nowcast	5.74	2.06*	1.90*	2.05*	1.98*	2.39
Fourth nowcast	5.74	2.03*	1.89*	1.99*	2.18*	2.24
Fifth nowcast	5.74	2.23*	2.49*	2.11*	2.00*	1.78*

Note: For abbreviations, see Table 3.

others, relative performance fluctuates across different cases. According to Table 3, the LBEM nowcasts GDP growth quite well in the final nowcast horizon, on average. However, Table 4 indicates that the GDBEM performs better in volatile periods when all informational content is available. Furthermore, the BVARM and RFBEM perform well in many cases, both in Tables 3 and 4. Finally, the DFM generally performs quite well but is not the best model in any nowcasting horizon.

Because single metrics cannot give us the whole picture, a visual inspection of the models' predictions may yield more information about their nowcasting performance. Figure 5 plots the models' nowcasts for the successive nowcasting periods. In 2016 and 2017, for all nowcasting horizons, the BVARM generally outperforms other models and nowcasts the downturn in 2016Q3 and the jump in 2017Q3 quite well. In 2018 and 2019, the RFBEM has relatively good nowcasting performance and correctly captures the recession between 2018Q4 and 2019Q3. However, in the fourth and fifth nowcasts in this period, the nowcasting performance of linear models, especially the BVARM and the LBEM, increases and outperforms the nonlinear models. Finally, in 2020, nonlinear models generally outperform linear models. In particular, in the final nowcasting horizons for 2020Q2, the GDBEM correctly captures the −10.3% GDP growth rate. Figure 5 also confirms that there is no single best model that performs exceptionally well during the full nowcasting period or in all nowcasting horizons.

4.2 | Which model to nowcast? Nowcast combinations

Tables 3 and 4 and Figure 5 show that there is no single best model that performs exceptionally well in all periods, and in many cases, models produce very volatile nowcasts. Therefore, combining models's nowcasts may provide better and more stable results. We combine the predictions of each model to produce a final nowcast as follows:

$$\hat{Y}_{t_q}^{(i)} = \sum_{l=1}^{n} w_{t_q,l}^{(i)} \hat{y}_{t_q,l}^{(i)},\ l = 1,2,\ldots,L \tag{13}$$

where $w_{t_q,l}$ is the weight for model l for the ith nowcast; $\hat{Y}_{t_q}^{(i)}$ shows the nowcast combination of models for the ith nowcast; $l = 1,\ldots,L$ is an index of all models. We use several types of weights to combine nowcasts in our study, including simple weights, relative performance weights, and rank-based weights.

First, we use simple averaging to calculate weights as follows: $w_{t_q,l}^{(i)} = 1/L$. We also use the median forecast combination scheme. However, even though an equally weighted forecast combination often outperforms sophisticated weighting techniques (Clemen, 1989; Hendry & Clements, 2004; Huang & Lee, 2010; Stock & Watson, 2004), Genre et al. (2013) and Soybilgen and Yazgan (2018) show that advanced combination schemes may outperform equal weights in some cases.

Next, we calculate relative performance weights as follows:

$$w_{t_q,l}^{(i)} = \frac{\left(\mathrm{MAE}_{t_q,l}^{(i)}\right)^{-1}}{\sum_{l=1}^{L}\left(\mathrm{MAE}_{t_q,l}^{(i)}\right)^{-1}}, \tag{14}$$

where $w_{t_q,l}^{(i)}$ donates MAEs of the individual model l for the ith nowcast calculated at time t_q. We calculate MAEs using the last 1 year nowcast performance.

We also use rank-based methods to compute weights, because Timmermann (2006) argues that this scheme is less sensitive to outliers than the relative performance weight method. The rank-based weights are calculated as follows:

$$w_{t_q,l}^{(i)} = \frac{\left(\mathrm{R}_{t_q,l}^{(i)}\right)^{-1}}{\sum_{l=1}^{L}\left(\mathrm{R}_{t_q,l}^{(i)}\right)^{-1}}, \tag{15}$$

