ECONOMIC STATISTICS CENTRE OF EXCELLENCE

A COLLABORATION WITH Office for National Statistics

Real-time turning point indicators: Review of current international practices

Cyrille Lenoël and Garry Young

ESCoE Discussion Paper 2020-05

April 2020

ISSN 2515-4664

Real-time turning point indicators: Review of current international practices
Cyrille Lenoël and Garry Young
ESCoE Discussion Paper No. 2020-05
April 2020

Abstract

This paper presents the results of a survey that identifies real-time turning point indicators published by international statistical and economic institutions. It reports the evidence on past and present indicators used, the methodology underlying their construction and the way the indicators are presented. We find that business and consumer surveys are the most popular source of data and composite indicators like diffusion or first component are the most popular types of indicators. The use of novel databases, big data and machine learning has been limited so far but has a promising future.

Keywords: business cycles, turning points, recession, leading indicator, composite indicator, diffusion index, bridge model, Markow-switching model

JEL classification: C22, C25, C35, E32, E37

Cyrille Lenoël, National Institute of Economic and Social Research, c.lenoel@niesr.ac.uk and Garry Young, National Institute of Economic and Social Research, g.young@niesr.ac.uk.

Published by:
Economic Statistics Centre of Excellence
National Institute of Economic and Social Research
2 Dean Trench St
London SW1P 3HE
United Kingdom
www.escoe.ac.uk

ECONOMIC STATISTICS CENTRE OF EXCELLENCE

A COLLABORATION WITH Office for National Statistics

Real-time turning point indicators
Review of current international practices

Cyrille Lenoël[1] and Garry Young[2]

ESCoE and NIESR

Abstract

This paper presents the results of a survey that identifies real-time turning point indicators published by international statistical and economic institutions. It reports the evidence on past and present indicators used, the methodology underlying their construction and the way the indicators are presented. We find that business and consumer surveys are the most popular source of data and composite indicators like diffusion or first component are the most popular types of indicators. The use of novel databases, big data and machine learning has been limited so far but has a promising future.

JEL classification: C22, C25, C35, E32, E37

Keywords: business cycles, turning points, recession, leading indicator, composite indicator, diffusion index, bridge model, Markow-switching model

DISCUSSION PAPER

April 2020

.

[1] c.lenoel@niesr.ac.uk

[2] We are grateful to Andrew Walton, Louisa Nolan and Jeremy Rowe from the ONS, Amit Kara, Barry Naisbitt and Martin Weale from NIESR for their useful comments, and to the rest of the ESCoE and ONS staff who made this paper possible. We would also like to thank the institutions that responded to our survey. This research has been funded by the ONS as part of the research programme of the Economic Statistics Centre of Excellence (ESCoE).

Contents

1. Introduction

Spotting economic turning points early is important to decision makers who may have to adapt their policies when the economy turns, especially when their actions take time to work through the economy. What makes the identification of turning points in real-time particularly difficult is that economic data are collected and published with a delay – up to several months - which makes them less effective turning point indicators. Economists and market analysts instead often use surveys of business and households as leading indicators to supplement official economic data. The advent of big data has also made possible the use of real-time databases (like transport, online sales, spending with cards) that provide more up to date evidence on current trends in trade and wider economic activity.

The purpose of this study is to gather information on and classify some of the turning points indicators used around the world. This exercise was facilitated by an online survey sent to key statistical and economic agencies in other countries. It should be stressed that the purpose of the study is not to adjudicate on the performance of the various indicators, only to report on which are used and how they are presented.

In this survey, we took a somewhat larger definition of turning points than in the seminal work of Burns and Mitchell (1947). The latter defined the business cycle as follows: "a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions and revivals that merge into the expansion phase of the next cycle: this sequence of change is recurrent but not periodic". In our survey, we consider all the indicators that suggest a change in economic regime: not just from contraction to expansion and vice-versa, but more generally accelerations and decelerations associated with faster and lower growth regimes, irrespective of whether there is a change in sign in the growth rate or not. Turning points are defined as the transition points between those successive regimes.

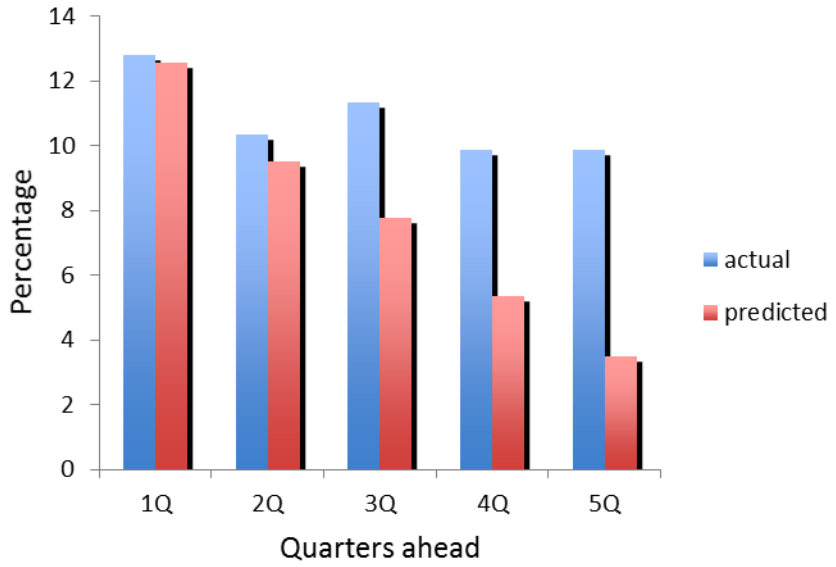
What is striking from the results of this survey is that the rapid expansion of data sources and improvement in forecasting methodology has not made predicting turning points in real-time much easier. A 'stylised fact' in the business cycle literature is that it is relatively more difficult to predict peaks than troughs of business cycles. In a study of 10 US economic analysts between 1948 and 1961, Fels and Hinshaw (1968) estimated that the analysts expected a trough with a probability of at least 50% as soon as 1 month *before* it happened, but the probability of a peak only reached 50% 3 months *after* the peak actually happened. In that period, the US economy experienced 4 recessions. Geoffrey Moore wrote in 1950: "If the user of statistical indicators could do no better than recognize contemporaneously the turns in general economic activity denoted by our reference dates, he would have a better record than most of his fellows."[3]

Close to 70 years later, it is difficult to argue that this is not the case anymore. Professional forecasters still find it difficult to identify turning points. For example, the Survey of Professional Forecasters (SPF), the oldest quarterly survey of macroeconomic forecasts in the United States, contains the forecasts of an average of 40 forecasters who forecast US GDP up to 5 quarters ahead, the first forecast being the one of the quarter of the survey. To focus specifically on peaks, we extract from the survey the forecasts for a decline in GDP between the latest quarter and 1 to 5 quarters ahead. In figure 1, we compare the proportion of the total forecasts predicting such a decline to how frequently such a decline in GDP actually occurred over the period between 1968Q4 and 2019Q3. If forecasters had a good understanding of the distribution of GDP growth process, one would expect the two measures to be close to each other on average: some forecasters predict

[3] Reprinted in Moore (1961), pp. 257-258.

downturns too frequently compared to what actually happens and others occasionally miss the downturns, but on average they should get the frequency of downturns roughly right. Figure 1 shows that forecasters have a good track record at forecasting the frequency of downturns one quarter ahead (we can call the one-quarter ahead forecast real time-time forecasting) but exhibit a widening forecast error the further ahead they try to forecast. The proportion of forecasts predicting a decline in GDP between the latest quarter and 5 quarters ahead is 3.5%, much lower than the frequency of 10% when such a decline occurred. This forecast error may reflect an optimism bias by the forecasters: they may think downturns are less frequent and, when they occur, that they won't be as severe as they turned out to be. Splitting the sample into periods of equal size does not show any reduction in the forecast bias, despite much more data being available for the forecasters and advancements in econometric methods.

Figure 1: Forecasters bias in predicting US GDP declines

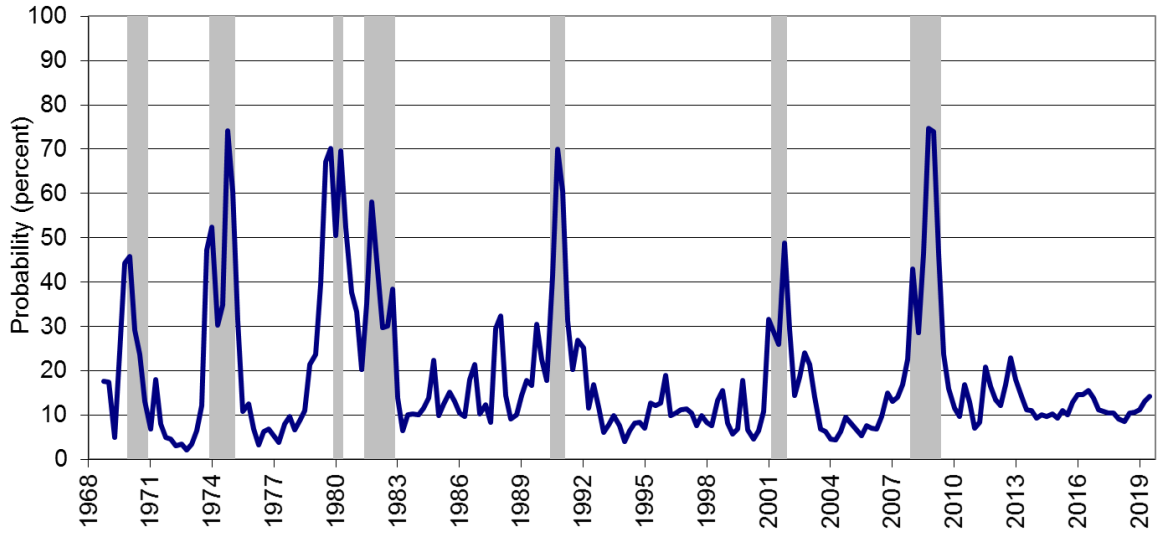


Note: Comparison of the proportion of all professional forecasts in the SPF survey predicting a decline in real GDP between the latest quarter and 1 to 5 quarters ahead, with how frequently such declines actually happened. Forecasts and GDP numbers are taken between 1968Q4 and 2019Q3.
Source: Survey of Professional Forecasters, US Bureau of Economic Analysis and authors' calculations

SPF survey respondents also provide their probabilities of a decline in real GDP one quarter ahead. Figure 2 is the average probability across all forecasters, referred to by the Philadelphia Fed as the "anxious index". One characteristics of this index is that it tends to go up significantly just before a recession begins, and as such it can be considered a useful contemporaneous turning point indicator.

In contrast to indicators based on the predictions of economic forecasters, which partly reflect the forecasters' judgement, our report focuses on data-based indicators that feed into those forecasts. The report is organised as follows. In section 2, we report on the survey of international organisations from other countries that we carried out and the high-level responses. In section 3, we summarise the existing literature on turning point methodologies. In section 4, we describe the composite turning-point indicators that were produced by the Central Statistical Office, the forerunner of the ONS. In section 5, we set out some of the different indicators that are released by organisations in other countries and how they are presented. In section 6, we conclude.

Figure 2: Anxious index (Source: Philadelphia Fed)



Note: Shaded areas represent recessions as defined by NBER.

2. Survey methodology and summary results

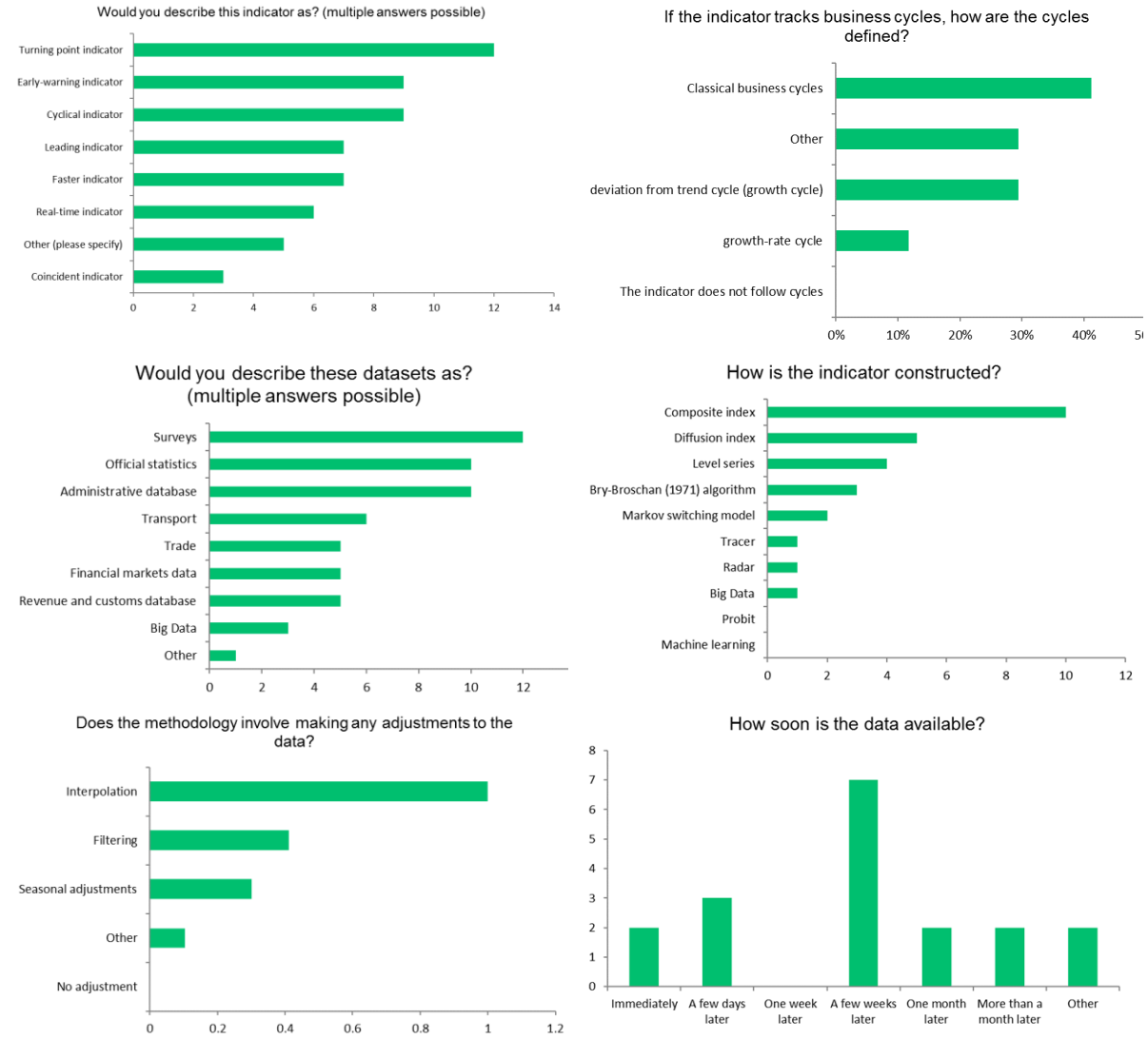
We sent an online questionnaire to a sample of leading international statistical and economic institutions about their use of real-time turning point indicators. If they used any, we asked in particular about the methodology, how long they have been using them, the challenges they had to overcome when producing those indicators and what feedback they had from users. We also asked them if they had done any quantitative analysis of the performance and reliability of those indicators. Each institution was allowed to respond with a maximum of five indicators, and the same set of questions was asked for each indicator. We then collected the results, followed up with direct questions if there were points to clarify, and presented the results in this report. The survey questions are attached as an appendix to this report.

