THE IMPACTS OF SPEECHES ON NOWCASTING GDP: A CASE STUDY ON EURO AREA MARKETS

Necmettin Alpay KOÇAK, PhD*

Abstract

The use of speech data in nowcasting models is a new topic while the use of sentiment and emotion indicators from microblogs and internet platforms in nowcasting models has been discussed in the literature. The effect of the speech data of European Central Bank's (ECB) officials on nowcasting Euro Area GDP is investigated in this paper. After performing a detailed descriptive analysis of the speech data, five emotion indicators are obtained as a result of the emotion analysis. The contribution of these emotion indicators is examined to a nowcasting model including indicators from the real sector and household/business surveys related to the Euro Area for the period of 1995:01-2019:12. The effects of emotion indicators on model are analysed root mean squared error (RMSE), impulse-response functions, variance decomposition analysis and revision analysis. Findings show that emotion indicators provide a decrease in RMSE of nowcasting model. It is found out that the shocks in the emotion indicators are significant on the GDP in the long term, and the emotion indicators are effective in explaining the variance of the forecast error variance of GDP. Revision analysis indicates that emotion indicators do not increase the revision of GDP nowcasts. As a result, it can be claimed that the emotion indicators obtained from the speeches of ECB officials have a noticeable effect on the nowcasting the Euro Area GDP.

Keywords: Emotion analysis, ECB speeches, Nowcasting, Euro Area

JEL Classification: C33; E52; E58

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* *Visiting Lecturer, Department of Economics and Administrative Sciences, Hacettepe University, Ankara, Turkey.*

1. Introduction

Gross domestic product (GDP) is the most important economic indicator which shows the general economic situation of a country. Especially, the underlying dynamics of the quarterly GDP have always been the subject of research because it is very important to know its possible future value to assess or steer of the economy in the short-term. In recent years, it has been more desirable to estimate the current value of the quarterly GDP than to forecast future values of the quarterly GDP by using the nowcasting techniques since the quarterly GDP has a relatively delayed publication schedule (*t*+45 *days* in average) compared to the reference quarter (*t*) (Combes et al., 2018).

There is a vast literature on nowcasting GDP, and the main purpose of the studies is generally to find the best method and variable combination to nowcast the quarterly GDP. The literature shows that the variables to be used in a nowcasting model are mainly chosen from the real, financial or (household/business) survey indicators, i.e. structured data. On the other hand, the use of unstructured data (simply text data) in a nowcasting model is relatively new topic in the literature (Basselier et al. (2017), and Kaminski and Gloor (2014)).

In addition to sentiments or emotions extracted from microblogs and the internet, it may be the case that the speeches of monetary authorities (i.e., central banks) can be effective economic indicators since they may affect the economic agents' behaviours, such as expectations, saving-consumption decision, investment risk appetite. Although it may be thought to focus on the impact of central banks' speeches on price stability (inflation) at first glance, the question of how much the effect of the speeches on a real indicator is still important.

This paper investigates the impacts of ECB speeches on nowcasting Euro Area quarterly GDP in this paper. The emotion analysis is applied to ECB's speeches, and construct several emotion indicators to be contained in a multivariate nowcasting model. Then, the effect of emotion indicators on Euro area quarterly GDP is examined by three dimensions. First, it is analysed how much the emotion indicators make the contribution to decrease the estimation error of nowcasting model for quarterly GDP. Second, it is tried to measure the impact of emotion indicators on the explaining the variance of the quarterly GDP. The third dimension is to measure the impact of emotions indicators on the revisions of the GDP nowcasts.

The rest of this paper is organized as follows. Section 1 presents a summary of related studies in the literature. Section 2 defines the unstructured (ECB speeches) and the structured (economic and survey indicators) data for nowcasting quarterly Euro Area GDP. The method to obtain emotion indicators by analysing unstructured data, and the nowcasting methodology are explained in Section 3. Besides, several approaches to measure the impact of emotions of speeches on nowcasting quarterly Euro Area GDP are also explained in the Section 3. The complete findings of the paper are presented in the Section 4. Final remarks are provided in the conclusion.

2. Literature review

A summary of related literature is given in Table 1 (in the Appendix). The studies of Varian and Choi (2009), McLaren and Shanbhogue (2011), Fondeur and Karamé (2013), Bortoli and Combes (2015), Baker et al. (2016), and Francesco and Marcucci (2017) tries to improve the nowcasting/forecasting models by including the unstructured data available on the internet. Specifically, word-search characteristics over searching platforms are often treated as unstructured data. It has been also becoming popular in the literature to analyse emotions and associate them with economic indicators.

However, there are very few studies that try to analyse the nowcasting models by including the sentiments or emotions. Combes et al. (2018) is a visionary paper which differs from the literature in terms of the data source used in the nowcasting model. They extracted several sentiment indicators from the newspapers to use in the nowcasting model for France GDP, and they investigated the effect of sentiment indicators on the nowcasting model.

The paper of Kaminski and Gloor (2014) is another visionary paper in terms of analysing emotions rather than sentiments. They examined the micro-blog data to extract several emotion indicators, and they analysed the effect of the indicators on the crypto-currencies. The studies of Bollen et al. (2010), Zhang et al. (2011), and Si et al. (2013) can also be given as the examples of associating economic analysis with emotion indicators obtained from micro-blog platforms.