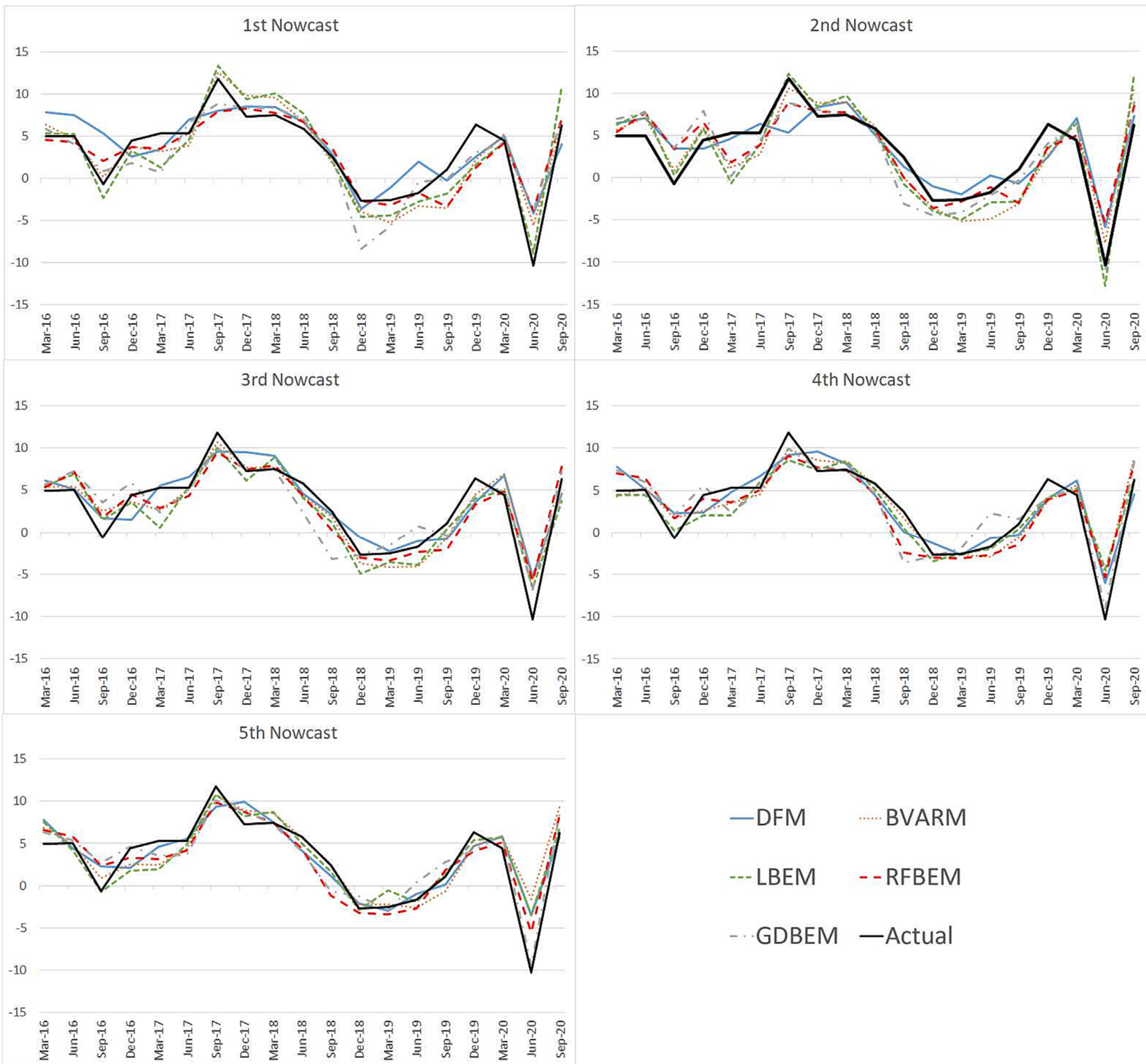

FIGURE 5 Nowcasting models' performance and gross domestic product (GDP). (March 2016 to September 2020, % year-on-year [YoY]). *Note*: For abbreviations, see Table 3

where $R^{(i)}_{t_q,l}$ is the rank of model l for the ith nowcast calculated at time t_q. Ranks are calculated according to MAEs.

Table 5 presents MAEs and RMSEs for various nowcast combinations and the benchmark AR model. Simple and median denote simple averaging and the median nowcast method, respectively. RPW and rank are nowcast combinations calculated by relative performance weights and rank-based weights, respectively. Similar to the results of individual models (Tables 3 and 4), all nowcasts combinations have much smaller loss measures compared with those of AR in all nowcasts horizons. We perform modified DM to evaluate the statistical significance of differences in prediction accuracy between the benchmark AR and other models. Like in the case of individual models (Tables 3 and 4), there is at least one model combination that has a statistically significant lower loss measure in all forecast horizons.