The survey questions were agreed in advance with ONS colleagues who also provided information on contacts in other statistical offices who might be asked to complete the survey. The survey was sent to 11 institutions, and we received answers from 9 of them: four national statistics offices (CBS from the Netherlands, INSEE from France, ONS from the United Kingdom and Instituto Nacional de Estadística y Geografía from Mexico), two international organisations (European Commission and OECD), one central bank (Federal Reserve, United States), one bank (DZ Bank, Germany) and another private institution (The Conference Board). Two central banks didn't respond on time (Bank of England and European Central Bank).

Figure 3 presents some summary statistics about the responses. We can highlight already a few interesting points. The first point is that surveys seem to be the most popular source of data for leading indicators. For example, surveys asking business managers about their order books and production plans have proved very useful leading indicators. The use of novel databases, big data and machine learning seems not to be widespread yet, despite its publicity and promising prospects. It may be because such methods are still in the development stage and have not yet reached the large production scale that could be expected eventually. Evidence for this is that the indicators developed by the ONS using innovative data and methodology are still considered "experimental" and "research output" and it will probably still be some time before such indicators are integrated in the standard suite of ONS outputs.

The second point is that composite indicators are the most popular type of turning point indicators. Composite indicators allow the use of information from different data sources to extract common trends and reduce the volatility of the underlying data. While the ONS has produced diffusion indices (a type of composite index) for example for the VAT returns data, it hasn't produced a summary indicator like that constructed by The Conference Board in the United States and this is one area the ONS could possibly develop to show how its innovative series can be used in practice. One downside however of summary indicators is that they tend to ignore the dispersion of the indicators, and the appropriate weighting method for combining indicators may be time/economic shock varying. Actually, the predecessor of the ONS, the Central Statistics Office (CSO) used to publish a suite of cyclical indicators, including leading indices, but those were discontinued, as explained in chapter 4.

Figure 3: Survey summary results



The various types of indicators used by different institutions are summarised in Table 1. These are described more fully in section 5.

Table 1: Survey results: turning point indicators

Institution	Indicator	Methodology
CBS	Business Cycle Tracer	2D representation
CBS	Business Cycle Tracer Indicator	Composite unweighted average of normalized and detrended components
CBS	Economic Radar	Radar representation
INSEE	Indicator of economic reversal	Markov switching dynamic model
DZ Bank	Euro-Indicator	TCB (composite index with components chosen by econometric analysis)
OECD	Composite Lead Indicators	TCB (composite index with components chosen by econometric analysis)
TCB	Leading Economic Indicator	Equally weighted average of (standardized) component contributions
European Commission	Economic Sentiment Indicator	Weighted average of confidence indicators in each sector
European Commission	Economic Sentiment Indicator Radar	Radar representation of ESI
European Commission	Economic Climate Indicator	Principal component analysis
European Commission	Economic Climate Indicator Tracer	2D representation of ECI
ONS	VAT Diffusion index	Diffusion index
ONS	VAT Returns behaviour	Level time-series
ONS	shipping indicators	Level time-series
ONS	road traffic	Level time-series

3. Turning point methodologies: literature review

Hamilton (2011) wrote a survey of the academic literature on identifying business cycle peaks. He highlighted why it is difficult to identify turning points in real-time. While the key determinants of long-term economic growth are generally identified to be population, capital and technology, there is much less consensus on what the drivers of short-term fluctuations in business activity could be. Recessions have been caused by financial crises, housing market crises, war or aggressive monetary or fiscal policy. Without an economic model incorporating such channels, it is necessary to rely on statistical inference and such models typically only work well if the next recession looks like the previous ones.

Business cycle analysis has a long history at the National Bureau of Economic Research (NBER) in the US (Ozyildirim, 2017). The indicator approach to business cycle analysis and forecasting was originated in the 1930s with the work of Arthur Burns and Wesley Mitchell. Mitchell and Burns (1938) screened for indicators that would ideally have 5 characteristics: (1) long-enough time-series (2) constant lead time to the reference series (3) smooth series (4) easily recognizable cyclical movements and (5) have a plausible economic explanation why it would be related to the business cycle. They called the indicators that best matched those characteristics: “indicators of cyclical revivals”.

A very simple and popular leading indicator of recessions is an **inversion of the yield curve**. Recessions have often been associated with the yield curve moving from a positive to a negative slope. A positive slope of the yield curve comes from the fact that investors require a premium for holding longer maturity bonds (the term premium) or expect the short-term rates to be higher in the

future. A negative slope is a more unusual event – it has occurred less than 10 per cent of the time in the US in the past 65 years – reflecting the fact that the economy is probably in a transitory phase and this period may signal that a recession is likely to happen soon.

Researchers from the Federal Reserve, in particular Arturo Estrella, played a large role in developing the literature on the predicting power of the yield curve. Laurent (1988) and Estrella and Hardouvelis (1991) first showed that the spread in yield between longer-dated Treasury notes and shortdated T-bills could help predict future real GNP growth. Harvey (1988) and Estrella and Hardouvelis found that the yield spread can also be used to help forecast other economic variables such as consumption and investment growth. Comparing the role of the yield spread to other financial and economic indicators, Estrella and Mishkin (1998) concluded that while stock market and Stock-Watson (1989) indicators have good predictive power in forecasting recessions one quarter ahead, the yield spread dominates at longer time-horizons, in particular one year ahead. International evidence is however more mixed than for the United States; Chinn and Kucko (2015) found that the yield spread performed relatively well predicting recessions in Germany and Canada but it performed less well in Japan and Italy. Lenoel (2018) discussed whether quantitative easing and the zero-lower bound may have reduced the ability of the yield curve to predict recessions in the US.

Stock and Watson (1989) made a significant contribution to business cycle analysis by providing a formal framework for defining **coincident and leading indicators**, as well as defining one of the first **recession indices**. Their model formalized the popular idea that the reference cycle was best measured by looking at co-movements across several aggregate time series. Their proposed Coincident Economic Index (CEI) was an estimate of the value of a single unobserved variable, also called dynamic factor, supposed to represent the state of the economy in the business cycle. Any movement in a particular coincident series, such as industrial production, might thus be decomposed into movements of the dynamic factor plus an idiosyncratic component. Stock and Watson defined a Recession Index as an estimate of the probability that the dynamic factor would decline for at least 6 consecutive months.

Composite leading indicators were also developed outside the US for European and other countries. Carstensen et al (2003) compared how different composite leading indicators performed at predicting euro area industrial production for different forecast horizons. They used different tests of model performance, including Diebold-Mariano (1995). They found for 1-month ahead forecasts, the European Commission business climate indicator and the OECD composite leading indicator performed well, for 6-month forecast the OECD composite leading indicator performed very well, and for 12-month forecasts the DZ Bank Euro indicator was the only one composite indicator that could beat the benchmark AR(1) model.

Bridge models combine the quarterly data from the national statistics with monthly data produced early in order to produce a nowcast of GDP one or two quarters ahead. Two examples of bridge models are Mogliani et al (2017) who use a mixed-frequency model (MIBA) to forecast French GDP with business surveys and Baffigi et al (2004) who forecast euro area GDP with business surveys. A slightly more elaborate method of combining mixed frequency data is explained in Giannonne et al (2008): the authors defined a **dynamic factor model with mixed frequency**. The European Commission **climate indicators** are also defined using principal components. The advantage of factor models is that they formalize the definition of business cycles as defined by an underlying trend that pushes a large range of economic indicators all in the same direction.

Armesto Engemann and Owyang (2010) compared the performance of mixed frequency models to forecast GDP, inflation and employment in the US and found that while MIDAS based models

sometimes performed better than more simple models, averaging higher frequency data sometimes gave as good results.

A distinctive set of turning point models are based on **regime-switching**. Neftçi (1982) defined a sequential probability model, where the probability of a turning point is calculated sequentially using current information together with the previously estimated posterior probability. Neftçi tested his model on the US index on leading indicators for the period from 1971 to 1975 and found that it predicted recessions more accurately than the heuristic rule of three consecutive declines in the index. Artis et al (1995) used among other methods Neftçi's model to evaluate the ability of the CSO leading indicators to predict turning points. Hamilton (1989) generalized Neftçi's model by modelling regime switches by a **discrete-state Markov process**. The paper proposed an algorithm for drawing probabilistic inference of when the discrete shifts occur in the form of a nonlinear iterative filter. The idea behind the model was to view business cycles as successive periods of expansions and contractions, rather than cyclical deviations from trend growth. Or more simply-put, the approach tried to account for the fact that the parameters of an econometric model are not constant over time.

With new and large databases being increasingly available, the opportunity has arisen se to use **big data** and **machine learning** techniques to predict economic turning points and a new strand of research has blossomed.[4] With a large number of regressors, standard techniques such as ordinary least squares, maximum likelihood, or Bayesian inference with uninformative priors magnify estimation uncertainty and produce inaccurate out-of-sample predictions. As a consequence, inference methods aimed at dealing with this curse of dimensionality have become increasingly popular. These methodologies can be divided into two broad classes as explained by Giannone Lenza and Primiceri (2018). **Sparse modelling** focus on selecting a small set of explanatory variables with the highest predictive power. Lasso is an example. Alternatively, **dense modelling** recognizes that all possible explanatory variables might be important for predicting, and it tries to assign a weight to each of them, even if their individual impact might be small. Dense modelling uses shrinkage or regularization techniques, which prevent overfitting by forcing parameter estimates to be small when sample information is weak. Factor analysis or ridge regressions are standard examples of dense statistical modelling.

For example, Buckles et al (2018) showed using big data that aggregate fertility tended to be a leading indicator of recessions in the US: the growth rate for conceptions generally begins to fall several quarters prior to economic decline. At the Federal Reserve Bank of Chicago, Brave, Butters and Kelley (2019) extended the Chicago Fed National Activity Index (CFNAI) to define what they called a "big data" index of US economic activity using a technique called **collapsed dynamic factor analysis** (Bräuning and Koopman, 2014) to aggregate around 500 macroeconomic time-series.

Bonham et al (2018) from the Data Science Campus at the ONS analysed port and shipping operations using big data from AIS and CERS. They successfully developed a machine learning model to classify the behaviour of ships and used it to predict ship delays at port arrival. While this model is interesting in its own right, what is even more interesting is how such models could be extended. Bonham et al (2018) wrote that "the AIS and CERS data could be used to explore, understand and capture these relationships between GDP and freight transport volumes. **Supervised machine learning techniques** could then be applied to produce early indicators of GDP and support GDP based decision-making in the period between formal quarterly releases."

[4] For instance, a large number of presentations at the International Statistics Institute World Statistics Congress in August 2019 dealt with Big Data. https://www.isi2019.org/scientific-programme-2/

Gogas et al (2015) used a machine-learning technique - **support vector machines** - to improve the predictions of recessions using the yield curve. They found that their model gave statistically more significant results than the standard probit model. Raihan (2017) did a similar exercise using **Dynamic Time Warping**, a technique often used in speech recognition. Ng (2014) and Berge (2015) used **boosting algorithms** to predict recessions with leading indicators. Nyman and Ormerod (2017) used a random forest approach to forecast recessions with financial market data. Junoh (2004) also found that using **neural networks** to forecast Malaysian GDP growth in Malysia showed promising results.

