A Proposal of a Real Time Economic Sentiment Indicator Based on Twitter and Google Trends for the Spanish Economy

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Abstract: The main aim of this paper is to build a real time economic sentiment indicator (RT-ESI) for Spain, based on text mining and deep learning from Twitter and Google Trends, that can anticipate GDP and household consumer behaviour. This work contributes to the literature, firstly by carrying out a sentiment analysis with a set of selected keywords that are related to emotions and expectations, then we apply a factor analysis to create the composite indicator, next we use a descriptive analysis to highlight the main associations between indexes, and finally we employ fractional integration and cointegration techniques (ARFIMA and FCVAR) to assess the RT-ESI behaviour against the European Commission´s consumer confidence indicator and the GDP. The results show that the GDP (YoY) presents the same behaviour as our leading indicator, finding mean reversion. The behaviour of the CCI series differs from the others.

Keywords: Economic Sentiment Indicator, Business Cycle, Text Mining, Twitter, Google Trends, Fractional Cointegration VAR.
JEL Classification: E32, E37.

1. INTRODUCTION

Leading economic indicators (LEIs) play an important role in monitoring business cycles and making efficient economic policy decisions. They allow analysts, researchers, and policy makers to track the economy and anticipate economic activity trends and turning points.

LEIs may be differentiated between quantitative and qualitative indicators (Poza, 2020). Within the quantitative ones, we can find objective variables such as car registrations, electricity consumption or cement consumption, among others; while the qualitative ones are linked to sentiment surveys, that gather information regarding business and consumer behaviour and expectations.

In this regard, the European Commission (2021) states that consumer surveys provide essential information for economic surveillance, short-term forecasting, and economic research. Moreover, they are widely used to detect turning points in the economic cycle.

This research paper contributes to the literature on business cycle analysis by proposing a real time economic sentiment indicator (RT-ESI) for Spain, based on text mining and deep learning from Twitter and Google Trends, that can anticipate GDP and household consumer behaviour. This step from intentions to behaviour can be thoroughly observed in the Theory of Planned Behaviour (TPB) (Ajzen, 1991).

To achieve this goal, we implement the following methodology: we first carry out a sentiment analysis with a set of selected keywords that are related to emotions and expectations, then we apply a factor analysis to create the composite indicator, next we use a descriptive analysis to highlight the main associations between indexes, and finally we employ fractional integration and cointegration techniques (ARFIMA and FCVAR) to assess the RT-ESI behaviour against the European Commission´s consumer confidence indicator and the GDP.

The layout of the research paper is as follows: Section 2 briefly reviews the relevant literature on leading economic indicators and sentiment analysis, Section 3 describes the data and the variables used, Section 4 outlines the methodology, Section 5 presents the empirical results, and Section 6 offers some concluding remarks.

2. LITERATURE REVIEW.

Big Data and Leading Economic Indicators

Big Data offers powerful information in order to predict the future to intervene early enough in the economy (Szármes, 2015). In this sense, many authors have applied text mining techniques to forecast not only macroeconomic trends (Antenucci et al., 2014; Varian, 2014; Huang, Rojas and Convery, 2018; Poza and Monge, 2020), but also mesoeconomic movements in the automobile and tourism sectors (Choi and Varian, 2012; Varian, 2014; Bangwayo and Skeete, 2015).

Poza and Monge (2020) construct a Leading Economic Activity Index, based on Google Trends searches and apply fractional cointegration and continuous wavelets techniques to evaluate the power of the indicator to forecast GDP behaviour.

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In the same line of research, Antenucci *et al.* (2014) analyze a massive number of tweets to study labour market imbalances and compare the findings to government statistics, thereby building a social media signal of job loss that closely tracks initial claims for unemployment insurance. Moreover, Dong et al. (2017) point out that social networks and geolocated data facilitate the measurement of real-time economic activity.

Varian (2014) has shown that web search data is certainly valuable in forecasting consumer behaviour and financial market activity. Toole et al. (2015) study employment shocks via mobile phone call records in Europe and Pappalardo et al. (2016) present a basis with which to “nowcast” socioeconomic indicators through mobility data created by mobile phone activity.