We recalculate MAEs and RMSEs for single models for the period of 20017Q3-2020Q3[16] in Table 6 to provide fair comparisons with model combinations presented in Table 5. Overall, although the differences are small in many cases, nowcasts combinations have smaller loss measures than individual models in general[17]. In

TABLE 5 MAEs and RMSEs of nowcasting combinations for successive nowcasting horizons between 2017q3 and 2020q3 and modified DM test results.

	AR	Simple	Median	RPW	Rank
First nowcast	4.42 (6.67)	1.73** (2.25)	1.80** (2.50)	1.75* (2.31)	1.79* (2.41)
Second nowcast	4.42 (6.67)	1.79 (2.08)	1.93 (2.19)	1.78* (2.06)	1.69* (1.95)
Third nowcast	4.58 (6.67)	1.42** (1.79*)	1.42** (1.80*)	1.53** (1.86*)	1.60** (1.91*)
Fourth nowcast	4.58 (6.67)	1.40** (1.88*)	1.48** (1.98*)	1.45** (2.02*)	1.50** (2.14*)
Fifth nowcast	4.58 (6.67)	1.33** (1.93*)	1.48** (2.23*)	1.40** (2.01*)	1.38** (2.08*)

Note: RMSEs are in parentheses.
Abbreviations: AR, autoregressive model; DM, Diebold–Mariano; MAE, mean absolute error; Median, the median nowcast; Rank, nowcast combination using rank-based weights; RMSE, root mean squared error; RPW, nowcast combination using relative performance weights; Simple, nowcast combination using simple averaging.
*Significance level for modified Diebold–Mariano test: $p < 0.10$.
**Significance level for modified Diebold–Mariano test: $p < 0.05$.
***Significance level for modified Diebold–Mariano test: $p < 0.01$.

TABLE 6 MAEs and RMSEs of the individual models for successive nowcasting horizons between 2017q3 and 2020q3 and modified DM test results.

	DFM	BVARM	LBEM	RFBEM	GDBEM
1st Nowcast	2.09* (2.69)	2.07 (2.55)	2.09 (2.46)	1.90** (2.86)	2.15** (2.90)
2nd Nowcast	2.24 (2.78)	2.37 (2.67)	2.29 (2.73)	1.74* (2.31)	1.70* (2.21)
3rd Nowcast	1.86** (2.21*)	1.63** (1.96*)	1.74** (1.93*)	1.62** (2.08*)	1.80* (2.40)
4th Nowcast	1.80** (2.05*)	1.51** (2.05*)	1.37** (2.09*)	1.81** (2.40)	1.66* (2.33)
5th Nowcast	1.63** (2.34*)	1.70*** (2.76*)	1.33** (2.12*)	1.65** (2.08*)	1.60* (1.77)

Note: For abbreviations, see Table 3. RMSEs are in parentheses.

nowcast, combination schemes seem to be less volatile and perform better than individual models. In volatile countries like Turkey, nowcast combination schemes may be a better alternative to nowcasts of individual models. The combination of linear and nonlinear models may also be important when analyzing Turkish data, because each type of model performs well in different cases, as shown in Figure 5. Therefore, combining them may increase nowcasting performance.

Simple averaging, on the other hand, seems to have the smallest loss measures among the all model combinations except the second nowcasts for RPW and rank. This performance of simple averaging is in line with the forecasting literature. Although these results single out simple averaging nowcasts as the most successful combination scheme, it should be stressed out that in many cases the improvements in loss measures are small and very likely to be statistically insignificant. Therefore, it may also possible to find an equally well-performing alternative combination scheme or a single model in many cases. However, if a single nowcast should be chosen, simple averaging nowcasts appear to be the safest choice among others.

4.3 | The impact of big data on nowcasting

Having shown that nowcasting with the variables listed in Table 2 including big data proxies for consumption and investment has significant contribution to the prediction accuracy of GDP growth rates, in this section, we evaluate the impact of big data proxies among other variables on nowcasting performance. To do that, we first measure the importance of each variable in nowcasting GDP growth rates by calculating each variable's permutation importance metric. We also calculate how much the inclusion of big data variables improves models' nowcasting performance throughout the nowcasting period. As shown in Section 4.2, since simple averaging produces the smallest loss measures in all cases in general, we measure the impact using the single averaging nowcasts instead of individual models.