One of the most challenging features of predicting turning points is how to deal with data revisions. As most of official statistics are made of surveys and self-reported revenues by households, businesses and other entities, the statistics are often revised as more data becomes available and errors and omissions are dealt with by reconciliation. The revisions don't only occur in the following weeks or months following the first publication of a statistics, but also sometimes in the following years. This fact makes the business of forecasting akin to trying to aim at a moving target, without ever knowing if you really hit it. Kara and Galvao (2019) consider the impact of **GDP data revisions** on predicting turning points for the UK. The find for example that a peak identified in 2011Q3 suggesting a recession in late 2011/early 2012 vanishes as data revisions are incorporated later on. They suggest instead looking at a wider range of monthly statistics and indicators to predict the business cycle phase in real-time.

4. The CSO/ONS system of cyclical indicators for the UK

The first monthly index of business activity for the UK was published by The Economist in 1934 (see Crowther, 1934). Compared to similar indices published by US newspapers (like the weekly index of economic activity published by the New York Times), the Economist index was not mainly tracking industrial activity, but aggregate real income. It was a composite index of initially 18 component series, including measures of railway, motor, postal and financial activity to cover a wide spectrum of activities. In 1937 Rhodes (Rhodes, 1937) showed that the first principal component could be used to produce the indicator and that his new indicator was less volatile. A milestone was achieved in 1975 when D.J. O'Dea produced a comprehensive analysis of the cyclical indicators for the UK in the Post-war era (O'Dea, 1975). Following on Burns and Mitchell methodology, O'Dea established a business cycle chronology, timing relationship between cyclically-sensitive indicator series and applied those indicators to forecasting. The indicators defined by O'Dea were focused on identifying turning points in production, investment and unemployment.

The predecessor of the ONS, the Central Statistical Office (CSO), subsequently published at a regular frequency a suite of cyclical indicators and their composite indices. The methodology of constructing the composite indices was described in CSO (1983) and was derived from the work of Burns and Mitchell at the NBER and O'Dea at NIESR. Each component series was detrended, smoothed and rescaled. The indices were computed as the equally weighted sum of their constituent series. When some data was missing for some constituents' series, it was estimated. The underlying cycle was given by a five-year moving average since this was taken to represent the length of the cycle.

Table 1 gives the constituents of the leading, coincident and lagging indicators as they were published in May 1976. Two things may surprise the modern economic statistician. One is that GDP entered the roughly coincident indicator in its three calculated forms (expenditure, input and income approaches), apparently to give it more weight in the index and average out any statistical discrepancies. Another one is that orders and investments were considered lagging indicators.

Table 2: CSO composite indicators constituents in May 1976

Longer leading indicators	Rate of interest, 3m prime banks bills Net acquisition of financial assets, industrial and commercial companies Total dwellings started, Great Britain Financial Times 500-shares index
Shorter leading indicators	New credit extended by finance houses and retailers New car registrations Bankruptcies: total for England and Wales Wages and salaries per unit output, manufacturing industries Gross trading profits of companies, excluding stock appreciation
Roughly coincident indicators	GDP (expenditure & output & income approaches) Index of volume of retail sales Index of production, manufacturing industry CBI capacity utilisation index
Lagging indicators	Unemployed, excluding school-leavers and adult students, Great Britain Vacancies notified to employment offices Investment in plant and machinery, manufacturing industry Engineering industries, volume index of orders on hand Level of manufacturing stocks and work in progress

Source: CSO (1976)

CSO (1983) assessed the performance of the indicators and concluded that they performed well at anticipating and tracking the end of the 1979-1981 recession in the UK. Artis et al (1995) evaluated the performance of the shorter and longer leading indicators to forecast turning points. They found using data from 1957 to 1992 that "the CSO leading indicators contain[ed] important predictive information", in particular the longer leading composite indicator, that was composed of four financial and economic variables, tended to lead turning points by 4 to 6 months.

However, there were several concerns with the methodology that led the ONS to stop publishing this suite of indicators in 1997. One issue was that the indicators needed to be reviewed on a regular basis: an indicator that gave an early signal ahead of one recession may not work so well ahead of another recession if the nature of the recession is different. Another issue highlighted by Yeend (1998) in its review of the indicators was that "the implicit assumption of a fixed five-year cycle to calculate the trend could be misleading if the latest cycle [was] atypical." A third criticism raised by Salazar et al (1997) was that the focus on the business cycle as an abstract concept could appear as a source of confusion because it is not well-defined and suggested instead to focus on GDP cycles.

If composite cyclical indicators were to be revived by the ONS, it would have to make use of the latest methodological advances, and therefore would probably be quite different from the one published previously. The purpose of this review is precisely to define which methodology for constructing turning point indicators is most popular and/or promising.

5. Detailed survey results

This section provides summary information on the various turning point indicators used by different agencies, including some description of how they are presented.

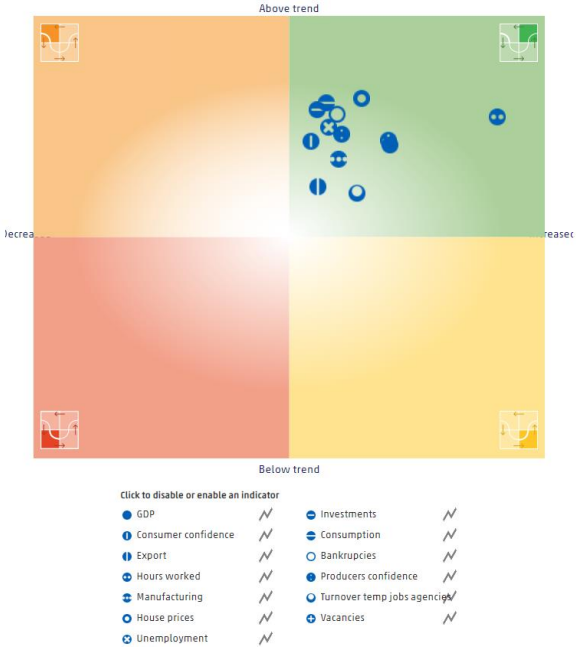
5.1. CBS Business cycle tracer

Statistics Netherlands' Business cycle tracer[5] is a graphical representation of the current state of the economy in two dimensions: deviation from trend and direction of change. A range of indicators from GDP to consumer confidence and investments are plotted. "The various series are normalized and detrended after which the coordinates of each data point is calculated with short term change and distance to the long-term average." The Business cycle tracer is displayed in figure 4 for September 2011 when the Netherlands' economy was in a state of recession and in figure 5 for April 2017 when the economy experienced robust growth. One can clearly see that the dots gather in the lower left quadrant during the downturn and the upper left quadrant during above trend growth.[6] The tracer concept has proved popular and is used by a lot of statistical institutes in the world, including South Africa, Singapore, Korea, D-Statis, IBGE (Brazil) and Australia.

"The data comes from various official statistics, each with their own data collection and processing. The value added of the indicator is in 1) extracting the business cycle component, 2) combining short term development with the long term 'position' and 3) using a combination of leading, lagging and coincident components so that a more or less real-time overall picture arises"

Figure 4: Business Cycle Tracer September 2011
(Source: Statistics Netherlands)

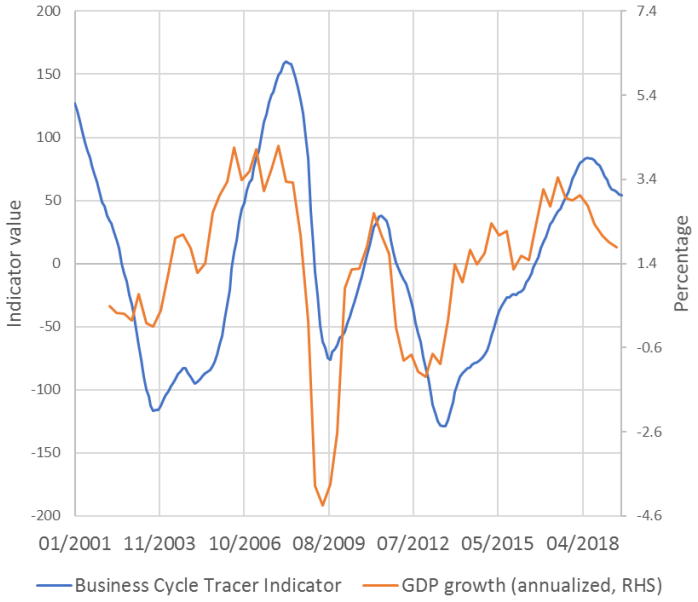
Figure 5: Business Cycle Tracer April 2017
(Source: Statistics Netherlands)



There is also a summary indicator called "Business Cycle Tracer indicator"[7] that is constructed as the unweighted average of the individual indicators in the CBS Business Cycle Tracer. The indicator is updated every month and adjusted in retrospect (end-time) based on the most recent information. The Business Cycle Tracer however shows real-time data. As 6 shows, the indicator tracks rather closely annualized GDP growth, and therefore the business cycle.

[5] Available at https://www.cbs.nl/en-gb/visualisaties/business-cycle-tracer
[6] The tracer is very well explained in a video at https://www.youtube.com/watch?v=5eN7A154FVI
[7] Available at https://www.cbs.nl/en-gb/visualisaties/business-cycle-tracer-indicator

Figure 6: Business Cycle Tracer Indicator (Source: CBS, author's calculations)



Note: 1.4% is the average annualized GDP growth rate over the sample period

Coverage:
"the indicator is widely used by various groups of users; the press releases and news articles are used by various newspapers and other news channels. Internationally, the approach was taken over by among others . Eurostat and the OECD"

The main characteristics of the indicator are summarised in table 3.

Table 3: Index summary card: Business Cycle Tracer indicator

Provider	CBS
Index name	Business Cycle Tracer indicator
Frequency	Monthly
Description	Faster indicator Turning point indicator Cyclical indicator
Dataset	Administrative database Surveys Official statistics
Methodology	Diffusion index Composite index
Adjustments	Filtering Seasonal adjustments
Reference series	business cycle
Business cycle definition	deviation from trend cycle (growth cycle)
Lag with the reference series	Coincident
Composite method	unweighted average
Frequency of review	annually

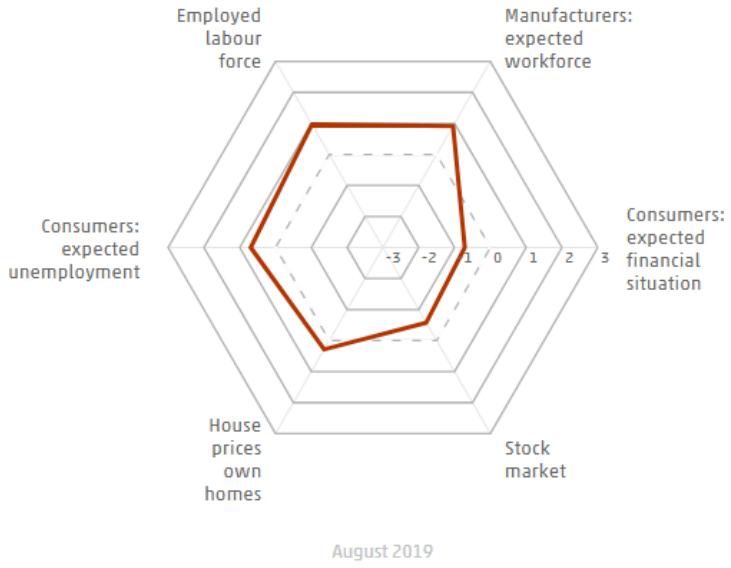
5.2. CBS Economic radars

The radars show the recent development of the main drivers behind important variables such as household consumption, investment and exports and shows whether these drivers are below or above their long-term level. The driver indicators are selected on the basis of economic theory, experience and empirical results, as explained in van Ruth (2010). Figure 7 shows the radar for household consumption. A more detailed explanation for the radars can be found on the website.[8] Indicators with low correlation or long lags are eliminated. The remaining indicators were entered one by one in an ARMA process with the target indicator to test their explanatory power. Explanatory indicators that lagged the target indicator, that had the wrong sign or that had little explanatory power were disposed of. The final phase of the development process consisted of analysing the remaining over indicators as a set, with the aim of making sure that the movement of the set was coincident and consistent with the target indicator. Indicators which exhibited very different behaviour from the rest of the indicators were removed. The final selection process was that smooth and monthly indicators were preferred to indicators with lower frequency or more erratic dynamics.

The radar illustrates the fact that household consumption is influenced by household expectations, developments in the labour market and developments in asset prices. “In the radar, the zero line is marked as a dark dotted line. The figure is divided into bands coloured from dark to light. The darker the band in which the indicator is located, the less favourable circumstances are for household consumption”. The radar can be used dynamically online to allow users to see at a glance which indicators show a positive picture, and which a more unfavourable picture. By moving the slide on the time bar, which runs from 2002 up to date, users can select previous months. “This makes it possible to see whether circumstances for Dutch household consumption have become more or less favourable, and which factors were significant in these developments.”

The radar methodology is explained in van Ruth (2010).