There are several studies in the literature about examining the relationship between the communication of central banks and economic indicators. The studies of Lucca and Trebbi (2009), Hansen and McMahon (2015) and Eskici and Koçak (2018) are good examples for pointing out the relationship, however it seems that there is a scarcity of literature in which the emotions extracted from the central banks' speeches and quarterly GDP have been considered together in a nowcasting model.

Varian and Choi (2009), Francesco and Marcucci (2017), Baker et al. (2016), Bollen et al. (2010), Lucca and Trebbi (2009), Hansen and McMahon (2015) studied the nowcasting of US economic indicators such as GDP, short-term interest rate, stock-exchange market index, initial claims. On the other hand, McLaren and Shanbhogue (2011), Fondeur and Karamé (2013), Combes et al. (2018) examined the nowcasting of real and financial variables. The common way to study nowcasting is seen as univariate or multivariate regression methods from the literature.

Unlike the literature, this paper tries to use semantic information such as ECB speeches in nowcasting model which is available to use mixed frequency data and to handle missing observations.

3. Data

3.1. Unstructured data

ECB (2019) provides speech data with metadata containing the content of all speeches made by ECB to assist researchers in the field of central bank communication. The data is currently updated every two months and presented in comma-separated-value format. All related information can be found in ECB (2019).

The data, which is downloaded as of 7 July 2020, consist of 2383 speeches record. The speeches are combined in the same date, so it is obtained a total of 2328 speeches in unique dates. The data contains speeches in several languages, but mostly in English. 92.7% of speeches are in English. There are also speeches in German, Spanish, French, Italian, Catalan and Dutch languages. Only English speeches are taken into consideration. In detail, 5 variables are included in the data.

These are *date, speakers, title, subtitle,* and *contents*. *date* variable extends from 1997-02-07 to 2020-01-27 in daily format, and the time span is restricted until the end of 2019 for this paper. This is due to avoid including the disruptive effects of COVID-19 pandemic to the nowcasting model. *Speakers* variable includes 23 speakers with their names and surnames. In addition to the ECB presidents', the presentations and speeches of other officials from the ECB are included in the data. The speeches made by all speakers are taken into consideration due to vice presidents, chief economists and other officials deliver a significant number of speeches. *subtitle* variable is excluded because it is unnecessary information for the analysis. The *contents* variable provides the textual information of the speeches.

3.2. Structured data

Mixed-frequency data is used for nowcasting GDP. A summary information for data is given in Table 2 (in the Appendix) and the data is accessible at https://tinyurl.com/yyvxo2tp.

By the following approach from the papers Kaminski and Gloor (2014) and Combes et al. (2018), the data can be explained by three groups such as real, survey, and emotions. Real indicators group include four variables. The first one is the Euro Area quarterly GDP which is the target variable of the nowcasting model. Flash estimates of quarterly GDP are usually published with a delay of 45 days compared to the reference period. The second variable is the final estimates of quarterly GDP which is generally finalized after two years from the reference period. The third variable is Euro area monthly industrial production index. The last variable in this group is Euro area total turnover index. The latter two variables are published with a minimum delay of 30 days compared to reference periods. All real indicators cover the period between 1995 and 2019, and they are obtained from ECB.

Similar to Bańbura and Modugno (2014) approaches, two variables are used in the survey indicators group in this paper. The Purchasing Managers Index™ (PMI™) related to the manufacturing sector at the monthly frequency by IHS-MARKIT. PMI™ variable covers the period between February 2008 and the end of 2019. The Eurozone Business and Consumer Survey (BCS) sentiment index, which is published at monthly frequency by European Commission, is released 7 days before the end of the reference period. BCS index covers the period between January 1995 and the end of 2019.

Five emotion indicators (structured) are calculated using the unstructured ECB speeches data described in the part 3.1 of this section. The emotion indicators are at monthly frequency and cover the period between February 1997 and December 2019.

In summary, the mixed-type data includes 11 variables which are at monthly or quarterly frequencies, and it covers the time period between January 1995 and December 2019 with missing observations. The data entirely consists of the first estimation of the variables. It is ignored the subsequent revisions on the indicators.

4. Method

4.1. Text analysis and construction of emotion indicators

It is explained how the unstructured ECB speeches data (defined in Section 2.1) is analysed to obtain emotion indicators those represent the emotions of ECB speeches. The approach can be summarized as follows:

- Pre-processing
- n-gram analysis (descriptive)
- Extraction emotions from the data
- Time aggregation

Pre-processing is a technique which aims to prepare the text data for text analysis. It comprises two stage, i.e. tokenization and cleaning text data. Tokenization is the process of breaking down a text document into those tokens, i.e. words (Welbers et al., 2017). The second stage of pre-processing is the determination of the words (stop-words) to be excluded from the text data. This is a recursive process (Loughran and McDonald, 2016). This paper uses the stopword lists which are already available in Benoit et al. (2018), Rinker (2018), Rinker (2020), Benoit et al. (2019), Silge and Robinson (2016) and Feinerer et al. (2008) studies in addition to a long user-defined stop-words list.