Variables' permutation importance is calculated as follows: 1. For a given nowcasting horizon (first, second,...fifth nowcasts), obtain nowcasts for all individual models that include all variables and take the simple average of nowcasts. 2. Obtain nowcasts for all individual models when the variable in consideration is omitted and take the simple average of nowcasts. 3. Calculate the performance of nowcasts obtained in Steps 1 and 2 using both the MAE and RMSE. 4. Finally, take the difference between the two nowcasting performances calculated in Step 3 to obtain the permutation importance of the variable examined. 5. Repeat Steps 2–4 to calculate the permutation importance for all variables. 6. We repeat Steps 1–5 to calculate variables' permutation importance metrics for each nowcasting horizon.

Figure 6 presents permutation importance metrics for each variable by taking the average permutation importance metrics across all nowcasting horizons (hence across all nowcasting periods). Note that we also perform DM tests comparing nowcasts without big data variables and nowcasts that include all variables. Our DM results show that nowcasts including all variables outperform nowcasts without big data variables at 5% significance level. Figure 6 clearly shows that the most important variable for our models is industrial production, because it is highly correlated with GDP. Other important variables, assessed using MAEs, are car exports and manufacturing PMI. These are also good predictors of industrial production in Turkey. Furthermore, big data

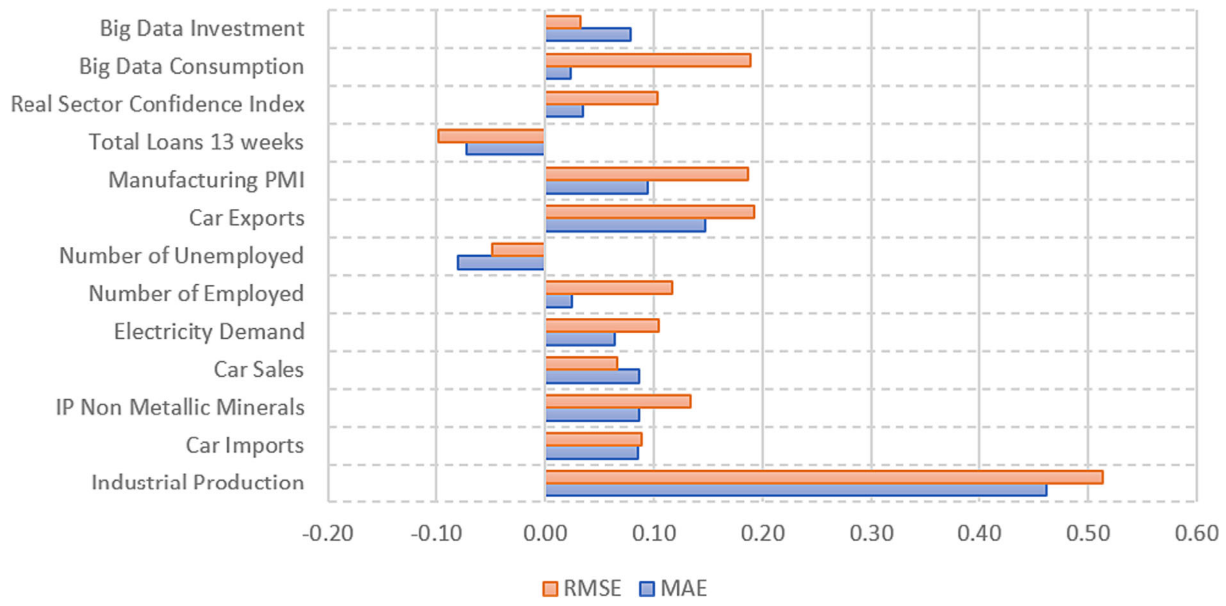

FIGURE 6 Average permutation importance of variables across all nowcasting horizons, assessed by mean absolute errors (MAEs) and root mean squared errors (RMSEs)