Figure 7: Household consumption radar (Source: Statistics Netherlands)



[8] https://www.cbs.nl/-/media/_pdf/2016/00/2011toelichtinginvesteringsradarengels.pdf
https://www.cbs.nl/-/media/_pdf/2016/00/exportradarexplanatorynotes.pdf
https://www.cbs.nl/-/media/_pdf/2016/00/2010toelichtingconsumptieradarengels.pdf

Table 4: Index summary card: Economic radar

Provider	CBS
Index name	{Exports / Investment / Household consumption} radar
Frequency	Monthly
Description	Other
Dataset	Administrative database Surveys Financial markets data Official statistics
Adjustments	Filtering Seasonal adjustments
Reference series	Investment, Household Consumption and Exports
Methodology	Other
Business cycle definition	n/a
Lag with the reference series	Coincident
Composite method	unweighted average
Frequency of review	annually

5.3. DZ Bank's Euro-Indicator

German bank DZ Bank publishes the Euro-Indicator[9] (previously known as FAZ Euro indicator when it was published in the Frankfurter Allgemeine newspaper). It is a monthly composite index of Euro-area economic situation built from 9 components that are supposed to be leading indicators: new job vacancies, order entries, Markit purchasing manager´s index (PMI), building and planning permissions, production expectations(EU Commission survey), interest rate spread, consumer confidence, Morgan Stanley- Capital-International Index (EMU) and real money growth (M3). The methodology is similar to how The Conference Board produces its composite leading indicators[10]: (1) compute month-to-month changes of the components (2) standardize the changes to equalize the volatility of each component (3) sum up the adjusted month-to-month changes and remove the long-term trend of the target index (4) from the trend-adjusted growth rate of the index, build the new level of the index.

The Euro-Indicator is supposed to track Euro-area GDP growth (figure 8) and Dr Michael Holstein, Economist at DZ Bank, writes that it typically leads the official statistics by 3 months. Empirical work by Carstensen et al (2011) shows that the Euro-indicator is a relevant leading indicator to forecast industrial production several months ahead.

[9] https://www.dzbank.com/content/dzbank_com/en/home/link_research/uebersicht-neu.html
[10] The methodology is described here https://www.conference-board.org/data/bci/index.cfm?id=2155

Figure 8: DZ Bank Euro-Indicator and Euro area GDP growth (Source: DZ Bank, Eurostat)

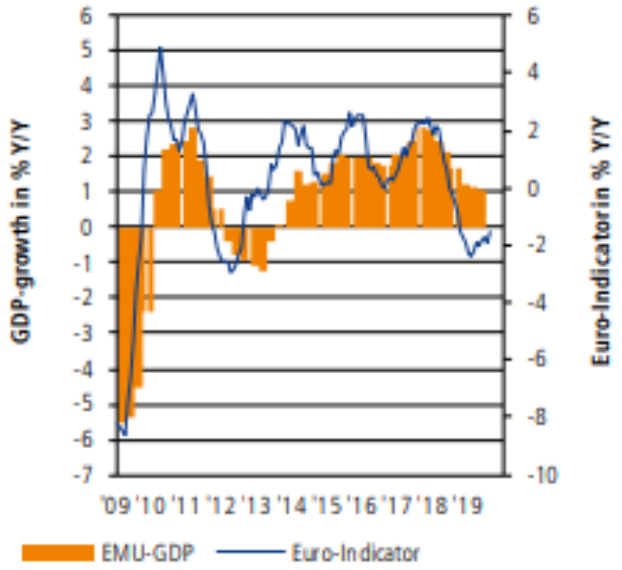


Table 5: Index summary card: DZ Bank Euro-Indicator

Provider	DZ Bank
Index name	DZ Euro-Indicator
Description	Leading indicator Turning point indicator
Dataset	Surveys Financial markets data Official statistics
Construction methodology	Composite index (like Conference Board CLI)
Adjustments	Seasonal adjustments
Frequency of publication	Monthly
Reference series	GDP, business cycle
Business cycle definition	Classical business cycles
Lag with the reference series	Coincident
Composite method	weighted sum
Frequency of review	annually

5.4. European Commission Economic Sentiment Indicator

The European Commission Economic Sentiment Indicator (ESI)[11] is a composite index built from the results of a pan-European Business and Consumer Survey.[12] This ESI dates back to 1985 and the survey to 1961. One of the main benefits of this survey is that its harmonized process makes cross-country comparisons possible and straight-forward. European Commission (2019) writes in its introduction that "Business and 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. Surveys are therefore a key complement to official statistics, which are often available after long delays. The survey data generated within the

[11] Available to download at https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en

[12] The methodology of the survey is described in European Commission (2019)

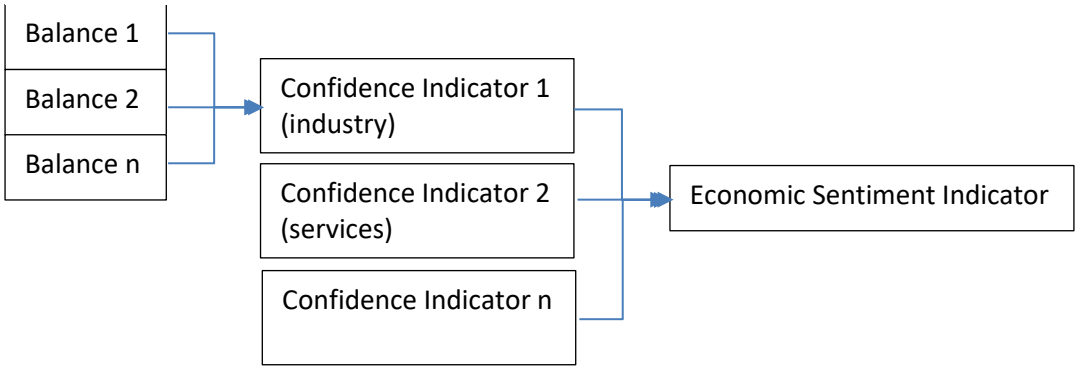
framework of the Joint Harmonised EU Programme of Business and Consumer Surveys are particularly useful for monitoring economic developments at Member State, EU and euro-area level. High frequency, timeliness and continuous harmonisation are among their main qualities."

The survey is run in a decentralized way, by statistical institutes in each member country. DG ECFIN then aggregates the results and builds composite indicators like the ESI to track cyclical movements in a specific sector or in the economy as a whole. Initially the survey covered only the manufacturing sector, but it has since then been expanded to the construction sector and investment plans in the manufacturing sector in 1966, to consumers in 1972, to retail trade in 1984, and to the services sector in 1996. Since 2007, the Commission conducts a survey in the financial services sector at EU and euro-area level. Meanwhile, the geographical coverage of the survey has been regularly extended to include all EU member States as well as candidate countries, reaching a total of 33 countries.

Figure 9: European Commission Euro area Economic Sentiment Index

The ESI is constructed in three steps, as illustrated in figure 10. First, survey answers are added in the form of balances, which are defined as the difference between the percentages of respondents giving positive and negative replies, aggregated across EU or Euro-area and seasonally-adjusted using the Dainties algorithm. Second, Confidence Indicators are computed for the five main surveyed sectors (industry, services, consumers, construction and retail trade) by arithmetic mean of the most relevant balances in each sector. These indicators are supposed to provide information on economic developments in the different sectors. Third, the ESI is constructed as the weighted average of the standardized Confidence Indicators and scaled to a long-term mean of 100 and a standard deviation of 10. The weights of each sector in the ESI are industry (40%) , services (30%) , consumers (20%) , construction (5%) and retail trade (5%). The weights have been determined according to two criteria, namely "representativeness" of the sector in question and tracking performance vis-à-vis the reference variable (assumed to be GDP growth in EU and Euro-area). The ESI is published every month, generally two working days before the end of the month, and 3 days after the data from the surveys are received from the national institutes.

Figure 10: Economic Sentiment Indicator construction diagram



The ESI was designed to be a coincident indicator of economic activity in the EU and Euro-area. As such, it can be compared to GDP growth to check if it has explanatory power in real-time. One method used by the European Commission to represent the ESI and its components is with a radar. The radar is a visual representation along 6 axes of the current state of the economy. The values for the 5 confidence indicators are displayed along the axes t, and the value of the ESI is displayed on the sixth axis. The choice of displaying the summary ESI index inside the same radar as its components is however debatable as the information content of the ESI index is already contained in the other axis.

Figure 11: European Commission Euro-area radar

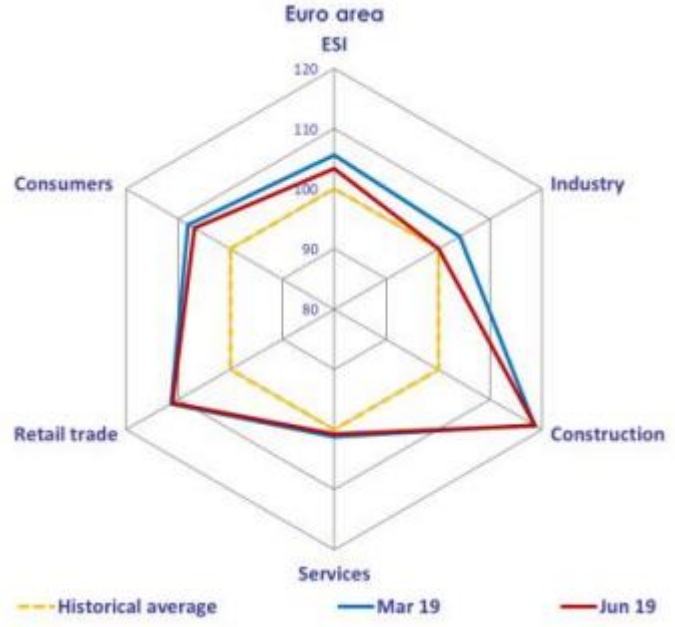


Table 6: European Commission confidence indicators and their reference series

Confidence indicators	Reference series (volume/year-on-year growth rates)
Total economy (ESI)	GDP, seasonally- and calendar-adjusted
Industry	Industrial production, working day-adjusted
Services	Gross value added for the private services sector, seasonally- and calendar-adjusted
Consumption	Household and NPISH final consumption expenditure, seasonally- and calendar-adjusted
Retail	Household and NPISH final consumption expenditure, seasonally- and calendar-adjusted
Building	Production index for building and civil engineering, trend-cycle component

Source: European Business Cycle Indicators, 2nd Quarter 2019, Technical Paper 033, July 2019

The survey results are used by DG ECFIN for economic analysis, surveillance and short-term forecasting. Outside the Commission, the ECB, central banks, research institutes and financial institutions frequently use the EU survey data for both qualitative and quantitative analysis.

Table 7: Index summary card: EC Economic Sentiment Indicator

Provider	European Commission
Index name	Economic Sentiment Indicator
Description	Coincident indicator
Dataset	Surveys
Construction methodology	Composite index
Adjustments	Seasonal adjustments Standardisation
Frequency of publication	Monthly
Reference series	GDP
Business cycle definition	Growth-rate cycle
Lag with the reference series	Coincident
Composite method	Weighted average
Frequency of review	Each 5 or 10 years we test if the questions entering the confidence indicators are still the best. For example, one year ago we change the composition of the Consumer confidence indicator (see special topic of the 2018Q2 EBCI, https://ec.europa.eu/info/publications/economy-finance/european-business-cycle-indicators-2nd-quarter-2018_en)

5.5. European Commission Economic Climate Indicator

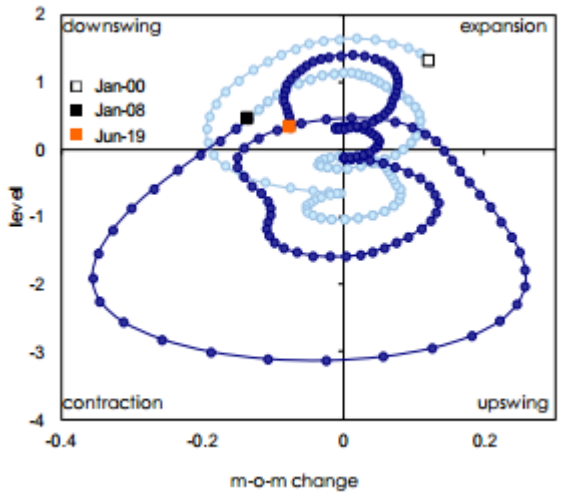
The European Commission also produces a complementary suite of business cycle indicators based on **principal component analysis** methodology. The aggregate index is called the Economic Climate Index (ECI). The methodology is similar to the Economic Sentiment index methodology except that it is the principal component rather than the arithmetic average that is used to aggregate series.

Economic climate indicators are built for the 5 economic sectors from the principal component of survey balances in those sectors. The aggregate economic climate indicator (ECI) is a weighted

average of the sectors, using the same weights as the ESI. One further difference with the ESI methodology is that all climate indicators are smoothed using the HP filter in order to eliminate short-term fluctuations of a period of less than 18 months. The smoothed series are then normalised (zero mean and unit standard deviation).

The Climate tracer is a visual representation of the ECI where the ECI is plotted against its first differences (figure 12). The four quadrants of the graph, corresponding to the four business cycle phases, are crossed in an anticlockwise movement and can be described as: above average and increasing (top right, 'expansion'), above average but decreasing (top left, 'downswing'), below average and decreasing (bottom left, 'contraction') and below average but increasing (bottom right, 'upswing'). Cyclical peaks are positioned in the top centre of the graph and troughs in the bottom centre. In order to make the graphs more readable, two colours have been used for the tracer. The darker line shows developments in the current cycle, which in the EU and euro area roughly started in January 2008.