The n-gram analysis, which it is observed the use of words together and the change of these uses over time, can provide important information about text data. Although it does not contribute to the process of obtaining emotion indicators, it provides important descriptive information for the ECB speech data. It is examined the group of two or three words (bigram and trigram, respectively) as well as a single word (unigram) by n-gram analysis. An *n−gram* is a sequence of *n* adjacent elements from a string of words (Jurafsky and Martin, 2008). A bigram is an *n−gram* for $n = 2$ and a trigram is an *n−gram* for $n = 3$. For simplicity, the relationship of Bayesian conditional probability is given in Eq.(1) only for a bigram which provides the conditional probability of a word given the preceding word.

$$P(W_n|W_{n-1}) = \frac{P(W_{n-1}, Wn)}{P(W_{n-1})} \qquad (1)$$

That is, the probability $P()$ of a word W_n given the preceding word W_n-1 is equal to the probability of their bigram, or the co-occurrence of the two words $P(W_n-1,Wn)$ divided by the probability of the preceding word.

It is performed the emotion analysis which aims to categorize words in the text data regarding several pre-defined emotions to extract emotions from the ECB speech data. It is a different approach from sentiment analysis which categorize words into symmetric measures such as “positive”, “neutral”, and “negative”. In general, a pre-defined dictionary is used in the emotions’ analysis however, a new comprehensive dictionary, which is a harmonization of mainly financial-purpose lexicons, are considered in this paper. The lexicons are following:

- bing dictionary (Hu and Liu, 2004),
- National Research Council of Canada (NRC) dictionary (Mohammad and Turney, 2013),
- Lexicoder Sentiment Dictionary (Young and Soroka, 2012),
- Harvard-IV dictionary as used in the General Inquirer software (Harvard, 2000),
- Henry’s Financial dictionary (Henry, 2008),
- Loughran-McDonald Financial dictionary (Loughran and McDonald, 2011),
- AFINN dictionary (Nielsen, 2011)

All mentioned lexicons are based on unigrams. They contain many English words, and the words are assigned to emotions. The Loughran and McDonald (2011) and Mohammad and Turney (2013) lexicons categorize words into emotions, the remaining lexicons are for sentiments. The AFINN lexicon only assigns words with a score that runs between -5 and 5, with negative scores indicating negative sentiment and positive scores indicating positive sentiment. Due to the scale problem, it is excluded the AFINN dictionary from the scope of the analysis.

After harmonization of all available lexicons, there are 17695 (15186 of them are unique) words in the new dictionary, and the number of total emotions is 7. These emotions can be listed as positive, negative, uncertainty, anticipation, and constraining. The distribution of words to emotions is given in Table 3. It is seen that the words are mostly flagged as negative-positive separation according to the distribution.

Table 3

Properties of the dictionary used in emotion analysis

Emotions	Number of words
Negative	9439
Positive	5171
Anticipation	839
Uncertainty	297
Constraining	184

Source: Author's own calculations from ECB (2019).

Emotions are extracted from ECB speech data using the methods explained in the studies of Plutchik (1962), Plutchik (2001) and Rinker (2019) through the dictionary explained above. The emotion analysis is done at the sentence level in the text data. Emotion’s score is calculated at the sentence level. The scores are between 0 (no emotion in the sentence) and 1 (all vocabulary used in the sentence represent emotions). It should be noted that emotion words prefixed with an ‘un-’ are treated as a negation. For example, “unhappy” would be treated as “not happy”.

The emotion’s score is obtained in daily basis since ECB speech data is at daily frequency. The daily scores should be aggregated to the monthly frequency since monthly emotion indicators are used in the nowcasting model defined in Section 3.2. Various approaches can be used in the aggregation process. For instance, daily speech texts in the relevant month can be evaluated as a single text if a speech is made once a month. However, there is a disadvantage that the score of the speech at the end of any month are only reflected to that month in this approach. For this reason, it is assumed the emotion’s score to show an exponential decay process running from the date of a speech until the next one. Afterward, the aggregation is performed by taking monthly averages on each emotion. Finally, the monthly emotion indicators are rescaled from 0 to 100.

4.2. Nowcasting model and estimation

The dynamic factor model (DFM) specification is used to build a nowcasting model (Stock and Watson, 2005) in this paper. In a DFM, a large amount of time series are represented by a smaller number of factors, both by carrying the time series features and by reducing their dimensions. A DFM can be represented as given in Eq.(2)-(4):

$$x_{i,t} = \Lambda_i f_t + \epsilon_{i,t};\ i = 1, \dots, n, \tag{2}$$

$$f_t = \varphi(L) f_{t-1} + \eta_t; \quad \eta_t \sim i.i.d.\mathcal{N}(0, \sigma_i^2) \tag{3}$$

$$\epsilon_{i,t} = \alpha_i \epsilon_{i,t-1} + \upsilon_{i,t}; \quad \upsilon_{i,t} \sim i.i.d.\mathcal{N}(0, Q) \tag{4}$$

Let *x* represent the standardized variables in terms of mean and variance, Λ is the *nxr* dimension matrix and represents the effects of *x*'s on invisible factors (*f*), which represents the loadings. There are three factors, namely real variables factor, survey variables and emotion variables. These factors are assumed to be followed by a VAR process in *p* lag. ϵ_t shows idiosyncratic residuals and they are assumed to be AR(1) process.