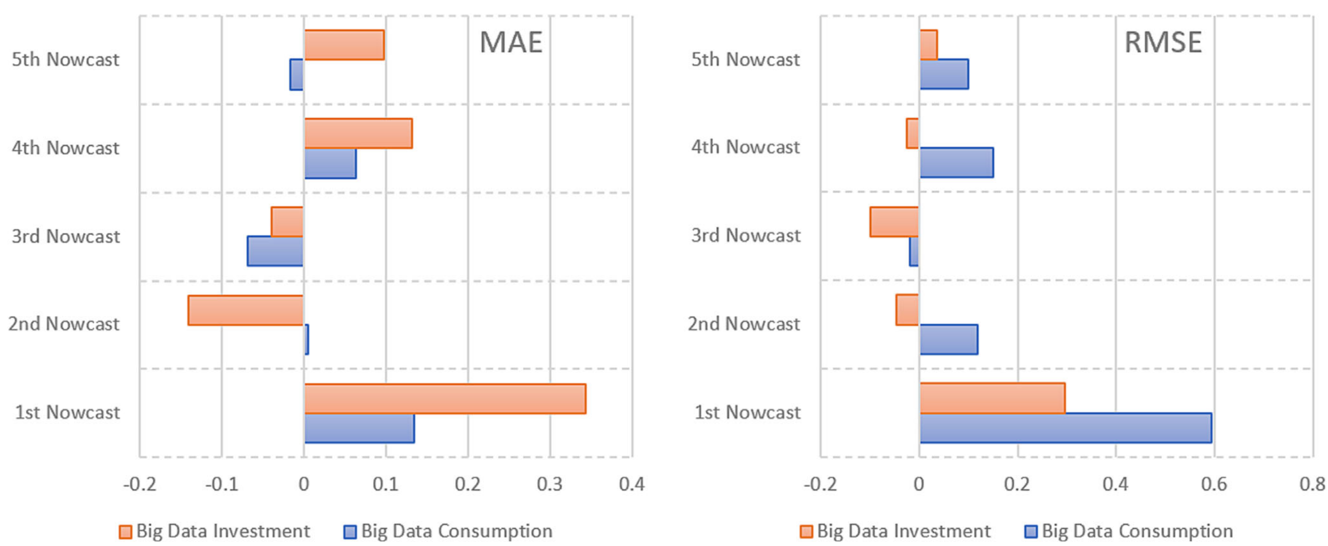

FIGURE 7 The evolution of importance metrics throughout the nowcasting horizons for big data variables.

investment, car sales, and industrial production of nonmetallic minerals reduce MAEs by 0.08 to 0.09 percentage points. Big data consumption seems to make little contribute to nowcasting performance in terms of MAEs. However, in terms of RMSEs, big data consumption is an important variable. Big data consumption, manufacturing PMI, and car exports decrease RMSE by around 0.19 percentage points, whereas big data investment only reduces RMSE by 0.03 percentage points. This suggests that big data consumption is more beneficial in volatile times. However, big data investment is more helpful in nowcasting on average. Interestingly, total loans and the number of unemployed decrease the models' performance.

Having obtained positive evidence on the additional predictive power obtained by the usage of big data variables, we further investigate the nowcasting horizons for which big data variables contribute the most. Figure 7 presents permutation importance metrics of big data variables for each nowcasting horizon. We see that big data variables make the biggest contributions in the first nowcasts. Their contributions are volatile in subsequent nowcasting periods and can be either positive or negative depending on the nowcasting horizon.

We continue our investigation on the contribution of big data variables by considering their performance through nowcasting periods. Figure 8 shows the evolution of importance metrics throughout the nowcasting period for big data variables. We use four quarter moving averages of the metrics to make the figures more interpretable. Figure 8 shows that big data consumption does not benefit nowcasting GDP until 2020. However, during the Covid-19 pandemic, big data consumption helps models track the state of the economy and successfully capture the slump in the second quarter of 2020. Because of its success in nowcasting the sharp decline in 2020, the permutation importance metric for big data consumption calculated using RMSE is quite high, as shown in Figure 6. In contrast, big data investment is successful in nowcasting GDP until 2019 but cannot capture the volatile periods in 2020, consistently with our earlier finding stating that the response in machinery investment was more differentiated and short lived after the Covid-19 shock. Thus, the two types of big data variables are beneficial in different periods.

We further investigate the effect of big data variables across nowcasting periods by running the models on a daily basis. One important advantage of big data variables is that they can be obtained daily, whereas other variables are only announced once a month. In line with the real availability of data, we assume that big data variables are released daily, but other variables are announced at specific dates.[18] For simplicity, we assume that each month consists of 30 days and calculate nowcasts for the reference quarter for the 150 days before GDP is announced. Figure 9 shows the daily MAE and RMSE figures during the 150 days. The daily big data variables are highly volatile, so we also show 7-day moving averages for MAE and RMSE. We find that big data variables improve models' nowcasting performance in the first 45 days using MAE and do so for an even longer time using RMSE. After this, they become less important and do not contribute to the nowcast performance in a significant way. We see the biggest improvement in models' nowcasting performance when the first industrial production index for the reference quarter is released on the 73rd day.