Huang, Rojas and Convery (2018) study the capacity to utilize news to obtain core economic sentiment. Bernanke (2008) affirms that a confidence index can influence the current economic performance, while Koenig (2002) states that confidence indices are more interesting to study the economic outlook than traditional indicators because they offer real-time instead of lagged data.

In this regard, Bollen et al. (2011) show evidence to forecast stock market fluctuations through applying sentiment analysis with Twitter, D’Amuri and Marcucci (2017) foresee unemployment in the USA using Google searches, Hisano et al. (2013) use news articles to estimate market instability, Choi and Varian (2012) exploit data from Google Trends to predict information in the automobile, labour market and tourism sectors.

In the touristic sector, for example, we can also find further evidence between massive online data and economic activity. Bangwayo and Skeete (2015) introduce a leading tourism index, based on Google Trends, to estimate demand. They build a composite indicator through searches such as “hotels and flights” from some source countries to the Caribbean. They use Autoregressive Mixed-Data Sampling (AR-MIDAS) models and suggest that Google Trends provides meaningful benefits to analysts in the touristic sector.

Rivera (2016) uses search query volume (SQV) data to foresee a given process of interest, using Google Trends data related to tourism. Meanwhile, Sun et al. (2019) use machine learning and internet searches in Baidu and Google to estimate tourist arrivals in China.

It is possible to observe that big data has become one of the main topics in economic research articles, producing a wide debate on its possible ability to be used as a complement or even a substitute for traditional statistical surveys and official indicators. Di Bella, Leporatti and Maggino (2018) analyzed these aspects through the metadata stored in Scopus, based on articles on big data.

A large part of the population uses the Internet for their daily activities, generating a large flow of data accessible through the World Wide Web (WWW), currently the largest repository of information in the world. All this data is easily traceable and through the analysis it is possible to monitor the economic variables. Based on this hypothesis, Blázquez Soriano (2019) studied the possibility of generating different economic indicators from the information available on the network and making short-term predictions.

Haldane and Chowla (2021). They explain how this use of big data for the creation of indicators has been precipitated since the COVID-19 pandemic, economists have resorted to new rapid 'indicators' based on big data. In their research, they detail how information from different sources of massive data storage can be used to analyze consumption habits and population movements.

Sentiment Analysis (SA)

Sentiment analysis is one of the best possible methods to be able to derive expressed emotions from unstructured texts by transforming data into a structured format (Ouyang et al., 2015). This model classifies sentiments into positive, negative, and neutral scores. A Natural Language Toolkit (NTLK) library has been used; this method acts as a text processor for language dealings. Starting from being a classification task at the document level (Turney, 2002; Pang and Lee, 2004), progress has been made at the sentencing level (Hu and Liu, 2004; Kim and Hovy, 2004) and finally and more recently, at the world level (Wilson et al., 2005; Agarwal et al., 2009).

Some of the first results on sentiment analysis with data obtained from Twitter belong to Go et al. (2009), and Pak and Paroubek (2010). Go et al. (2009) use models obtained from Naive Bayes, MaxEnt and Support Vector Machines (SVM), and confirm that SVM obtains better results than the rest of the models.

Barbosa and Feng (2010) propose another system for sentiment analysis with Twitter data, using polarity predictions obtained from web pages as tags to train the model, and manually tagged tweets to fit the data and finally another dataset of tweets for testing.

A study on data extracted from social networks by Bermingham and Smeaton (2010) concludes that short texts are more compact and explicit in terms of how they project sentiment, after analyzing more than 60 million tweets, they argue that it is easier to classify feelings of short texts than any other lexical structure.

Ojo et al., (2020) They study the importance of eliciting emotions from texts, ensuring that they can provide valuable information on how events influence public opinion. In his work, economic texts were analyzed, based on keywords that could be considered positive, negative and neutral, with the aim of obtaining a classification of sentiment.

Hassan, Hudaefi, and Caraka, (2021) explored Twitter users' views of cryptocurrencies from lexical sentiment analysis through machine learning. Allowing with his finding to study in advance the public's reaction to the bubble prices of cryptocurrencies.