Figure 12: European Commission Euro area Climate tracer

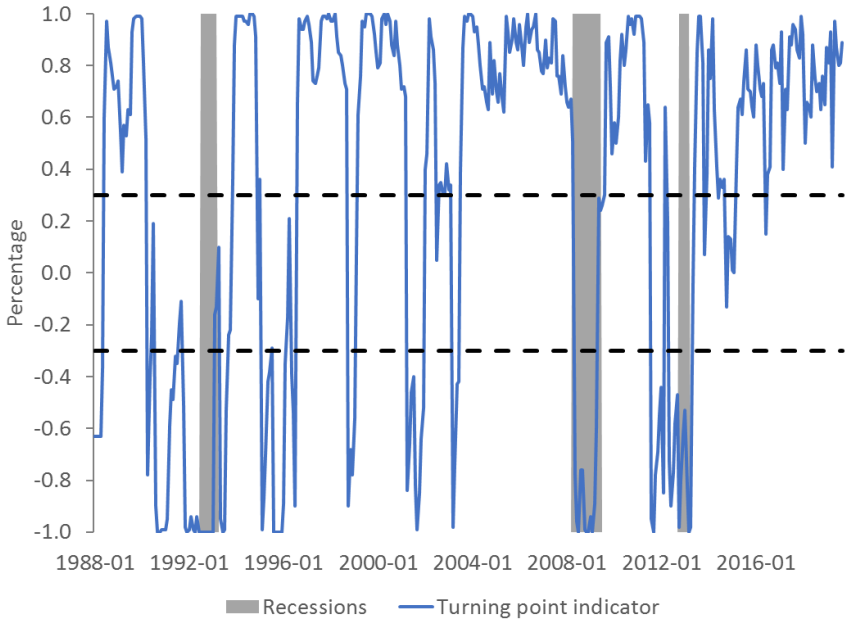


5.6. INSEE's turning point indicators

The French statistics office, INSEE, has developed an indicator[13] to identify in real-time if the French economy's overall situation is about to change, based on different outlook surveys published internally. The indicator is published once a month. It does not directly track reversal in GDP growth but can be compared to a statistical extraction of the cycle of GDP (obtained by Christiano Fitzgerald filter). This indicator ranges from -1 to 1. Changes of signs of the indicator indicate that the economy is likely to be in reversal. When the indicator is close to +1 (resp. –1), it shows a favourable business climate (resp. unfavourable). The area between –0.3 and +0.3 is considered as uncertain business climate. Figure 13 compares the indicator with the periods of recessions. There exists no official committee in France for dating business cycles – like the NBER in the US - , so we used computed the peaks and troughs using Bry-Boschan (1971) methodology. One can see that for the last 3 recessions, the indicator turned very negative ahead of 2 of those recessions (1992-1993 and 2012-2013) but turned only contemporaneously in the 2008-2009 recession. Another apparent feature of the indicator is that it occasionally turns negative even when there is no recession, but just slower growth periods, like it did in the period between 1995 and 2003.

[13] available at https://www.insee.fr/en/statistiques/serie/001565531

Figure 13: Turning point indicator for France (Source: INSEE and authors' calculations)



Note: Recessions were computed with the Bry-Boschan (1971) methodology

The methodology is based on Markov switching dynamic model like Hamilton (1989) and is explained in Gregoir and Lenglart (2000). The indicator uses some balances of opinion in the sectors of industry manufacturing, building construction, services. Each balance of opinion is modelled with an AR process. The series which are then considered are the sign (+1 or -1) of the innovations. As it uses Markov chain, the model takes into account its dynamics. And as the model is founded on unobserved states, the indicator involves unobserved components.

Such a reversal indicator can be used in combination with a business climate index: the business climate gives a quantitative assessment of the situation, whereas the reversal index indicates if the situation is likely to be reversed.

Similar indicators have been developed for reversals in more specific sectors of the economy, like services (Ast, 2010), construction and industrial sectors. A further indicator focuses on the Euro area (Baron and Baron, 2002).

Table 8: Index summary card: Turning point indicator

Provider	INSEE
Index name	{Whole economy / Services / Industry / Construction / Wholesale trade} turning point indicator
Description	Turning point indicator Cyclical indicator
Dataset	Surveys
Construction methodology	Markov switching dynamic model like Hamilton (1989)
Adjustments	Seasonal adjustments
Frequency of publication	Monthly
Reference series	GDP or output in a specific sector
Business cycle definition	deviation from trend cycle
Lag with the reference series	Coincident

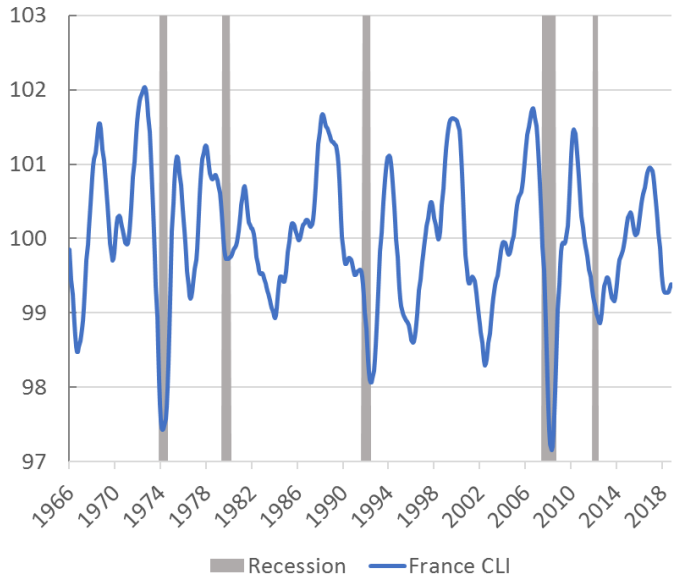
Composite method	The indicator uses some balances of opinion in the sectors of industry manufacturing, building construction, services. Each balance of opinion is modeled with an AR process. The series which are the considered are the sign (+1 or -1) of the innovations. As we use Markov chain, we can consider its dynamic. As the model is funded on unobserved states, the indicator involves unobserved components.
Frequency of review	annually

5.7. OECD Composite Leading Indicator

The first OECD Composite Leading Indicators (CLIs) were developed in the early 1970s with the aim of providing "qualitative indicators of the business cycle outlook for the short-term future".[14] The methodology is derived from NBER/The Conference Board Leading Economic Indicators (paragraph 5.11) and is described in Astolfi et al (2017). Candidate component series are chosen from a long list of series for each country, and are selected based on their economic relevance, correlation with the reference series, timeliness, typical lag and frequency of publication to name a few criteria.

CLIs initially targeted the industrial production index as a reference series for the business cycle because it was available on a monthly basis for all OECD countries, whereas GDP was not even available in quarterly series for half the OECD countries. Since April 2012, in response to improvements in national statistical information systems (i.e all OECD countries now produce quarterly estimates of GDP) and because of the industrial sector's diminishing share of total GDP in recent decades in most OECD economies, the CLI system switched to using GDP as the reference series for all countries.

Figure 14: OECD Composite Leading Indicator for France (Source: OECD and author's calculations)



Note: Recessions in shaded areas were computed with the Bry-Boschan (1971) methodology

[14] Astolfi R, Gyomai G, Ahmad N (2017)

Figure 14 shows the CLI for France. One can see that the CLI tends to decline sharply ahead of the beginning of a recession, and this fact is confirmed by the analysis of Astolfi et al (2016): CLIs did anticipate the Great Recession in G7 countries. But CLIs may also fall if there is just a slow-down in activity, similarly to the INSEE's turning point indicators.

Weale (1996) found mixed results when testing the predictive power of the CLIs for 14 countries over the period from 1966 to 1994. A non-parametric test of whether an above-average increase in the indicator was followed several quarters later by an above-average growth in industrial production showed that the CLIs had some predictive power from 3 to 4 quarters ahead, but the predictive power was limited as it was predicting the correct direction of growth only about 60% of the time. Integrating the CLIs in a VAR framework for forecasting monthly industrial production led only to a small decrease in the standard error compared to a simple autoregressive model.

Table 9: Index summary card: OECD leading indicator

Provider	OECD
Index name	Composite Leading Indicator
Description	Leading indicator Turning point indicator Cyclical indicator
Dataset	Administrative database Surveys Revenue and customs database Financial markets data Trade Transport Official statistics
Construction methodology	Composite index Bry-Boschan (1971) algorithm of detecting turning points
Adjustments	Filtering Seasonal adjustments Interpolation
Frequency of publication	Monthly
Reference series	GDP
Business cycle definition	Deviation from trend cycle
Lag with the reference series	Leading by 6 to 9 months
Composite method	Components are selected based on NBER classical measures (number of missed & extra turning points) Average/median lead and its st.dev, cross-correlation. A dynamic analysis of the evolution of the leading performance is undertaken using rolling analysis.
Frequency of review	annually

5.8. ONS Faster Indicator: VAT returns

The Office for National Statistics (ONS) developed a suite of experimental statistics called Faster Indicators.[15] They are called faster because they are published ahead of official statistics[16] from novel data sources. The goals of the Faster Indicators were threefold: "[1] to identify close-to-real-time big data or administrative data sources which represent useful economic concepts [2] to create a set of indicators which allow early identification of large economic changes and [3] to provide insight into economic activity, at a level of timeliness and granularity not possible for official economic statistics." [17]

The first four faster indicators developed by the ONS are VAT diffusion, VAT reporting behaviour, shipping indicators, road traffic. The VAT diffusion and reporting behaviour indicators use data from HMRC UK Value Added Tax turnover and expenditure returns, the shipping indicators uses data from the international Automatic Identification System (AIS) of maritime shipment tracking, and road traffic indicator uses data from Road traffic sensor database for England from Highways England.

While those indicators provide early information about business activity, Dr Louisa Nolan, Lead Data Scientist who led the development of those indicators for the ONS explains in our survey that "we do not claim that this [indicator] tracks official statistics closely, rather that it should be used as an early warning indicator. It may be possible to use it to improve nowcasting models".

Reported VAT data is particularly useful in tracking the economy for several reasons. First, because value added enters directly into the GDP calculation.[18] Second, the sample of companies reporting VAT monthly is large. Third, the quality of the data is good because Her Majesty's Revenue and Customs (HMRC) does various manual and automated checks on the raw data and has the power to issue penalties to firms that report errors on their VAT returns. Rowe (2019) notices that the VAT indicators tend to be good at identifying large turning points in real-time but may, at times, give differing signals to official data, in particular when the scale of the economic changes are small.

As part of the faster indicators project, the ONS has developed some novel indicators tracking changes in VAT reporting behaviour. These include:

- repayments, where firms claim VAT back
- re-input returns, where initial data checks are failed and returns are re-input by HMRC
- replacements, where initial returns are revised.
- a proxy for firm births, based on new VAT reporters.

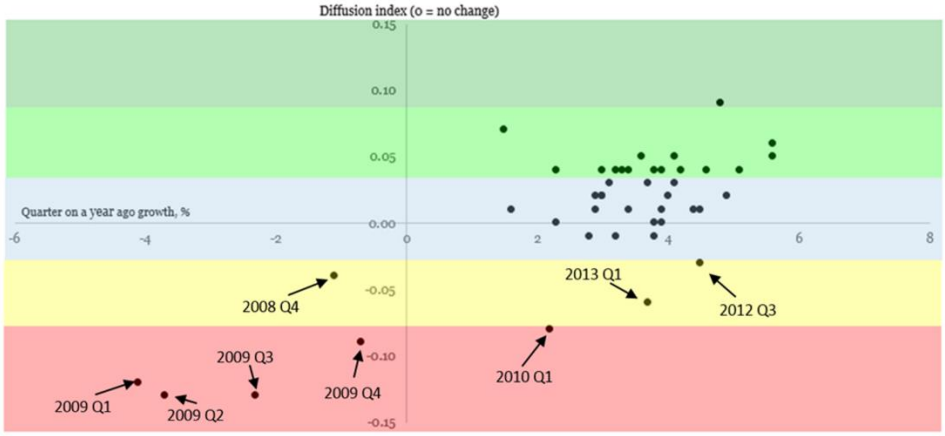
[15] Found at https://www.ons.gov.uk/economy/economicoutputandproductivity/output/articles/economicactivityfasterindicatorsuk/previousReleases and on the Data Science Campus website https://datasciencecampus.ons.gov.uk/projects/faster-indicators-of-uk-economic-activity/

[16] "Up to one month in advance of official estimates of gross domestic product" ONS (2019)

[17] https://datasciencecampus.ons.gov.uk/projects/faster-indicators-of-uk-economic-activity-shipping/

[18] Explanations can be found in https://datasciencecampus.ons.gov.uk/projects/faster-indicators-of-uk-economic-activity-value-added-tax-returns/

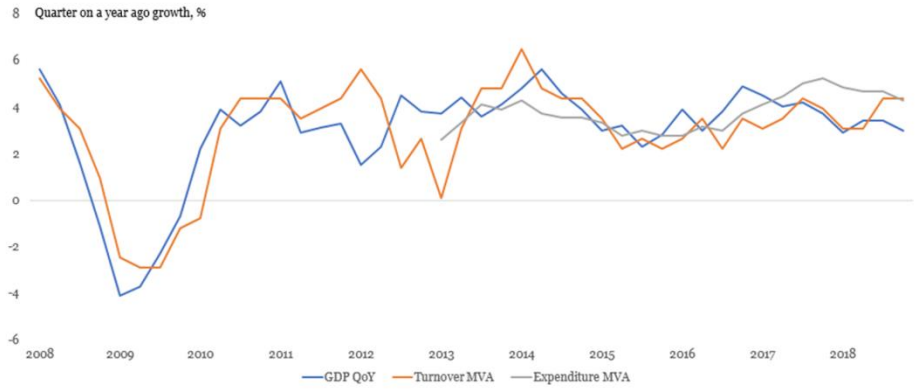
Figure 15: ONS VAT turnover diffusion index (NSA) vs GDP growth, quarter on a year ago, current prices (Source: Rowe, 2019)



Coloured bands show different levels of the turnover diffusion index with the highest values in the dark green band and the lowest values in the red band. Values in the light blue band are close to the average level of the turnover diffusion index. The values chosen for the bands are based on standard deviations of the turnover diffusion index between 2008 and 2018.