These results together with our previous finding that big data variables make the biggest contributions in the first nowcasts clearly show that the big data variables

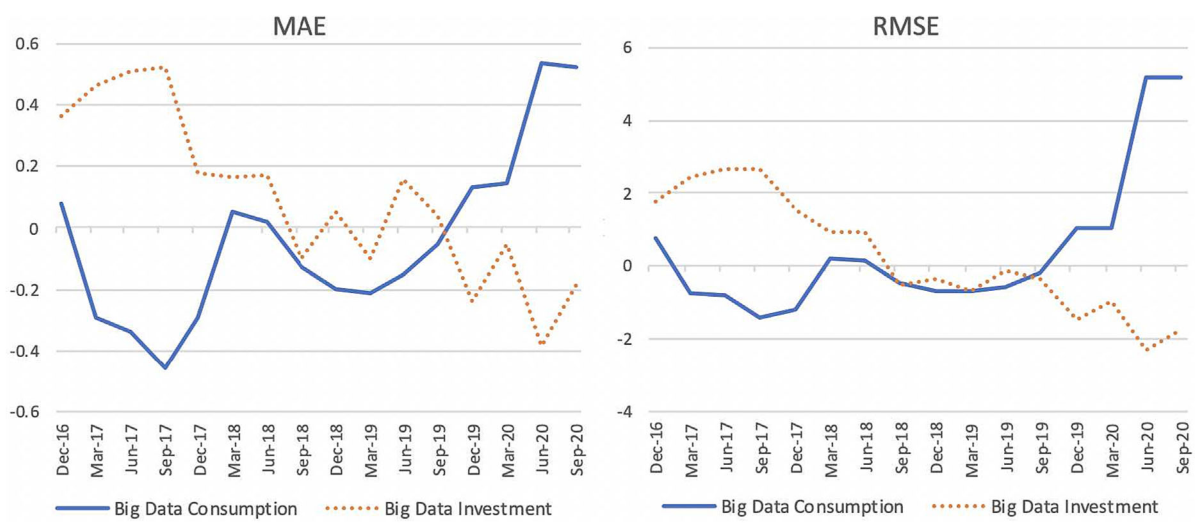

FIGURE 8 The evolution of importance metrics throughout the nowcasting period for big data variables (four quarter moving averages)