Mixed-frequency data can be used in DFM by following the method explained in the paper of Camacho and Perez-Quiros (2010). The DFM also allows to use unbalanced data, which contains missing observations, following the method in the paper of Bańbura and Modugno (2014). The authors suggest a solution for the problems of estimating missing observations in the system estimation in the case of mixed frequency data. The transformations of variables in DFM are given in relevant column of Table 2.

This paper uses the expectation-maximization (EM) algorithm as defined by Marta and Michele (2010) is used to estimate DFM. The lag length is determined as three for the factors according to the Akaike information criterion. As proposed by Doz et al. (2012), the restriction of the effects of variables on the factors is applied in a subjective approach in the form of real/survey/emotion separation explained in Section 2.2.

4.3. Impulse-response functions and variance decomposition analysis

Impulse-response functions are examined to present the evolution of GDP in reaction to shocks in the three factors estimated in Emotion-Included model. It measures the changes in the future responses of GDP in the Emotion-Included model when the factors are shocked by an impulse in one standard deviation unit. Impulse-response functions are obtained by Cholesky factorization of Q, i.e. $Q = AA'$ which is the innovations of equation (2). First, moving average (MA) representation of equation (2) are obtained. Then, it is defined a new error vector $\tilde{\epsilon}_t$ as (linear transformation of old error vector ϵ_t). The coefficient in the MA representation measures the impulse-response which are defined in equations (5)-(7).

$$x_{i,t} = \epsilon_{i,t} + \phi\epsilon_{i,t-1} + \phi^2\epsilon_{i,t-2} + \cdots + \phi^j\epsilon_{i,t-j} \tag{5}$$

$$x_{i,t} = AA^{-1}\epsilon_{i,t} + \phi AA^{-1}\epsilon_{i,t-1} + \phi^2 AA^{-1}\epsilon_{i,t-2} + \cdots + \phi^j AA^{-1}\epsilon_{i,t-j} \tag{6}$$

$$x_{i,t} = A\tilde{\epsilon}_{i,t} + \phi A\tilde{\epsilon}_{i,t-1} + \phi^2 A\tilde{\epsilon}_{i,t-2} + \cdots + \phi^j A\tilde{\epsilon}_{i,t-j} \tag{7}$$

Equations (5)-(7) implies that the impulse-response to the orthogonal error $\tilde{\epsilon}_t$ after j periods is j^{th} orthogonal impulse-response which equals $\phi^j A$ where A in $Q = AA'$.

The variance decomposition analysis measures the amount of information each factor contributes to the GDP in the Emotion-Included model. It determines how much the forecast error variance of GDP can be explained by exogenous shocks to the three factors. Variance decomposition of forecast errors are calculated as follows. The amount of forecast error variance of factor i accounted for by exogenous shocks to GDP is measured by $\omega_{i,GDP,h}$ for h-step as shown in equation (8).

$$\sum_{j=o}^{h-1} (\phi_i A\tilde{\epsilon}_i \phi_{GDP})^2 / MSE[x_{i,t}(h)] \tag{8}$$

where the mean squared error of the h-step forecast of variable i is given in equation (9).

$$MSE[x_{i,t}(h)] = (\sum_{j=o}^{h-1} \phi_i\, Q\phi_i{}') \tag{9}$$

4.4. Revision analysis

The revision analysis is important to show the changes in the nowcast/forecast values regarding the upcoming information in new data releases. It is tried to measure the effect of emotion indicators group to the revisions of GDP nowcasts. It is followed the approach suggested by Basselier et al. (2017) to extract model-based revisions in the nowcasting framework. In this case, y_t^Q is quarterly GDP growth at time t, and Ω_v is the data set at time v. Hence, the quarterly GDP growth nowcast is the expected value of y_t^Q using the available information, $E[y_t^Q|\Omega_v]$. The new nowcast value can be decomposed by:

$$\underbrace{E[y_t^Q|\Omega_{v+1}]}_{\text{New nowcast}} = \underbrace{E[y_t^Q|\Omega_v]}_{\text{Old nowcast}} + \underbrace{E[y_t^Q|I_{v+1}]}_{\text{Revision}} \tag{10}$$

where I_{v+1} is the new information, and it is orthogonal to Ω_v.

Therefore, the revision can be explained as a weighted sum of revisions from the updated variables at time v + 1.

$$E[y_t^Q|I_{v+1}] = \sum_{j \in J_{v+1}} b_{j,v+1}\,(x_{i_j,t_j} - E[x_{i_j,t_j}|\Omega_v]) \tag{11}$$

where $b_{j,v+1}$ represents the weights which measure the marginal contribution of every release of indicators in the new value of the nowcast.

Using the Emotion-Included model structure, the model is refreshed in terms of loadings by adding new data for each month starting from January 2019 until December 2019.

5. Findings

Descriptive statistics for ECB's speech data are presented in Table 4. It is observed that the number of speeches has increased over the years. On the other hand, it has been observed that the annual mean of the number of words used per speech has not changed much over the years.