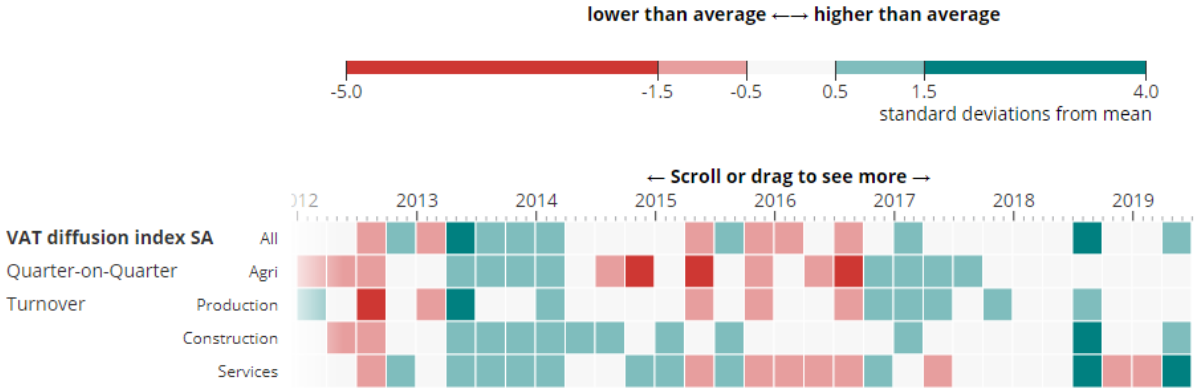
One of the challenges with the VAT data is that it has an industry bias. Early data may be available for some sectors of the economy much faster than others: for example, the sector that composes agriculture, forestry and fishing seems to be a sector that reports VAT disproportionately early. And one well-known drawback of the diffusion index methodology is that it doesn't take into account the weight of each sector in the economy. As Rowe (2019) remarked, the VAT turnover diffusion index turned negative in 2015 when GDP was still growing at a healthy rate. This was the result of a marked fall in the price of agricultural produce and the agricultural sector being overly represented in the diffusion index.

Figure 16: Quarter on a year ago GDP CP SA vs mean variance adjusted (MVA) VAT turnover and expenditure diffusion indices NSA



The ONS publishes on its website a heatmap of VAT diffusion index to allow users to look for common trends across sectors and time (figure 17). The heatmap also includes the novel metrics like repayment claims or the proxy for firm births.

Figure 17: ONS VAT heatmap (August 2019)

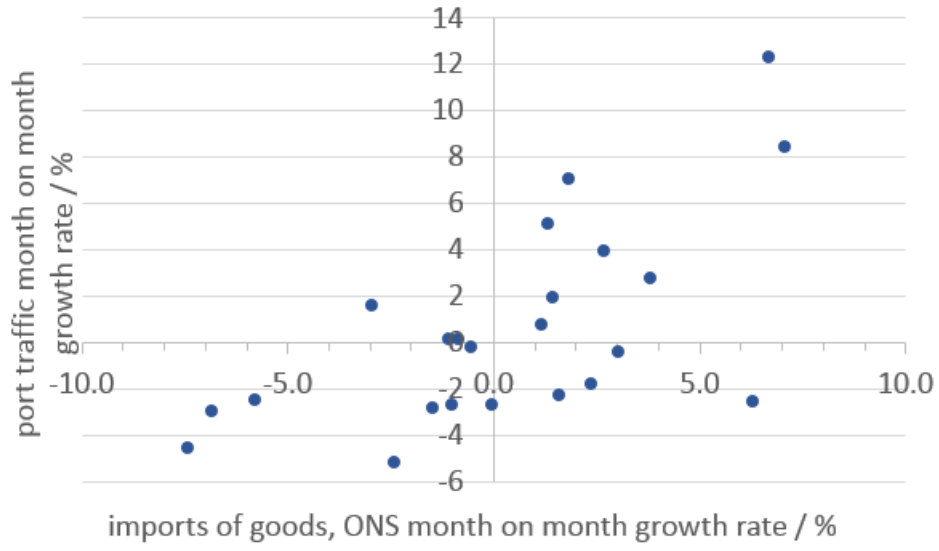


5.9. ONS Faster Indicator: Shipping

The ONS has constructed two monthly shipping indicators from the AIS data:
'Time-in-port' is based on aggregate time spent by ships in important UK ports and 'Total traffic' is based on the number of unique ships entering important UK ports each month. The AIS database is huge: it receives about 28 million messages per day including ships position and identification. The processing of such data requires using big data methods.

Noyvirt (2019) finds when analysing the data between July 2016 and August 2018 that there is a surprisingly good correlation between the shipping indicators and imports, even if shipping indicators are much more volatile (figure 18). Because of lack of historical data, the two series are not seasonally adjusted.

Figure 18: Port traffic and imports of goods for UK



5.10. ONS Faster Indicator: Road traffic

The ONS developed experimental statistics of the average number of transport vehicles passing sensors on major roads in England. The raw data comes from Highway England, and therefore only

covers England, not the rest of the UK.[19] Aggregates published by the ONS group these data to show movements across all English sensors and movements around important English ports. The time-series are available on a monthly basis and are decomposed into transport vehicles of different size. Rowland (2019) notes that "larger vehicles track imports and exports somewhat better than smaller vehicles. One might expect this to be the case, as international road freight is generally carried out using heavy goods vehicles rather than small cars." As such, analysis in the publications has tended to focus on the two largest vehicle categories: vehicles between 6.6 and 11.66 metres in length (which typically include lorries and buses) and vehicles over 11.66 metres in length (which typically include larger lorries, coaches and articulated lorries). Because most of the goods trading domestically and internationally are transported on the road, then such metrics have the potential to give early indications about the demand and supply conditions in England. Figure 19 and figure 20 illustrate how the new metrics compare to international trade and gross value added. Rowland (2019) adds that this metric "has the scope to offer some new understanding of the supply potential of the UK, and how traffic by different types of vehicle relate to local economic activity involving the transport of goods and people."

The aggregate road traffic indicators are published with a two-month lag (for example, publishing indicators for February in April), due to delays in then raw data becoming available from Highways England. The monthly series are seasonally adjusted using the JDemetra+ seasonal adjustment package.

Figure 19: ONS Road traffic for England and international trade

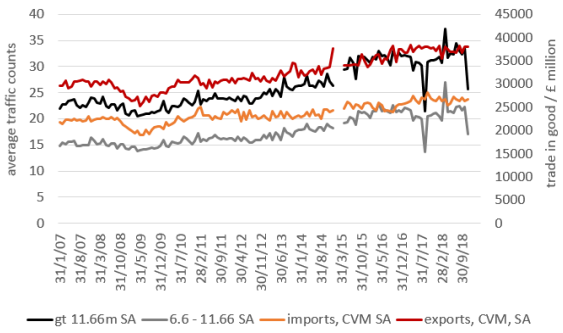
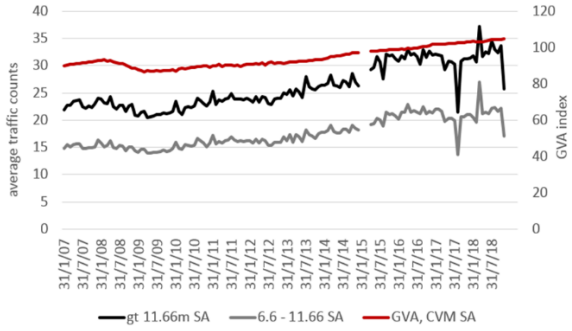


Figure 20: ONS Road traffic for England and Gross Value Added



[19] Details on how the data is collected and constructed can be found in Rowland (2019)

Table 10: Indices summary card: ONS faster indicators

Provider	Office for National Statistics			
Index name	VAT diffusion	VAT reporting behaviour	shipping indicators	road traffic
Description	Faster indicator Turning point indicator Early-warning indicator	Faster indicator Turning point indicator Early-warning indicator	Faster indicator Turning point indicator Early-warning indicator	Faster indicator Turning point indicator Early-warning indicator
Dataset	Administrative database Revenue and customs database	Administrative database Revenue and customs database	Big data Trade Transport	Big data Transport
Construction methodology	Diffusion index	Simple counts	Ship time-in-port and port visits are constructed from aggregating the data in the AIS message	Aggregated and then average over sensors; average traffic counts by vehicle length, average speed
Adjustments	Seasonal adjustments	Seasonal adjustments	Filtering No seasonal adjustment as yet, as we don't have a sufficiently long time series	Seasonal adjustments
Frequency of publication	Monthly	Monthly	Monthly	Monthly
Reference series	Not designed to track official statistics but provide another view on economic activity which could provide early warning indicators.	Not designed to track official statistics but provide another view on economic activity which could provide early warning indicators.	Not designed to track official statistics but provide another view on economic activity which could provide early warning indicators. Most related to international trade (goods exports and imports)	Not designed to track official statistics but provide another view on economic activity.
Type of time-series	deviation from average values	deviation from average values	Level time-series	Level time series
Lag with the reference series	Leading by 1 to 2 months	Leading GDP by 1 month	Leading by 1 month	
Composite method	Not composite index	Not composite index	Not composite index	Not composite index
Frequency of review	Not defined yet	Not defined yet	Not defined yet	Not defined yet

5.11. The Conference Board Leading Economic Indicators

The Conference Board reported 5 types of turning point indices in the survey: Leading Economic Indicators (LEI), Consumer Confidence Index, Employment Trends Index, Help Wanted OnLine and CEO Confidence.

Business cycle analysis has a long history in the US (Ozyildirim, 2017). The indicator approach to business cycle analysis and forecasting or originated in the 1930s at National Bureau of Economic Research (NBER) with the work of Wesley Mitchell and Arthur Burns (Burns and Mitchell, 1938 and 1946). Over subsequent decades the approach was developed and refined, mostly at the NBER under the leadership of Geoffrey H. Moore. Starting in the late 1960s, the U.S. Department of Commerce Bureau of Economic Analysis (BEA) began publishing the business cycle indicator data and composite indexes of leading, coincident, and lagging indicators. In late 1995, the Business Cycle Indicators program was privatized, and starting in 1996, The Conference Board took over the responsibility of maintaining the database and publishing the monthly report.

Ataman Ozyildirim, Senior Director for Economic Research at The Conference Board, writes in our survey that "the US LEI is considered the official Leading Economic Index for the US". The same approach and methodology are applied to 13 other economies and The Conference Board also provides a global aggregate LEI. The methodology is explained in Ozyildirim (2017).

The question of which series to put in a composite leading index is a difficult one. Generally, average weekly hours, new orders, consumer expectations, housing permits, stock prices, and interest rate spread are series that tend to shift direction in advance of changes in economic activity and are therefore considered as leading indicators. On the contrary, employment, production, personal income, manufacturing output, and trade sales are series that measure aggregate economic activity and are thus generally considered coincident indicators. The Conference Board uses a rigorous methodology to select business cycle-related component series. The would-be series must satisfy 6 criteria described in Ozyildirim (2017): consistent timing, conformity, smoothness, economic significance, statistical adequacy and timeliness.

Another leading indicator proposed by Ozyildirim (2017) is the ratio of the coincident index to lagging index. It can be interpreted as the cost of doing business, because it represents the level of current economic activity relative to the lagging index.

The point of constructing a composite index is to capture a common trend or factor across a variety of component indices that may be more volatile. One problem with composite leading indicators is that, because they include both stationary and non-stationary variables, then they may have a different trend from a composite coincident indicator. It is a problem because that trend would have no economic meaning: it would just depend on the selection of the component series. To alleviate this problem, The Conference Board does a **trend adjustment** to its leading index series: it removes the current trend and adds the trend from the Coincident economic index (CEI).

The components of the LEI have changed significantly in the 81 years since Mitchell and Burns (1938) first published a list of leading indicators. We compare the two lists in Table 11. One can notice four major differences:

(1) There are now fewer indices (less than half), suggesting the new composite index is more streamlined

(2) Production and sales indices which represented together one third of the composite index in the original composition have disappeared in the latest LEI. They are now considered as coincident indicators.

(3) New orders and consumer expectation have been added to the latest composition, reflecting the availability of such data from surveys

(4) Financial markets indicators play a bigger role: increase from 1 to 3 indices

The composite indices are reviewed annually in January.

Empirical studies have proved the relevance of the LEI and its components for forecasting turning points. For example, Levanon et al (2015) have shown that adding the Leading Credit Index (LCI) improves recession forecasts by taking into account specific aspects of financial conditions. The LCI was subsequently added to the LEI.

The LEI and CEI are drawn in figure 21.