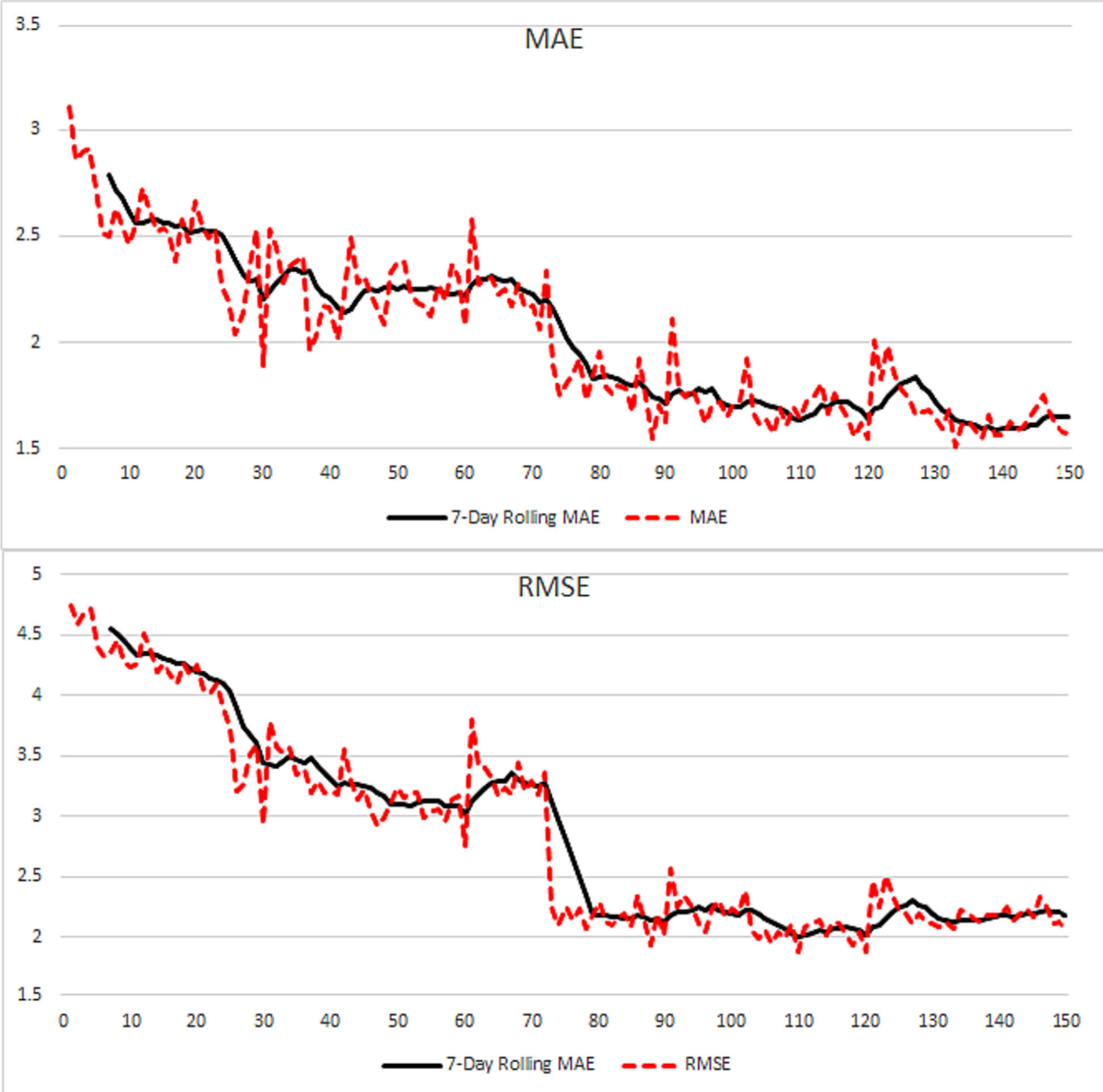

FIGURE 9 Daily mean absolute errors (MAEs) and root mean squared errors (RMSEs) of equally weighted nowcast combinations between 2016Q1 and 2020Q3

are more important at times when hard data are not available.

5 | CONCLUSION

This paper develops consumption and investment big data indexes based on individual-to-firm and firm-to-firm transactions from the Garanti BBVA Bank's big data database. We show that official consumption and investment figures, observed at quarterly frequency, can be successfully captured by their high-frequency proxies. Providing an high-frequency proxy for investment flows in this way constitutes a novel contribution the literature. We also present a historical analysis of the impact of three different shocks on investment patterns, distinguishing sectoral and geographical components.

Deriving consumption and investment patterns from high-frequency big data leads us to consider using these proxies to nowcast GDP. For this purpose, we combine the big data proxies with traditional variables that are frequently used in GDP nowcasting. We measure overall contribution of all variables to nowcasting performance and find that they signifcantly contribute nowcasting performance. To control the effect of model differentiation, we estimate alternative models, including a DFM, BVARM, and bridge equations with linear and nonlinear machine learning specifications, and their combinations. We also evaluate the relative contribution of big data proxies to nowcasting accuracy among the other variables.

The first relevant result is that using the proxies derived from financial transaction data improves the models' nowcasting performance in general, but does even more so, especially in the first nowcasts, when hard data are scarce. When we run the models daily, we find that big data variables improve models' nowcasting performance for at least the first 45 days. Daily results of the models strengthen our conclusion that big data variables are important when hard data are scarce. This is an important finding for emerging markets, where long lags in statistical releases are common.

The second relevant result is that big data consumption and big data investment are beneficial in nowcasting GDP in different periods. Big data investment is relevant until 2019, whereas big data consumption is important during the Covid-19 pandemic. Therefore, it is important to use different kinds of big data variables to improve models' nowcasting performance.

In sum, this paper shows the relevance of real-time financial transaction data to enhance the performance of nowcasting models. Such data are most relevant when hard data information is scarce and can help to capture turning points in the economy. These are important results as the research on big data continues to grow.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] The Garanti BBVA is one of the top private deposit banks in Turkey. Its majority shareholder is Banco Bilbao Vizcaya Argentaria (BBVA), a customer-centric global financial services group operating in several countries.