The European Commission Consumer Confidence Indicator (CCI)

According to the European Commission (2021), the consumer confidence indicator is the arithmetic average of the balances of the answers to the questions on the past and expected financial situation of households, the expected general economic situation, and the intentions to make major purchases over the next 12 months. Balances are seasonally adjusted.

The survey data generated within the framework of the Joint Harmonised EU Programme of Business and Consumer Surveys are particularly useful for monitoring economic developments at Member State, EU and euro-area level. High frequency, timeliness and continuous harmonisation are among their main qualities.

The Commission's harmonised survey programme, managed by the Directorate-General for Economic and Financial Affairs (DG ECFIN), was set up in 1961, and its scope has since expanded considerably in terms of both the countries and the sectors covered. The data published every month by DG ECFIN are derived from surveys conducted by national institutes in the Member States and the candidate countries.

3. DATA AND VARIABLES

3.1. Data

The data-sources used in this research paper are Twitter, Google Trends, and the European Commission. Regarding Twitter and Google Trends, we carry out a text mining based on a keywords search related to personal emotions and expectations, that represent people's intentions as well as their mood. As far as the European Commission is concerned, we focus on the GDP and the consumer confidence indicator.

All the data we exploit from Twitter and Google are released in real time for the Spanish economy, but we build the indicator monthly to compare the results with the European Commission's consumer confidence indicator, which is published every month, and with the Spanish GDP, interpolated monthly at constant prices. The time series starts in January 2011 and ends in February 2021; therefore, the number of observations amounts to 122.

The dataset used for sentiment analysis is made up of the tweets containing the keywords specified in Table **1**, obtained through the Tweepy API provided by Twitter.

According to Kharde (2016), after carrying out the tracking of the twitter data, it is necessary to process the information by cleaning the tweets by eliminating repetitions, similarities, and duplicate rows, after which symbols, numerical values and signs must be eliminated. A final score is calculated which is stored in a CSV (Comma Separated Values) file.

Having finished this process, the tweets were translated into English to obtain an improvement in precision; this is because most of the models used for sentiment analysis have been trained in this language. The translation was carried out by the Google Translation API.

To calculate the polarity of the dataset, the Textblob model has been used. Textblob is a Python text library, that provides an API to drill down into Natural Language Processing (NTP) such as classification, translation, noun phrase extraction, and sentiment analysis, returning a value between -1 and 1 depending on whether the result is negative or positive.

3.2. Variables

In line with the most recent research concerning economic indicators and the principle of parsimony (Hair et al., 2007), we select 12 variables to create the Real Time Economic Sentiment Indicator (RT-ESI) for Spain (see Table 1). The variables are grouped into a final index. The selection of the variables aims to improve the CCI capacity to anticipate GDP's turning points and trends. This enhancement is based on the use of representative variables about emotions, expectations, and mood, according to the literature, along with real-time data, in comparison to CCI.

Table 1. Set of variables to build the Real Time Economic Sentiment Indicator.

<table>
<tr><th>Variables</th><th>Definition</th><th>Data source</th></tr>
<tr><td>"Boom"</td><td rowspan="3">Keywords focused on positive expectations and optimistic economic sentiment, that maintain a positive correlation with GDP (Huang, Rojas and Convery, 2018 | Nyman et al., 2014 | Musat and Trausan-Matu, 2009 | Pang and Lee, 2008 | Wiebe, Wilson and Cardie, 2005)</td><td>Twitter</td></tr>
<tr><td>"Optimism"</td><td>Twitter</td></tr>
<tr><td>"Passion"</td><td>Google Trends</td></tr>
<tr><td>"Crisis"</td><td rowspan="7">Keywords focused on negative expectations and pessimistic economic sentiment, that present a negative correlation with GDP (Huang, Rojas and Convery, 2018 | Nyman et al., 2014 | Musat and Trausan-Matu, 2009 | Pang and Lee, 2008 | Wiebe, Wilson and Cardie, 2005)</td><td>Twitter</td></tr>
<tr><td>"Pessimism"</td><td>Twitter</td></tr>
<tr><td>"Uncertainty"</td><td>Google Trends</td></tr>
<tr><td>"Worry"</td><td>Google Trends</td></tr>
<tr><td>"Stress"</td><td>Google Trends</td></tr>
<tr><td>"Vulnerability"</td><td>Google Trends</td></tr>
<tr><td>"Panic"</td><td>Google Trends</td></tr>
<tr><td>"Scoundrel"</td><td rowspan="2">Keywords related to swearing, that represent emotions. These emotional expressions maintain a negative correlation with economic activity (Stephens and Zile, 2017 | Kawate and Patil, 2017 | Celdrán, 2008).</td><td>Google Trends</td></tr>
<tr><td>"Shit"</td><td>Google Trends</td></tr>
<tr><td colspan="3">Note:

For Twitter: The results obtained refer to the polarity classification of the analyzed tweets using TextBlob algorithm, the objective of which is to indicate whether the text expresses a positive, negative or neutral opinion. The resulting value will be the closest to 1 if the text has a positive charge, in the same way the result obtained will be close to -1 if the tone tends towards negativity. Values close to 0 will be the consequence of a sentence with neutral polarity.

For Google Trends: The numbers reflect the search interest in relation to the maximum value in a given region and period (index). A value of 100 indicates the maximum popularity of a term, while 50 and 0 indicate that a term is half popular in relation to the maximum value or that there was not enough term data, respectively.</td></tr>
</table>

4. METHODOLOGY

4.1. Factor Analysis: The Multivariate Technique To Construct The Rt-Esi

The 12 variables were integrated into the real time economic sentiment indicator (RT-ESI) by means of a factor analysis (principal component). Also, the weights were calculated according to the component matrix.

We have studied our set of variables (X_1, X_2,..., X_{12}) on our observations and calculated, from them, the new factor F_1 as a linear combination of the original X_1, X_2, ..., X_{12}, that is:

$$F_j = a_{j1}X_1 + a_{j2}X_2 + \dots + a_{j12}X_{12}$$

where a'_j is a vector of constants.

This technique has been broadly applied to construct indicators because it allows researchers to create composite indexes through linear combinations with non-arbitrary weights (Munda and Nardo, 2005; Poza and Monge, 2020).

4.2. UNIT ROOTS

It is important to determine the integration order of time series analysed in this research paper because statistics and econometrics use single-equation or multi-equation regressions models of time series for modelling economic variables and their interrelations based on Box and Jenkins (1970) methodology. Therefore, if the fundamental assumption to use this type of models is that the time series are stationary or the linear combination, in the case of multi-equation models, is also stationary, we have to verify this fact to conclude that the process is non-stationary I(1) when it contains a unit root or it is stationary I(0) when it does not contain a unit root.

So to verify the order of integration d of the time series analysed, exist an extensive list of tests known as unit root tests. Dickey-Fuller test (see Dickey and Fuller, 1979) is one of the best known and most widely used unit root tests. In the case when a non-systematic component in Dickey-Fuller models is autocorrelated, so called Augmented Dickey-Fuller test is constructed (see Dickey and Fuller, 1981). There are many other tests available to calculate unit roots that have greater power such as Phillips (1987) and Phillips and Perron (1988) in which a non-parametric estimate of spectral density of u_t at the zero frequency has been used. Also, with regard to the deterministic trend we used the methodology based on Kwiatkowski et al. (1992), Elliot et al. (1996) and Ng and Perron (2001) and produced the same results.

4.3. ARFIMA (p, d, q) model

To carry out this research, we also employ fractionally integrated methods with the purpose of making the time series be stationary. We achieve this objective ($I(0)$) by differentiating the time series with a fractional number.