Table 4

Number of Words in Speeches by Year

Year	Number of speeches	Minimum number of words	Mean of words	Maximum number of words
1997	19	1109	2975	4252
1998	37	428	3560	7578
1999	90	642	4611	18863
2000	70	224	4449	21697
2001	64	1030	3985	16619
2002	64	1242	3714	12517
2003	62	1021	3842	11254
2004	89	50	3545	9627
2005	81	1100	3920	8707
2006	93	48	3994	11032
2007	115	35	4052	13638
2008	130	63	3655	11099
2009	105	222	3918	14089
2010	112	50	3514	10005
2011	117	42	3371	8823
2012	89	54	3245	9777
2013	132	44	3001	7233
2014	101	41	3430	9048
2015	103	39	3284	14809
2016	106	43	3068	11565
2017	142	44	2990	13739
2018	111	51	3288	14300
2019	105	328	3075	10346

Source: Author's own calculations

Table 5 presents the unigrams, bigrams and trigrams together over the years. When n-grams are analysed by years, it is easy to understand which economic topics are discussed in the relevant year. According to Table 5, the words “stability” and “foreign exchange” were the most frequently used during the 1997 Asian financial crisis. Also, it is underlined the phrases “stability”, “foreign exchange markets”, and “cross border payments” during and after the 1998 Russian financial crisis. It is emphasized “growth”, “securities”, and “structural reforms” between the years 2000 to 2003. During the years from 2003 to 2005, Trichet used the terms “real GDP growth” and “integration”, but an important point that draws attention is the emphasis on “labour productivity growth” and “cross border” in the years before the 2009 global economic crisis (2005-2008).

Table 5
Most used unigrams, bigrams and trigrams in the ECB speeches by year

YEAR	UNIGRAM-BIGRAM-TRIGRAM
1997	STABILITY-FOREIGN EXCHANGE-FINE TUNING OPERATIONS
1998	STABILITY-STABILITY ORIENTED-CFA FRANC ZONE
1999	STABILITY-CROSS BORDER-FOREIGN EXCHANGE MARKETS
2000	GROWTH-CROSS BORDER-PROFESSOR OTMAR ISSING
2001	GROWTH-CASH CHANGEOVER-CROSS BORDER PAYMENTS
2002	SECURITIES-SECURITIES ACTIVITIES-TOMMASO PADOA SCHIOPPA
2003	GROWTH-STRUCTURAL REFORMS-CURRENT ACCOUNT DEFICIT
2004	STABILITY-STRUCTURAL REFORMS-REAL GDP GROWTH
2005	INTEGRATION-CROSS BORDER-CURRENT ACCOUNT DEFICIT
2006	GROWTH-PRODUCTIVITY GROWTH-LABOUR PRODUCTIVITY GROWTH
2007	GROWTH-PRODUCTIVITY GROWTH-LABOUR PRODUCTIVITY GROWTH
2008	LIQUIDITY-CROSS BORDER-SEPA DIRECT DEBIT
2009	CRISIS-SYSTEMIC RISK-MACRO PRUDENTIAL SUPERVISION
2010	CRISIS-MACRO PRUDENTIAL-MACRO PRUDENTIAL OVERSIGHT
2011	CRISIS-BANKING SECTOR-SOVEREIGN DEBT CRISIS
2012	LIQUIDITY-MACRO PRUDENTIAL-SOVEREIGN DEBT CRISIS
2013	CRISIS-BANKING UNION-SINGLE RESOLUTION MECHANISM
2014	BANKING-MACRO PRUDENTIAL-MACRO PRUDENTIAL POLICIES
2015	CAPITAL-MACRO PRUDENTIAL-SHADOW BANKING SECTOR
2016	FISCAL-MEDIUM SIZED-MEDIUM SIZED INSTITUTIONS
2017	CONDITIONS-CAPITAL MARKETS-ASSET PURCHASE PROGRAMMES
2018	GROWTH-ASSET PURCHASES-CAPITAL MARKETS UNION
2019	INTERNATIONAL-YIELD CURVE-CAPITAL MARKETS UNION

Source: Author's own calculations

Then, the global economic crisis and the measures taken are frequently mentioned and it is used “systemic risk”, “macroprudential supervision” and “sovereign debt crisis” during the years between the years 2009 and 2011. it is emphasized “fiscal” issues, the speeches are made on “macro prudential”, “banking union”, “liquidity” in the years between 2012-2016. Most frequently n-grams are “asset purchase programmes”, “capital markets union”.

Two DFMs models are estimated to measure the marginal contribution of the emotion indicators group to the nowcasting model for Euro Area GDP. The “Benchmark” model is the base model which the emotion indicators group is not included, that is, only real and survey group of indicators are represented as two factors in the model. The second is the “Emotion-Included” model in which the emotion indicators group is included as a single factor in addition to two factors of Benchmark model. The two models are estimated over full-time span which is from January 1995 to December 2019. Table 6 presents RMSE values for two DFMs and gain of the Emotion-Included model respect to Benchmark model. The RMSE value is 0.0019 in the Benchmark model while the RMSE value is 0.00171 in the Emotion-Included model. Thus, 9.7% gain is achieved by the Emotion-Included model comparing with the Benchmark model. This result indicates that the error of the nowcasting model can be expected to decrease by approximately 10% in case of the emotion indicators obtained from ECB speeches are included in the model compared with non-included one.