Figure 21: The Conference Board Leading Economic Index

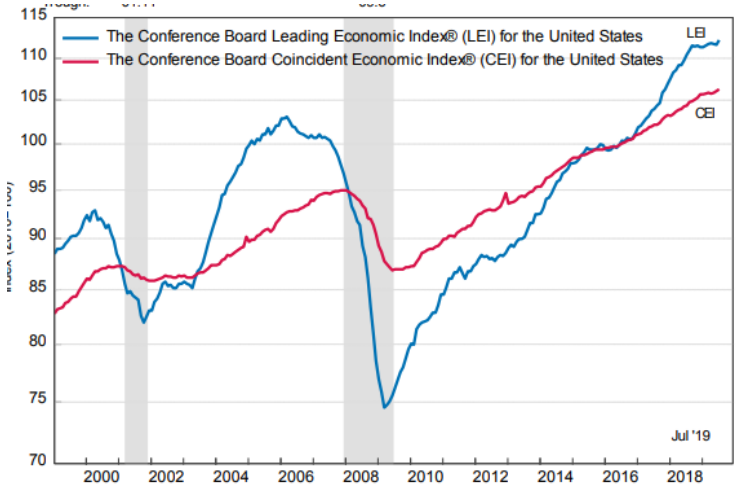


Table 11: Comparison of Leading Economic Indices constituents in 1938 and 2019

Current LEI index	Mitchell and Burns (1938) index
1. Average weekly hours (manufacturing) 2. Average weekly initial claims for unemployment insurance 3. Manufacturers' new orders, consumer goods and materials 4. ISM® new orders index (Institute for Supply Management) 5. Manufacturers' new orders, nondefense capital goods excl. aircraft 6. Building permits, new private housing units 7. Stock prices, 500 common stocks (S&P 500 Index) 8. Leading Credit Index™ 9. Interest rate spread, 10-year Treasury bonds less federal funds 10. Average consumer expectations for business conditions	1. Total liabilities of business failures 2. Dow-Jones Index of Industrial (DJIA) Stock prices 3. Passenger car production 4. Inner tube production 5. Total railroad operating income 6. Total paper production 7. Truck production 8. Ton-miles of freight hauled 9. Total residential building contracts, floor space 10. Average hours worked, 'all' wage earners 11. Index of wholesale prices, Bradstreet's 12. Bank Clearings outside New York 13. Index of industrial production 14. Pig-iron production 15. Steel-ingot production 16. Industrial building contracts, floor space 17. Index of business activity, American Telephone and Telegraph Company (AT&T) 18. Index of production, standard statistics company 19. Department store sales 20. Factory employment, total 21. Other employment series

Table 12: Index summary card: The Conference Board turning point indicators

Provider	The Conference Board				
Index name	Leading Economic Index	Consumer Confidence Index	Employment Trends Index	Help Wanted OnLine	CEO Confidence
Description	Real-time indicator Leading indicator Turning point indicator Coincident indicator Cyclical indicator Early-warning indicator Part of a system of composite indexes (Coincident, Lagging)	Real-time indicator Leading indicator Cyclical indicator Early-warning indicator	Real-time indicator Leading indicator Turning point indicator Cyclical indicator Early-warning indicator	Faster indicator Real-time indicator Leading indicator Turning point indicator Cyclical indicator Early-warning indicator	Survey of CEO outlook on business and the economy
Dataset	Administrative database Surveys Financial markets data Official statistics	Surveys	various public and private surveys Official statistics	web scraping Big data Administrative database	Surveys
Construction methodology	Diffusion index Composite index Bry-Boschan (1971) algorithm of detecting turning points	Composite index	Diffusion index Composite index Bry-Boschan (1971) algorithm of detecting turning points Markov switching dynamic model like Hamilton (1989)	Big data	It's not formally an indicator or index. We call it the "measure " of CEO confidence.
Adjustments	Seasonal adjustments Interpolation volatility adjustment	Seasonal adjustments	Filtering Seasonal adjustments Interpolation	Filtering Seasonal adjustments	
Frequency of publication	Monthly	Monthly	Monthly	Monthly	Quarterly
Reference series	business cycle turning points, coincident economic index	business cycle, consumer confidence, consumer spending	Employment	Labour demand	Economic conditions

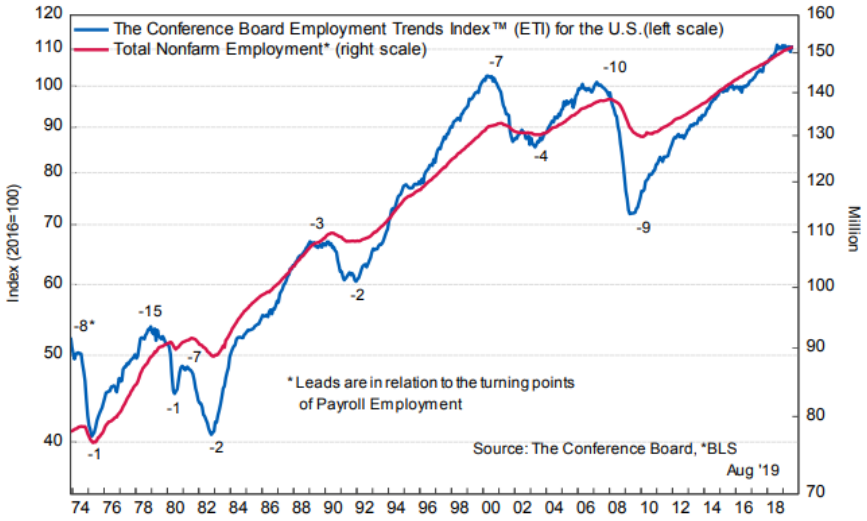
Business cycle definition	Classical business cycles	Classical business cycles	Classical business cycles	Classical business cycles	Economic outlook
Lag with the reference series	Leading by about 11-12 months on average	Leading by 3-6 months	Leading by 10-11 months		
Composite method	equally weighted average of (standardized) component contributions	composed of present situation and expectations sub-indexes	equally weighted average of (standardized) component contributions		
Frequency of review	annually	several years	several years		

The eight labour-market indicators aggregated into the Employment Trends Index[20] include:

- Percentage of Respondents Who Say They Find "Jobs Hard to Get"
- Initial Claims for Unemployment Insurance
- Percentage of Firms With Positions Not Able to Fill Right Now
- Number of Employees Hired by the Temporary-Help Industry
- Ratio of Involuntarily Part-time to All Part-time Workers
- Job Openings **
- Industrial Production *
- Real Manufacturing and Trade Sales**

*Statistical imputation for the recent month
**Statistical imputation for two most recent months

Figure 22: The Conference Board Employment Trends Index

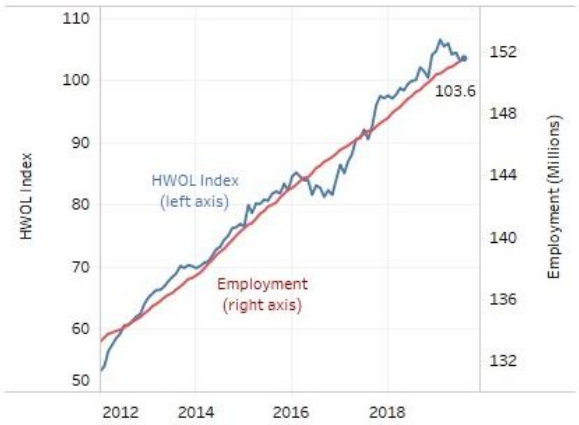


This Conference Board Help Wanted OnLine (HWOL)[21] provides monthly measures of labour demand (advertised online vacancies) , reflecting monthly trends in employment opportunities across the US. It uses a web scrapping methodology. Ads in the HWOL universe are collected in real-time from over 28,000 different online job boards including traditional job boards, corporate boards, social media sites, and smaller job sites that serve niche markets and smaller geographic areas. This index replaced the Help Wanted Advertising Index that was discontinued as most of the jobs ads are now available online.

The HWOL Index tracks well the Job Openings and Labor Turnover Survey (JOLTS) published by the Bureau of Labor Statistics, while at the same time being smoother, which is a desirable property to identify turning points.

[20] Available at https://www.conference-board.org/data/eti.cfm
[21] Available at https://www.conference-board.org/data/helpwantedonline.cfm

Figure 23: The Conference Board Help Wanted OnLine



5.12. Miscellaneous other indictors reported as turning point indicators

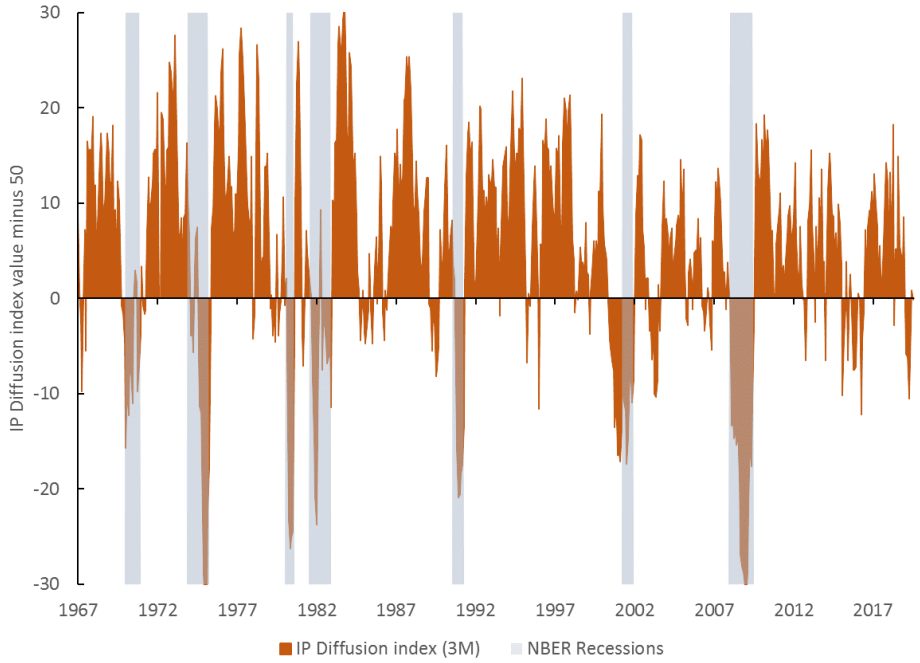
US Industrial production (IP)[22] is one of the indicators used by the NBER dating committee to date recessions. And while industrial production cycles may be somewhat different from business cycles, they seem to have spillover effects that make industrial production a rather good leading indicator. For example, Andreou et al (2019) find that than 61% of the variability of GDP output growth is explained by a single common factor that also explains 89% of industrial production output growth, despite the diminishing role of manufacturing in the economy. Foerster et al (2011), using a structural factor analysis also find that aggregate shocks continue to be the dominant source of variation in industrial production.

Christopher Kurz, Economist/Chief of the industrial output section at the Federal Reserve writes that "IP might not be exactly what you are thinking when you envision real-time turning point indicators, but it has performed reliably over its life cycle and has quite a bit of history, as well. As mentioned, the NBER considers index of industrial production (IP) when dating business cycles. Importantly, dating the peak of the last business cycle in 2007 occurred 11 months after that date. IP, in real time, reflected the change in the business cycle long before the business cycle was dated."

The Fed also publishes a diffusion index of industrial production that Kurz finds to "have predictive power for future activity and turning points." The diffusion index is calculated as the percentage of series that increased over the indicated span (one, three, or six months) plus one-half the percentage that were unchanged. Figure 24 shows that periods when the diffusion index is consistently below 50 tend to also be recession periods.

[22] Available at https://www.federalreserve.gov/releases/g17/

Figure 24: US Industrial Production Diffusion index (Source: Federal Reserve and NBER)



Flash GDP estimate was reported by Instituto Nacional de Estadística y Geografía as turning point indicator.

6. Conclusion

Our survey and literature review have shown that there are many ways to look at turning points. Official business cycle dating committees like the NBER[23] in the US, the Euro Area Business Cycle Dating Committee (EACBDC)[24] in the Euro Area, and the proposed UK business cycle dating committee[25] use a range of economic indicators to determine the peaks and troughs of business cycles; but they only announce their decisions several months after the turning point occurred. To determine turning-points in real-time requires the use of leading or coincident indicators that extract from economic or financial data information about which phase of the business cycle the economy is in.

The ONS has recently made an important contribution to conjunctural analysis by publishing GDP at a monthly frequency with a lag of about six weeks. To a large extent this negates the need for more timely indicators, especially if they need a lot of interpretation. Nevertheless, while the ONS is not in the business of forecasting, it could provide a useful public service by compiling the statistics and indicators on which such forecasts could be based. These would inform policy makers, businesses and the public about the state of the economy. Of course, the new indicators would need to be clearly focused, based on robust methodologies and involve as little judgement as possible in order to learn from the lessons of the abandoned CSO/ONS cyclical indicators. In that regard, the Data Science campus seems to be the ideal environment to produce innovative statistics, building on the successful experience of the Faster Indicators.

This survey shows that the ONS is leading other institutions in the development of innovative statistics based on new data sources. The use of new databases like shipping, road traffic and VAT returns in the Faster Indicators is promising and should be explored further. The Conference Board also uses online job ads for one of its indicators of the labour market. The ONS could expand its set of real-time or near-real-time indicators to add more data sources like payments, weather and online job ads to name a few.

How to display complex and sometimes contradicting trends in data so that the user can make something useful out of it is a challenging task. The heatmap and colour bands in the ONS Faster Indicators provide a good summary view. Tracers and radars are popular alternative representations that allow to display several statistics in the same figure.

One area where the ONS has not made much progress is in the development of composite indicators. Our survey shows that they are very popular tools to understand the state of the economy because they give a summary indicator. The composite indicators produced by The Conference Board and the OECD seem to reach a large audience, but they have been criticized because their methodology involves some judgement in the selection of the component series and they need to be periodically revisited.