[2] As emphasized in an earlier version of this paper (Barlas et al., 2020), real-time investment information has several advantages for analysts and policymakers. First, we supplement the available data on Turkey's domestic private demand by adding nearly a third of GDP to average consumption during the last 3 years. Second, investment is more volatile than consumption but has special relevance as a source of fluctuations, particularly in emerging economies. Third, some types of investment, such as residential investment, can have systemic implications for the banking and financial systems, as the 2008 global financial crisis revealed.

[3] Similar to our work, Marchetti and Parigi (2000), Giannone et al. (2009), and Aprigliano (2020), among others, test the relevance of high-frequency soft information contained in business surveys and confidence indicators in improving forecasting performance of either GDP or GDP components.

[4] Since, for security reasons, credit card transactions are usually identified for individuals, it is difficult to distinguish between transactions on personal and corporate credit cards, because all corporate cards are associated with individuals. This distinction is important because personal expenditures are considered to be final consumption whereas some corporate credit card expenditures should be treated as intermediate consumption. Therefore, for some activities, our data may overaccount consumption expenditures. However, we do not think that this is a major problem because the proportion of corporate credit cards in the total is marginal, constituting less than 5% of total expenditures.

[5] In 2019, the Garanti BBVA big data database recorded a mean of around 469,000 daily credit card consumption transactions (and a median of 478,000 daily transactions). In 2020, mean daily transactions decreased to 373,000 (median 409,000 transactions).

[6] Note that although for aggregate purposes this assumption is reasonable, the resulting indicator should be considered a proxy rather than a substitute for the investment concept used in national accounts. For example, some transactions to firms producing fixed assets could be for maintenance rather than investment. Moreover, transactions replicate turnover because we do not deduct transactions for intermediate goods.

[7] In this study, we do not capture intangible assets, which accounted for 12.9% of Turkey's gross fixed capital formation in 2020.

[8] To the best of our knowledge, this means the database is the most complete database of firms in Turkey using administrative data.

[9] Note that our indicator is a proxy of investment from the supply side. First, we assume that all transactions from all paying firms

to firms in NACE categories producing real assets are payments for investment goods. Second, transactions are an approximation of the turnover of the activities, rather than the gross value added, which would require us to subtract intermediate consumption.

[10] As an alternative method, we also follow Van Buuren and Groothuis-Oudshoorn (2011) to fill missing values. The alternative imputation methods increase the nowcasting performance of nonlinear bridge equations model in some cases. Results are available upon request.

[11] For the linear bridge equation model (LBEM), we use a linear autoregressive (AR) distributed lag model (ARDL). For bridge equations models based on RF and gradient boosted decision trees (GBM), we use RF and GBM-based ARDL as auxiliary models.

[12] As shown in Table 2, the sample for our big data indicators starts in 2015, whereas the other samples start from either 2003 or 2006. We first estimate our models using data up to January 2016 using data with mixed starting points because our estimation procedure allows unbalanced data. We then continue estimation using an expanding window. We also estimate our models using a rolling estimation window; the results are similar to our main models and are available upon request.

[13] Hyperparameters for the RF-based bridge equation model (RFBEM) and gradient tree boosted bridge equation model (GDBEM) are selected in the initial estimation period using a threefold cross-validation and grid search approach. For the RFBEM, the number of variables for each split is optimized. For the GDBEM, the number of levels of tree, the number of trees, the learning rate, and the number of terminal nodes are optimized. For the DFM, the optimal number of factors are determined by Bai and Ng (2002) information criteria in the initial estimation period. For both the BVAR and DFM, we use four lags in the VAR.

[14] We produce three nowcasts and two backcasts

[15] We also perform a White (2000) reality check and find that at least one of our models outperforms the benchmark model. Results are available upon request.

[16] We use previous 1-year performances to calculate weights.

[17] There are only two exceptions: MAE, second nowcast; RFBEM and RMSE, fifth nowcast, GDBEM

[18] We assume that monthly data are released as follows: the manufacturing PMI is announced on the first of each month; total loans are announced on the 10th of each month; labor force statistics are announced on the 12th of each month; industrial production statistics are announced on the 13th of each month; car-related statistics are announced on the 15th of each month; the real sector confidence index is announced on the 26th of each month; and electricity demand is announced on the 30th of each month.

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