Table 6

Comparison of the Model's RMSE

Models	Number of Factors	RMSE	Gain in RMSE (respect to Benchmark)
Benchmark	2	0.0019	-
Emotion-Included	3	0.00171	9.7%

Source: Author's own calculations

Furthermore, these two DFMs are estimated by increasing the number of observations in a recursive basis (one-period-ahead) from January-2019 to December 2019 to directly observe the contribution of the emotion indicators to the nowcast figures. Table 7 presents the quarterly GDP growth rates and nowcasted figures produces by the Benchmark model and the Emotion-Included model for the 2019 by recursive estimation. It is seen that nowcast values of the Emotion-Included model seems to closer to the published quarterly GDP growth rates in comparison with the Benchmark model. It is calculated from Table 7 that RMSE of Emotion-Included model (0.00249) is lower than the Benchmark Model's (0.00269).

As a result of the evaluation of Table 6 and 7 together, it can be claimed that the inclusion of the emotion indicators group as a single factor to the Benchmark model creates a noticeable gain in RMSE and in the nowcasting performance for GDP. From the perspective of policy makers, the use of emotion indicators implied by ECB speeches will make a tangible contribution to in the process of nowcasting Euro Area GDP growth by reducing the RMSE. It can be said that the contribution of the emotion indicators group to the real and survey groups is not very high in terms of RMSE, as expected, but it affects positively in terms of proximity to flash estimates.

Table 7

Comparison of the nowcasting model performances

Month	Reference Quarter	Quarterly GDP growth rate (%)	Benchmark Model Nowcasts (%)	Emotion-Included Model Nowcasts (%)
2019-M1	2019-Q1	0.49	0.33	0.43
2019-M2	2019-Q1	0.49	0.38	0.44
2019-M3	2019-Q1	0.49	0.46	0.50
2019-M4	2019-Q2	0.10	0.48	0.52
2019-M5	2019-Q2	0.10	0.53	0.53
2019-M6	2019-Q2	0.10	0.51	0.52
2019-M7	2019-Q3	0.30	0.29	0.32
2019-M8	2019-Q3	0.30	0.28	0.31
2019-M9	2019-Q3	0.30	0.35	0.30
2019-M10	2019-Q4	0.06	0.37	0.36
2019-M11	2019-Q4	0.06	0.34	0.28
2019-M12	2019-Q4	0.06	0.45	0.31

Source: Author's own calculations

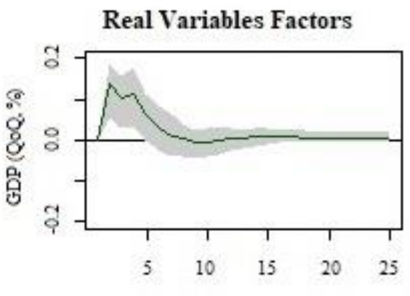
The impulse-response functions and the forecast error variance decomposition analysis are examined using the Emotion-Included model estimation results. Figure 1 presents the impulse-response analysis results. Each graph in Figure 1 provides the response of quarterly GDP growth rate to one standard deviation innovations in relevant factor i.e., real variables factor, survey variables factor and emotion variables factor. It is understood from two graphs in the upper part of the Figure 1 that the responses of the quarterly GDP growth rate to the real and survey variables factors are positively significant in the short term. In contrast, an impulse in the emotion variables factor causes a significant response in the quarterly GDP growth rate in the longer periods. The sign of the response is not one-way due to the factor of emotion variables include opposite emotions such as positive-negative.

The forecast error variances decomposition of the quarterly GDP growth rate is presented in Figure 2 using the estimates of Emotion-Included model. The forecast error variances of quarterly GDP growth rate are mainly explained by itself, real variables and survey variables and emotion variables, respectively. The ratio of explanation of the variance by emotion variables factor is minimal but noticeable and increases in longer forecast horizon.

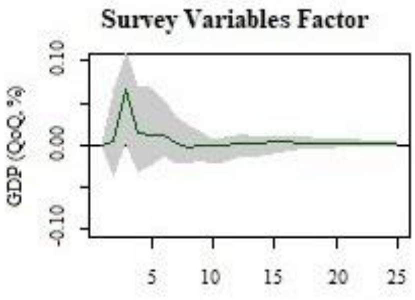
Finally, the revision analysis results are given in Table 8 using by Emotion Included model estimates. The first column in Table 8 shows the month in which Emotion-Included model run using the available dataset until that month. The second column represents the quarter for which the nowcast of quarterly GDP growth are produced. The third column shows the nowcast value produced in the previous month. The columns between 4 and 7 represents the amount of the total revision in the nowcast value of quarterly GDP growth and the source of the revision by the factors due to the new information available in the variables. The last column is the final value of the nowcast for the relevant quarter in that month.