Following a mathematical notation, a time series $x_t, \; t = 1, 2, \dots$ follows an integrated order process d (and denoted as $x_t \approx I(d)$) if:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \dots, \quad (1)$$

where d refers to any real value, L refers to the lag-operator $(Lx_t = x_{t-1})$ and u_t refers to I(0) which is the covariance stationary process where the spectral density function is positive and finite at the zero frequency, displaying in the weak form a type of time dependence. So, for example, if u_t is ARMA (p, q), x_t is then said to be ARFIMA (p, d, q). Depending on the value of the parameter *d*, several specifications based on (1) can be observed. Thus, if $d < 0$, x_t is said to be anti-persistent, with the series exhibiting zero spectral density at the origin (Dittmann and Granger, 2002) and switching signs more frequently than a random process. The process is short memory or I(0) when $d = 0$ in (1). This occurs because $x_t = u_t$. Long memory process (d>0) is the name given when there is a high degree of association over a long time. With this last assumption, the process is still covariance stationary if $d < 0.5$ because the infinite sum of the autocovariances is still finite. Our interpretation of this can also be related to the issue of mean reversion. If the series reverts to the mean, shocks will be transitory, and this happens when *d* is smaller than 1. In contrast to the above, the shocks are expected to be permanent when $d \geq 1$.

Although there are several procedures for estimating the degree of long-memory and fractional integration (Geweke and Porter-Hudak, 1983; Phillips, 1999, 2007; Sowell, 1992; Robinson, 1994, 1995a,b; etc.) we follow the Akaike information criterion (AIC) (Akaike, 1973) and the Bayesian information criterion (BIC) (Akaike, 1979) to select the most appropriate ARFIMA model and we follow Sowell (1992) and his likelihood process to present our results.

4.4. FCVAR MODEL

A method known as Fractionally Cointegrated Vector Auto-Regressive (FCVAR) was introduced by Johansen (2008) to check for a multivariate fractional cointegration model. It was further expanded by Johansen and Nielsen (2010, 2012). It is one step ahead of the Cointegrated Vector AutoRegressive model (Johansen, 1996), which is named CVAR, and it allows for series integrated of order d and that cointegrate with order d - b, with b > 0. To introduce the FCVAR model, we present first the non-fractional CVAR model.

Let $Y_t, t = 1, \dots, T$ be a p-dimensional I(1) time series. The CVAR model is:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \textstyle\sum_{i=1}^{k} \Gamma_i \, \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \, \Delta L^i Y_t + \varepsilon_t \quad . (1)$$

Δ^b and $L_b = 1 - \Delta^b$, representing the difference and the lag operator, is used to derive the FCVAR model. We then obtain:

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \textstyle\sum_{i=1}^{k} \Gamma_i \, \Delta L_b^i Y_t + \varepsilon_t, \qquad (2)$$

which is applied to $Y_t = \Delta^{d-b} X_t$ such that

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \textstyle\sum_{i=1}^{k} \Gamma_i \, \Delta^b L_b^i Y_t + \varepsilon_t \qquad (3)$$

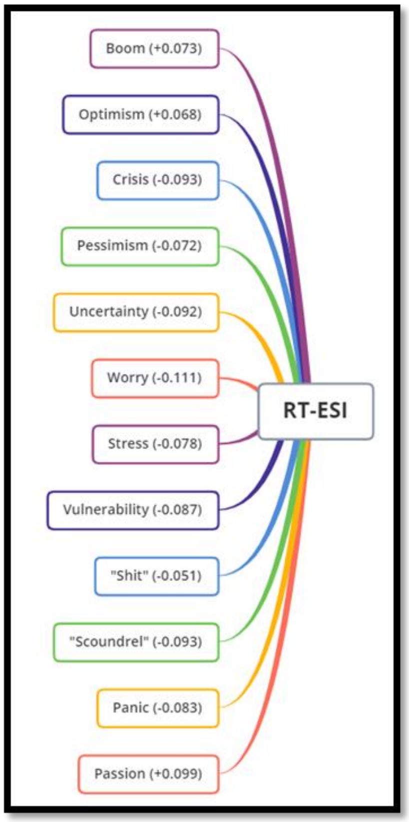

Fig. (1). Real Time Economic Sentiment Indicator (RT-ESI).

Source: Own elaboration.

Where, ε_t is a term with mean zero, and variance-covariance matrix Ω is p-dimensional independent and identically distributed. As in the CVAR model, the parameters can be interpreted as follows. α and β are $p \times r$ matrices, where $0 \leq r \leq p$. The relationship in the long-run equilibria in terms of cointegration in the system is due to the matrix β. The parameter Γ_i controls for the short-run behaviour of the variables. Finally, the deviations from the equilibria and their speed in the adjustment is because of the parameter α.