Other methodologies identified in this review are factor analysis and regime-switching models. As there is a lot of uncertainty in the measurements in real-time, probabilistic inference should play a key role. New methodologies related to big data and machine learning are expected to contribute to the development of more timely and accurate turning point indicators.

[23] https://www.nber.org/cycles/recessions.html

[24] Organized by CEPR and Euro Area Business Cycle Network https://cepr.org/content/euro-area-business-cycle-dating-committee

[25] The committee is expected to be hosted by NIESR. https://www.niesr.ac.uk/uk-business-cycle-%E2%80%93-dating-and-implications

References

Andreou, Elena and Gagliardini, Patrick and Ghysels, Eric and Rubin, Mirco (2019) Inference in Group Factor Models with an Application to Mixed Frequency Data (January 5, 2019). Swiss Finance Institute Research Paper No. 16-11.

Armesto, M. T., Engemann, K. M., & Owyang, M. T. (2010). Forecasting with mixed frequencies. Federal Reserve Bank of St. Louis Review, 92(6), 521-36.

Artis, M. J., Bladen-Hovell, R. C., Osborn, D. R., Smith, G. W., & Zhang, W. (1995). Turning point prediction for the UK using CSO leading indicators. Oxford Economic Papers, 397-417.

Ast, D. (2010) Un indicateur de retournement conjoncturel dans les services. INSEE Décembre 2010.

Astolfi, R., Gamba, M., Guidetti, E., & Pionnier, P. A. (2016). The use of short-term indicators and survey data for predicting turning points in economic activity.

Astolfi R, Gyomai G, Ahmad N (2017) The OECD System of Composite Leading Indicators, in Handbook on Cyclical Composite Indicators for Business Cycle Analysis, edited by G. L. Mazzi and A. Ozyildirim for Eurostat and United Nations, 2017 edition

Baffigi, A., Golinelli, R., & Parigi, G. (2004). Bridge models to forecast the euro area GDP. International Journal of forecasting, 20(3), 447-460.

Baron, H., Baron, G. (2002). Un indicateur de retournement conjoncturel dans la Zone Euro. Économie et Statistique n° 359-360, 2002

Bonham, C., Noyvirt, A., Tsalamanis, I., & Williams, S. (2018). Analysing port and shipping operations using big data. Data Science Campus, Office for National Statistics.

Bräuning, F., & Koopman, S. J. (2014). Forecasting macroeconomic variables using collapsed dynamic factor analysis. International Journal of Forecasting, 30(3), 572-584.

Brave, S. A., Butters, R. A., & Kelley, D. (2019). A New “Big Data” Index of US Economic Activity. Economic Perspectives, Vol. 43, No. 1, 2019, 1-30.

Bry, G., & Boschan, C. (1971). Front matter to" Cyclical Analysis of Time Series: Selected Procedures and Computer Programs". In Cyclical analysis of time series: Selected procedures and computer programs (pp. 13-2). National Bureau of Economic Research.

Buckles, K., Hungerman, D., & Lugauer, S. (2018). Is Fertility a Leading Economic Indicator? (No. w24355). National Bureau of Economic Research.

Burns, A. F., & Mitchell, W. C. (1947). Measuring business cycles. National Bureau of Economic Research, New York.

Carstensen, K., Wohlrabe, K., & Ziegler, C. (2011). Predictive ability of business cycle indicators under test. Jahrbücher für Nationalökonomie und Statistik, 231(1), 82-106.

Chauvet, M., & Hamilton, J. D. (2006). Dating business cycle turning points. Contributions to Economic Analysis, 276, 1-54.

Central Statistical Office (1975), 'Changes to the Cyclical Indicator System', Economic Trends, 271.

Central Statistical Office (1976), 'Changes to the Cyclical Indicator System', Economic Trends, May 1976

Central Statistical Office (1983), 'Cyclical indicators: some developments and an assessment of performance', Economic Trends No 360, October 1983, pp. 148-153

Chinn, M. and Kucko, K. (2015), 'The predictive power of the yield curve across countries and time', International Finance, 18(2), pp. 129–56.

Crowther, G. (1934). The Economist Index of Business Activity. Journal of the Royal Statistical Society, 97(2), 241-276.

European Commission (2019) The Joint Harmonised EU Programme of Business and Consumer Surveys, User Guide, DG ECFIN, updated January 2019

Estrella, A. and Mishkin, F. (1998), 'Predicting U.S. recessions: financial variables as leading indicators', The Review of Economics and Statistics, MIT Press, 80(1), February, pp. 45–61.

Estrella, A. and Hardouvelis, G. (1991), 'The term structure as a predictor of real economic activity', Journal of Finance, 1991, 46, 2, pp. 555–76.

Fels, R., & Hinshaw, C. E. (1968). Forecasting and recognizing business cycle turning points. NBER Books.

Foerster, A. T., Sarte, P. D. G., & Watson, M. W. (2011). Sectoral versus aggregate shocks: A structural factor analysis of industrial production. Journal of Political Economy, 119(1), 1-38.

Galvão, A. B., & Kara, A., (2019) UK Business Cycle Turning Points and Recession Predictions: the impact of GDP data revisions, Research Output for EsCoE Project 1.2 extension - Measuring GDP at different publication horizons, March 2019

Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. Journal of Monetary Economics, 55(4), 665-676.

Giannone, D., Lenza M., & Primiceri, G.E. (2018). Economic Predictions with Big Data: The Illusion of Sparsity, Federal Reserve Bank of New York Staff Reports, no. 847, April 2018

Gogas, P., Papadimitriou, T., Matthaiou, M., & Chrysanthidou, E. (2015). Yield curve and recession forecasting in a machine learning framework. Computational Economics, 45(4), 635-645.

Gregoir, S., & Lenglart, F. (2000). Measuring the probability of a business cycle turning point by using a multivariate qualitative hidden Markov model. Journal of forecasting, 19(2), 81-102.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica: Journal of the Econometric Society, 357-384.

Hamilton, J. D. (2005). What's real about the business cycle? (No. w11161). National Bureau of Economic Research.

Hamilton, J. D. (2011). Calling recessions in real time. International Journal of Forecasting, 27(4), 1006-1026.

Harvey C. (1988), 'The real term structure and consumption growth', Journal of Financial Economics, 22, 2, pp. 305–33.

Junoh, M. Z. H. M. (2004). Predicting GDP growth in Malaysia using knowledge-based economy indicators: a comparison between neural network and econometric approaches. Sunway Academic Journal, 1, 39-50.

Laurent, R.D. (1988), 'An interest rate-based indicator of monetary policy,' Economic Perspectives, Federal Reserve Bank of Chicago, January, pp. 3–14.

Levanon, G., Manini, J. C., Ozyildirim, A., Schaitkin, B., & Tanchua, J. (2015). Using financial indicators to predict turning points in the business cycle: The case of the leading economic index for the United States. International Journal of Forecasting, 31(2), 426-445.

Lenoel (2018) Predicting recessions in the United States with the Yield Curve. Box B in National Institute Economic Review No. 244 May 2018, pp. F42-43

O'Dea, D. J. (1975). Cyclical Indicators for the Postwar British Economy. Cambridge University Press.

ONS (2019) Research Output: Economic activity, faster indicators, UK: January to March 2019, Office for National Statistics, 15 April 2019

Mitchell W.C. and Burns A.F. (1938). Statistical Indicators of Cyclical Revivals, National Bureau of Economic Research, Bulletin 69.

Mogliani, M., Darné, O., & Pluyaud, B. (2017). The new MIBA model: Real-time nowcasting of French GDP using the Banque de France's monthly business survey. Economic Modelling, 64, 26-39.

Moolman, E. (2003). Predicting turning points in the South African economy. South African journal of economic and management sciences, 6(2), 289-303.

Moore, G. H. (1961). Business Cycle Indicators, Volume 1. NBER Books.

Neftçi, S. N. (1982). Optimal prediction of cyclical downturns. Journal of Economic Dynamics and Control, 4, 225-241.

Ng, S. (2014). Viewpoint: boosting recessions. Canadian Journal of Economics, 47(1), 1-34.

Noyvirt, Alex (2019) Faster indicators of UK economic activity: shipping, Office for National Statistics, 18 March 2019 https://datasciencecampus.ons.gov.uk/projects/faster-indicators-of-uk-economic-activity-shipping/

Nyman, R., & Ormerod, P. (2017). Predicting economic recessions using machine learning algorithms. arXiv preprint arXiv:1701.01428.

Ozyildirim, Ataman (2017) Business Cycle Indicator Approach at the Conference Board, published in Handbook on Cyclical Composite Indicators for Business Cycle Analysis, edited by G.L. Mazzi and A. Ozyildirim for Eurostat and United Nations, 2017 edition

Raihan, T. (2017). Predicting US Recessions: A Dynamic Time Warping Exercise In Economics. Available at SSRN 3047649.

Rhodes, E. C. (1937). The Construction of an Index of Business Activity. Journal of the Royal Statistical Society, 18-37

Rowe, Jeremy (2019) Faster indicators of UK economic activity: Value Added Tax returns, https://datasciencecampus.ons.gov.uk/projects/faster-indicators-of-uk-economic-activity-value-added-tax-returns/

Rowland, Edward (2019) Faster indicators of UK economic activity: road traffic data for England, 18 March 2019, https://datasciencecampus.ons.gov.uk/projects/faster-indicators-of-uk-economic-activity-road-traffic-data-for-england/

Salazar, E., Smith, R., Weale, M., & Wright, S. (1997). A monthly indicator of GDP. National Institute Economic Review, 161(1), 84-89.

Stock, J. H., & Watson, M. W. (1989). New indexes of coincident and leading economic indicators. NBER macroeconomics annual, 4, 351-394.

Weale, M. (1996). An assessment of OECD and UK leading indicators. National Institute Economic Review, 156(1), 63-71.

Van Ruth (2010) Monitoring conditions for consumption, exports and fixed capital formation; the radar concept, CBS discussion paper (201019)

Yeend, C. (1998), Cyclical Indicators for the UK Economy. Economic Trends. Digest of Articles No 1, Office for National Statistics, pp 23-30.

Draft questionnaire

International survey of real-time turning point indicators

1. Background

The objective of this study funded by Economic Statistics Centre of Excellence (ESCoE) is to review which turning point indicators are used by leading statistical and economic institutions in the World using a targeted survey. We will look at the methodologies, scope and publication frequencies of such indicators. This review will then serve as a basis for the Office of National Statistics (ONS) to develop or enrich its own turning point indicators.

Real-time turning point indicators are useful tools for policy makers and private sector agents to understand the current state of the economy and whether current trends are likely to change in the near future. With appropriate information, economic agents can then adjust their behaviour more appropriately to changing economic conditions.

Turning point indicators can be based on business surveys, credit and equity indices, consumer expectations or other economic and financial indicators. They can be built on some composite leading indicators – like the one produced by The Conference Board in the United States - or on some single series. Examples such turning point indicators are the ONS faster indicators which use data from VAT returns and ship and road traffic data to provide early identification of large economic changes.

This survey is designed to take *XX* minutes to be completed.

2. Respondent

Information on the respondent and the institution he is responding on behalf of.

First name: Last name:
Institution:
Location: Town: Country:
Job title:
Email: Phone:

3. The indicators

What real-time turning point indicators does your institution produce? If there are more than five, please group them by category and provide a representative example for each category. The questionnaire will then produce detailed questions for each indicator that you specified.

Answer:
Indicator 1: Name: Link:
Indicator 2: Name: Link:
…
Indicator 5: Name: Link:

The form will then produce questions for each (group of) indicator that the user specified

Would you describe this indicator as? (multiple answers possible)

[] Faster indicator [] Real-time indicator [] Leading indicator [] Turning point indicator [] Coincident indicator [] Cyclical indicator [] Early-warning indicator [] Other

3.1. Dataset and collection

What dataset(s) do you use for this indicator?

Would you describe those datasets as? (multiple answers possible)
[] Big Data [] Administrative database [] Surveys [] Revenue and customs database [] Financial markets data [] Trade [] Transport [] Official statistics [] other …

How soon is the data available?

How do you collect the data? Please describe your methodology in X words. Use examples, references and links if possible.

3.2. Processing and construction of the indicator

How do you construct the indicator? Would you classify your methodology as? (multiple answers possible)
[] Diffusion index [] Composite index [] Big Data [] Machine learning [] Probit [] Bry-Broschan (1971) algorithm of detecting turning points [] Markov switching dynamic model like Hamilton (1989) [] Other

Please describe your methodology in X words. Use examples and references where appropriate.

Do you make any adjustments to the data? [] Filtering [] Seasonal adjustments [] Interpolation [] Other (please describe)

How long does it take to process the data and publish the indicator?

What is the frequency of update of the indicator?

What is the economic statistic the indicator is supposed to track or lead?
Is the indicator focused on? [] turning points [] growth rates [] deviations from trend [] other
How many months ahead does the indicator typically lead the economic statistic?

If the indicator is a composite index, how do you select the components? And how do you aggregate the selected variable into a composite indicator? Do you use weighted sum or simple average? Or more complex statistical methods, involving lagged variables, dynamic factors, unobserved components or structural models?

How frequently is the indicator reviewed?

3.3. Users feedbacks and empirical evidence

Do you have empirical evidence supporting the use of this indicator? Please provide a short description of the work done, examples and references.

How was the indicator received by users?

Do you have any development plans on this indicator?

3.4. Comment

Is there any other information you would like to add with regards to this indicator?

4. Final question

Is there anything you would like to add?

This is the end of the questionnaire. Thank you for taking the time to respond to all the questions.