Figure 1

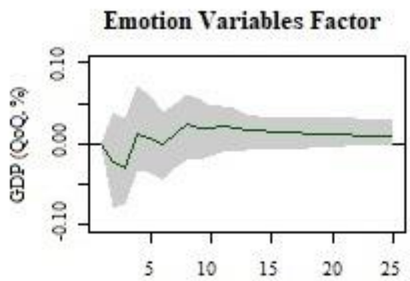
Orthogonal Impulse-responses from Factors to GDP



95% Bootstrap CI, 1000 runs



95% Bootstrap CI, 1000 runs

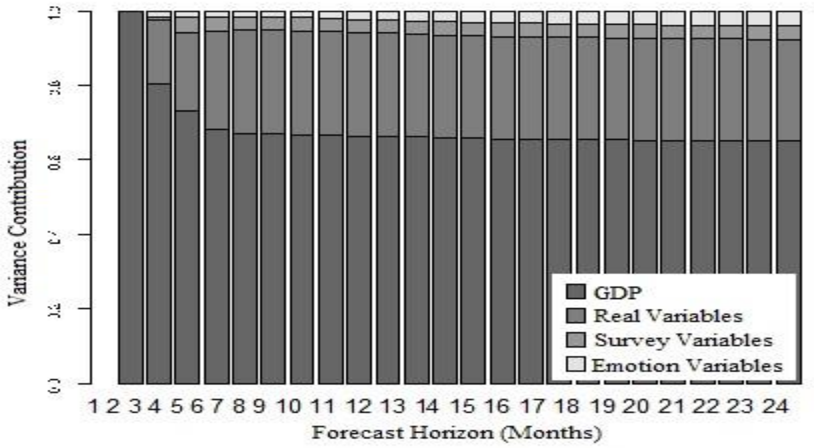


95% Bootstrap CI, 1000 runs

Source: Author's own calculations

Figure 2

Orthogonal Forecast Error Variance Decomposition of GDP



Source: Author's own calculations

Table 8

Revision analysis results for GDP nowcasts

Month	Quarter	Old Nowcast Value (O,%)	Total Revision (R=R1+R2+R3) (%)	Real Variables (R1,%)	Survey Variables Factor (R2,%)	Emotion Variables Factor (R3,%)	New Nowcast Value (N=O+R,%)
Jan-2019	**2019-Q1**	0.368	0.066	0.053	0.010	0.003	0.434
Feb-2019	**2019-Q1**	0.434	-0.088	-0.070	-0.013	-0.004	0.439
Mar-2019	**2019-Q1**	0.439	-0.074	-0.059	-0.011	-0.004	0.499
Apr-2019	**2019-Q2**	0.499	-0.037	-0.030	-0.006	-0.002	0.517
May-2019	**2019-Q2**	0.517	-0.086	-0.069	-0.013	-0.004	0.527
Jun-2019	**2019-Q2**	0.527	0.098	0.078	0.015	0.005	0.517
Jul-2019	**2019-Q3**	0.517	0.082	0.066	0.012	0.004	0.323
Agu-2019	**2019-Q3**	0.323	-0.080	-0.064	-0.012	-0.004	0.309
Sep-2019	**2019-Q3**	0.309	0.063	0.050	0.009	0.003	0.302
Oct-2019	**2019-Q4**	0.302	0.033	0.026	0.005	0.002	0.364
Nov-2019	**2019-Q4**	0.364	-0.018	-0.014	-0.003	-0.001	0.282
Dec-2019	**2019-Q4**	0.282	0.021	0.017	0.003	0.001	0.315

Source: Author's own calculations

Table 8 shows that the effects of emotional indicators are negligible in the revision of quarterly GDP growth rate nowcasts. The main source of the revision is the real variables group. Therefore, it can be suggested that adding emotion indicators to the nowcast model does not have an effect to increase the variance of nowcast values.

6. Conclusion

Recently, it has been discussed that inclusion of information extracted from microblogs and internet platforms into forecast or nowcast models for economic variables in the literature. On the other hand, it seems that the evaluating the impact of speech information on the economic models is a new subject.

In this paper, it is investigated the effect of speeches made by ECB officials on nowcasting Euro Area quarterly GDP. As a result of the descriptive analysis of the speech data, it is seen that the number of speeches increased over the years between 1997-2019, and it can be claimed that the words and word groups frequently used in the speeches may reflect the economic conditions of those periods. Then, five emotion indicators (indices between 0 and 100) are calculated by applying the emotion analysis method on the speech data.

It is observed that the marginal contribution of emotion indicators is found effective in terms of reduction of RMSE of the nowcasting model established in dynamic factor model representation for Euro Area quarterly GDP. The emotion indicators also provide a noticeable improvement in the nowcasts. Impulse-response functions and forecast error variance decomposition analysis have shown that the impact of emotion indicators on nowcasts is noticeable in the long term, not in the short term. Finally, revision analysis indicates that emotion indicators cause a negligible effect in the revision of the nowcasts.

The findings of the study show that the forward-guidance practices of central banks can affect real indicators as well as monetary conditions such as monetary policy and inflation. The findings of the study show that the advanced guideline practices of central banks may have an effect on real indicators, as well as monetary conditions such as monetary policy and inflation. In addition to the fact that central bank speeches can be included in nowcasting models, it is thought that using the speeches of the press and government officials can increase the performance of nowcast models.