The FCVAR model is developed in a computer programming language such as Matlab (Nielsen and Popiel, 2018) and has been employed in numerous empirical papers (Baruník and Dvořáková, 2015; Maciel, 2017; Aye et al., 2017; Dolatabadi et al., 2018; Jones, Nielsen and Popiel, 2014; Gil-Alana and Carcel, 2018; Poza and Monge, 2020; etc.).

5. EMPIRICAL RESULTS

5.1. Real Time Economic Sentiment Indicator (RT-ESI)

Through implementing the factor analysis by means of the 12 variables previously outlined, we generate the final indicator. Results are displayed in detail in Fig. (**1**).

RT-ESI = 0.073 Boom + 0.068 Optimism – 0.093 Crisis – 0.072 Pessimism – 0.092 Uncertainty – 0.111 Worry – 0.078 Stress – 0.087 Vulnerability – 0.051 Shit – 0.093 Scoundrel – 0.083 Panic + 0.099 Passion.

The two most important variables to measure economic sentiment are “worry” and “passion”, closely followed by “crisis”, the swearword “scoundrel” and “pessimism”. All the variables have an important weight on the economic sentiment; thus, emotions are hidden behind multiple ways.

5.1. Units Roots

We have calculated the three standard unit root/stationary tests (the Augmented Dickey-Fuller (ADF) test, the Phillips Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test) to analyse the statistical properties of the GDP, ICC and the new RT-ESI time series. The results, displayed in Table **1** suggest that the selected time series are non-stationary I(1). Performing the analysis on the first differences we observe that the only time series that become stationary is ICC. We will still need second differences for the

Table 2. Unit Root Tests.

	ADF			PP			KPSS	
	(i)	**(ii)**	**(iii)**	**(i)**	**(ii)**	**(iii)**	**(ii)**	**(iii)**
Original Data								
GDP (YoY)	-1.6146	-1.4685	-0.3999	-1.3684	-1.5758	-1.5184	0.2285	0.2309
CCI	-0.9198	-1.4179	-1.0118	-0.8857	-1.3903	-0.9279	0.5995	0.2283
RT_ESI	-0.6231	-3.6472	-4.0158	-0.6390	-3.4497	-4.0158	0.4152	0.2238
First differences								
GDP (YoY)	-1.1290	-1.0873	-1.2489	-3.1524*	-3.0815*	-2.9010	0.1454*	0.0632*
CCI	-10.4550*	-10.4098*	-9.3232*	-10.4459*	-10.3966*	-10.4124*	0.2482*	0.1122*
RT_ESI	-13.9234*	-13.8869	-13.8309	-19.4785*	-20.9265	-22.9999	0.2527	0.2740

(i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. * Denotes a statistic significant at the 5% level. For ADF and PP, the 5% critical value with T=310 is -1.9418 for no deterministic components; -2.8707 with an intercept; -3.4245 with a linear time trend. For KPSS, the 5% critical value with T=310 is 0.4630 with an intercept component; 0.1460 with a linear time trend.

Table 3. Results of Long Memory Tests.

Long Memory Test						
Data analyzed	**Sample size (weeks)**	**Model Selected**	**d**	**Std. Error**	**Interval**	**I(d)**
GDP (YoY)	116	ARFIMA (0, d, 0)	0.8305827	0.1135782	[0.64, 1.02]	I(1)
CCI	120	ARFIMA (1, d, 2)	1.1369768	0.1973322	[0.81, 1.46]	I(1)
RT_ESI	120	ARFIMA (2, d, 2)	0.6364521	0.1230041	[0.43, 0.84]	I(d)

GDP and RT-ESI time series to become stationary.

5.2. Fractional Integration

Following the results obtained using unit root methods in the three time series, we assume that we have to consider first and second differences as we have verified that the data is non-stationary I(1). However, due to the low power of the unit root methods under fractional alternatives[1], we also employed fractional methods, and used ARFIMA (p, d, q) models to study the persistence of GDP, CCI and new Real Time Economic Sentiment Indicator (RT-ESI) time series. The Akaike information criterion (AIC; Akaike, 1973) and the Bayesian information criterion (BIC; Akaike, 1979) were used to select the appropriate AR and MA orders in the models.[2]

Table **2** displays the fractional parameter d and the AR and MA terms obtained using Sowell's (1992) maximum likelihood estimator of various ARFIMA (p, d, q) specifications with all combinations of p, q $\leq$ 2, for each time series.

We observe from Table **3** that the estimates of d in GDP and RT-ESI are similar, being $d < 1$ in both cases. We observe that both time series have the same behaviour, finding mean reversion. Add that we cannot reject the I(1) hypothesis for the GDP time series. On the other hand, the behaviour of the ICC series differs from the others. There is lack of mean reversion and shocks are expected to be permanent, causing a change in trend. Thus, strong measures will be required by the authorities to recover the original trends.

5.3. FCVAR Model ($d \neq b$)

Next, the FCVAR model proposed by Johansen and Nielsen (2012), where the fractional integration and the classical CVAR model join is used in order to contrast the possible existence of persistence in the long run co-movements of the series. Table **4** summarizes the results of the FCVAR model.

Table 4. Results of the FCVAR Model

	d	**b**
Panel I: GDP, RT_ESI	d = 0.636 (0.000)	b = 0.636 (0.000)
Panel II: GDP, CCI	d = 1.554 (0.410)	b = 0.203 (0.247)
Panel III: GDP, CCI, RT_ESI	d = 0.938 (0.221)	b = 0.938 (0.345)

We follow the indications suggested by Jones, Nielsen and Popiel (2014) about the lag value (k = 3). Also, we consider deterministic components and cointegration rank (r) to get our results. We observe from Panel I and Panel III that the order of integration of the individual series are about 0.636 and 0.938, respectively while the reduction in the degree of integration in the cointegrating regression is exactly of the same magnitude, implying that the order of integration ($d - b$) = 0, which in turn implies I(0) cointegration errors. Thus, we cannot reject the hypothesis in which the error correction term shows short-run stationary behaviour and where the shock duration is short-lived.

These results are in line with those obtained using fractional integration.

6. CONCLUSIONS.

After reviewing the literature concerning leading indicators about the past and expected financial situation of households, the expected general economic situation, and the intentions to make major purchases, we have constructed a real time economic sentiment indicator (RT-ESI) for Spain, based on text mining and deep learning from Twitter and Google Trends that can anticipate GDP and household consumer behaviour.

As far as RT-ESI is concerned, we have used 12 variables, including those that represent emotions, expectations, and mood, according to the literature, along with real-time data, to construct our leading indicator, trying to improve the CCI capacity to anticipate GDP's turning points and trends.

We use fractional integration to analyse the statistical properties of the time series and to measure the degree of persistence. Also, we use a Fractional Cointegration VAR (FCVAR) model to analyse the long-term relationship of the time series.

The results obtained using fractional integration and the FCVAR model suggest that the GDP and RT-ESI are mean reverting implying that both time series show short-run stationary behaviour and the shocks will have temporary effects and will disappear by themselves in the long term.

[1] See Diebold and Rudebusch (1991), Hassler and Wolters (1994) and Lee and Schmidt (1996).
[2] A point of caution should be adopted here since the AIC and BIC may not necessarily be the best criteria for applications involving fractional models (Hosking, 1981).

This means that the impact of COVID on economic activity will be transitory, thus consumer sentiment based on RT-ESI and GDP will probably improve in the second semester of 2021. In addition, we can highlight that our RT-ESI works well enough to anticipate GDP trends, even more consistently than the CCI (see Table 2), not only because the higher release frequency (daily against monthly or quarterly), but also due to type of data exploited (RT-ESI uses massive data and CCI data from surveys).

This line of research can be developed in other European countries in order to assess the capacity of RT-ESI to replicate results. Furthermore, new API or data-sources could be used to evaluate the consistency of these outcomes.

CONFLICT OF INTEREST

The authors reported no potential conflict of interest.

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