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APPENDIX

Table 1

Brief summary of the related literature

Studies	Target Variable	Input Variables	Analysis Period	Model & Estimation Method	Main Findings
Varian and Choi (2009)	Retail Sales, Automotive Sales, Home Sales, Travel data of USA	Internet search data	From January 2004 to August 2008	Regression & Ordinary Least Squares	Predictions can be significantly improved by the inclusion of Internet search data
McLaren and Shanbhogue (2011)	Labor and housing market of UK	Internet search data	From June 2004 to January 2011	Regression & Ordinary Least Squares	Internet search data can help predict changes in unemployment in the United Kingdom
Fondeur and Karamé (2013)	Youth Unemployment of France	Internet search data	from January 2004 to July 2011	Unobserved Component Model & Model & Kalman Filter	including Internet search data improves unemployment predictions relative to a restricted model.
Francesco and Marcucci (2017)	Initial Claims of USA	Internet search data	From July 1997 to February 2014	Standard autoregressive model with explanatory variables & Ordinary Least Squares	Google-based models are better to predict at the turning points, not for whole sample.
Bortoli and Combes (2015)	Household consumption of goods	Internet search data	From March 2004 to December 2014	Multiple regression & Bayesian Approach	Internet search data does not improve the forecasting of monthly household expenditure.
Baker et al. (2016)	Several short-term economic indicators	US newspapers Uncertainty Index	From January 1985 to December 2014	Vector Auto Regression & Ordinary Least Squares	It can be suggested that there are negative economic effects of uncertainty shocks of newspapers.
Combes et al. (2018)	GDP of France	Media Sentiment from newspapers	From second quarter of 2000 to third quarter of 2017	Multiple Regression & Ordinary Least Squares	Media information can be a tool for economic analysis.
Kaminski and Gloor (2014)	Bitcoin market indicators	Microblog emotions	From November 23, 2013 to March 7, 2014	Granger causality	The microblogging platform emotionally reflecting Bitcoin trading dynamics

Studies	Target Variable	Input Variables	Analysis Period	Model & Estimation Method	Main Findings
Bollen et al. (2010)	Dow Jones Industrial Average of USA	Microblog emotions & Data from Internet-search platforms	From February 28, 2008 to November 3, 2008	Granger causality	DJIA predictions can be significantly improved by the inclusion of specific public mood dimensions but not Microblog emotions.
Lucca and Trebbi (2009)	Short Term Interest Rates of USA	Semantic scores from FOMC Statements	From May 1999 December 2008	Regression & Ordinary Least Squares	Longer-dated Treasury yields mainly react to changes in FOMC statements.
Hansen and McMahon (2015)	76 economic variables of USA	Semantic scores from FOMC Statements	From January 1998 to December 2014	Factor-Augmented Vector Auto Regression	FOMC Statements has not particularly strong effects on real economic variables
Eskici and Koçak (2018)	Consumer Price index of Turkey	Topics of Monthly Price Developments Report	From June 2006 and January 2018	3-way ANOVA	The clusters of MPDRs can help to explain the movements in the annual CPI figures.

Source: Author's own review

Table 2

Description of the data for nowcasting

Series ID	Series Name	Frequency	Units	Time Span	Transformation	Delay (in days, "-" means leading)
GDP	Calendar and seasonally adjusted chain linked Euro area Flash Gross domestic product	Quarterly	2015=100 Index	1995Q1-2019Q4	Quarterly rate of change	45
GDP_FINAL	Calendar and seasonally adjusted chain linked Euro area Gross domestic product (Final Estimates	Quarterly	Millions of Chained 2010 Euros	1995Q1-2017Q4	Quarterly rate of change	720
IPI	Working day and seasonally adjusted Euro area Industrial Production Index	Monthly	2015=100 Index	Jan.1995-Dec.2019	Monthly rate of change	40
RS	Working day and seasonally adjusted Euro area Total Turnover Index	Monthly	2015=100 Index	Jan.1995-Dec.2019	Monthly rate of change	30
PMI-M	Markit PMI (Manufacturing) by IHS Markit	Monthly	Index (0,100)	Feb.2008-Dec.2019	Monthly rate of change	-7

Series ID	Series Name	Frequency	Units	Time Span	Transformation	Delay (in days, "-" means leading)
BCS	Eurozone Business and Consumer Survey Sentiment Indicator	Monthly	Index (0,200)	Jan.1995-Dec.2019	Monthly rate of change	-7
ANTICIPATION	Anticipation index of ECB speeches	Monthly	Index (0,100)	Feb.1997-Dec.2019	Original values	0
CONSTRAINING	Constraining index of ECB speeches	Monthly	Index (0,100)	Feb.1997-Dec.2019	Original values	0
NEGATIVE	Negativity index of ECB speeches	Monthly	Index (0,100)	Feb.1997-Dec.2019	Original values	0
POSITIVE	Positivity index of ECB speeches	Monthly	Index (0,100)	Feb.1997-Dec.2019	Original values	0
UNCERTAINTY	Uncertainty index of ECB speeches	Monthly	Index (0,100)	Feb.1997-Dec.2019	Original values	0

[*] *All the indicators in the data are taken from the source as seasonally adjusted. Emotion indicators have no significant seasonality.*

Source: Author's own calculations