Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics

Document de Treball 2020/06, 31 pàg.
Working Paper 2020/06, 31 pag.

Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group

Document de Treball 2020/02, 31 pàg.
Working Paper 2020/02, 31 pag.

"Spectral analysis of business and consumer survey data"

Oscar Claveria, Enric Monte and Salvador Torra

UBIREA
Research Institute of Applied Economics

AQR
Regional Quantitative Analysis Research Group

Institut de Recerca en Economia Aplicada Regional i Pública
UNIVERSITAT DE BARCELONA

WEBSITE: www.ub-irea.com • CONTACT: irea@ub.edu

AQR
Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group

WEBSITE: www.ub.edu/aqr/ • CONTACT: aqr@ub.edu

Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona

Abstract

The main objective of this study is two-fold. First, we aim to detect the underlying existing periodicities in business and consumer survey data. With this objective, we conduct a spectral analysis of all survey indicators. Second, we aim to provide researchers with a filter especially designed for business and consumer survey data that circumvents the a priori assumptions of other filtering methods. To this end, we design a low-pass filter that allows extracting the components with periodicities similar to those that can be found in the dynamics of economic activity.

The European Commission (EC) conducts monthly business and consumer tendency surveys in which respondents are asked whether they expect a set of variables to rise, fall or remain unchanged. We apply the Welch method for the detection of periodic components in each of the response options of all monthly survey indicators. This approach allows us to extract the harmonic components that correspond to the cyclic and seasonal patterns of the series. Unlike other methods for spectral density estimation, the Welch algorithm provides smoother estimates of the periodicities. We find remarkable differences between the periodicities detected in the industry survey and the consumer survey. While business survey indicators show a common cyclical component of low frequency that corresponds to about four years, for most consumer survey indicators we do not detect any relevant cyclic components, and the obtained lower frequency periodicities show a very irregular pattern across questions and reply options.

Most methods for seasonal adjustment are based on a priori assumptions about the structure of the components and do not depend on the features of the specific series. In order to overcome this limitation, we design a low-pass filter for survey indicators. We opt for a Butterworth filter and apply a zero-phase filtering process to preserve the time alignment of the time series. This procedure allows us to reject the frequency components of the survey indicators that do not have a counterpart in the dynamics of economic activity. We use the filtered series to compute diffusion indexes known as balances, and compare them to the seasonally-adjusted balances published by the EC. Although both series are highly correlated, filtered balances tend to be smoother for the consumer survey indicators.

JEL Classification: C65, C82

Keywords: Business and consumer surveys, Spectral analysis, Seasonality, Signal processing, Low-pass filter

Oscar Claveria: AQR–IREA, Department of Econometrics, Statistics and Applied Economics, University of Barcelona, Diagonal 690, 08034 Barcelona, Spain. Tel. +34-934021825. Email: oclaveria@ub.edu

Enric Monte: Department of Signal Theory and Communications, Polytechnic University of Catalunya (UPC). Email: enric.monte@upc.edu

Salvador Torra: Riskcenter–IREA, Department of Econometrics, Statistics and Applied Economics, University of Barcelona (UB). Email: storra@ub.edu

1. Introduction

Sentiment analysis is increasingly used for anticipating the evolution of the economy and for assisting in the design of economic policies and business decision making. One of the main sources of information for sentiment analysis is agents' expectations about future developments of the economy. Every month, the European Commission (EC) publishes the European Sentiment Indicator (ESI), which synthesises the beliefs and expectations of economic agents. The ESI is a composite indicator based on business and consumer survey results, so it offers a perspective both from the supply side and from the demand side of the economy.

In the surveys, respondents are asked about their expectations regarding a wide range of economic variables, and they are mostly faced with three reply options: "up", "unchanged" and "down". Results are published as balances, which can be regarded as diffusion indexes consisting on the subtraction between the aggregate percentages of response corresponding to the extreme categories. Seasonally-adjusted balances are published each month by the EC, but the series corresponding to each response category are only available in raw form, that is, the aggregate percentage of respondents in each category[1].

The main objective of this study is two-fold. On the one hand, we aim to detect the underlying existing periodicities in business and consumer survey indicators. With this objective, we conduct a spectral analysis of all survey indicators. We use all monthly survey information from the EC industry and consumer surveys in the euro area (EA). On the other hand, we aim to provide researchers with a filter for business and consumer survey data that allows circumventing the application of filters based on a priori assumptions on the structure of the components. For this purpose, we design a low-pass filter that allows extracting the components with periodicities similar to those that can be found in the dynamics of economic activity.

Given that the periodic components may vary across survey questions, this approach gives insight into the specificities of the different survey indicators and also provides researchers with information to improve the design of ad-hoc filters for signal processing of survey data (Gottman, 1981).

[1] The raw data of business and consumer surveys corresponding to each reply option have been used, inter alia, for the quantification of agents' survey expectations (Claveria, Pons and Ramos, 2007), for the design of indicators of economic uncertainty (Claveria, 2020) and with forecasting purposes (Claveria, 2019a,b).

In this research we apply the Welch method (Welch, 1967; Oppenheim and Schafer, 2010) for spectral density estimation to detect periodicities in the time domain. Welch's algorithm can be regarded as spectral density estimation procedure that allows reducing the high variability in the estimation obtained by means of the periodogram. This is achieved through sequential windowing of the signal and averaging the estimated periodogram in each window. This reduction of noise in the estimated power spectra is particularly desirable when dealing with finite data, as is the case for survey indicators.

The fact that most methods for seasonal adjustment are based on a priori assumptions about the structure of the components and, do not depend on the features of the series, has led us to design a low-pass filter for survey indicators. We use a Butterworth filter and apply a zero-phase filtering process to preserve the time alignment of the series. This procedure allows us to reject the frequency components of the survey indicators that do not have a counterpart in the dynamics of economic activity. Finally, we assess the performance of the filtered survey indicators by comparing them to the seasonally-adjusted balances published by the EC.

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 presents the methodological approach used for transforming the information from the time domain to the frequency domain. Section 4 provides the results of the spectral analysis of survey indicators. In Section 5, we describe the filter design for business and consumer survey data. Finally, concluding remarks are given in Section 6.

2. Data

This study uses in the EA firms' and consumers' qualitative expectations about a wide array of economic variables. Specifically, we use all monthly raw data from the joint harmonised EU industry and consumer surveys conducted by the EC (see Table 1). The sample period goes from 1993.M1 to 2019.M2. In the industry survey, manufacturers are asked about their expectations regarding firm-specific factors such as production, selling prices and employment and, they are faced with three options: "up", "unchanged" and "down". P_t measures the percentage of respondents reporting an increase in the variable, E_t no change, and M_t a decrease. The most common way of presenting survey data is the balance, B_t, which is computed as the subtraction between the two extreme categories:

$$B_t = P_t - M_t \quad (1)$$

Consumers, for their part, are asked about objective variables (e.g. how they think the general economic situation, the cost of living, and the level of unemployment in the country will change over the next twelve months) and subjective variables (e.g. major purchases, savings, etc.). Consumers have three additional response categories: two at each end ("a lot better/much higher/sharp increase", and "a lot worse/much lower/sharp decrease"), and a "don't know" option. As a result, PP_t measures the percentage of respondents reporting a sharp increase in the variable, P_t a slight increase, E_t no change, M_t a slight fall, MM_t a sharp fall and, N_t don't know. See Gelper and Croux (2010) for an appraisal of the data from the EU business and consumer surveys. Again, the most common way of presenting survey data is the balance, which in the case of five reply options is computed as a weighted mean as follows:

$$B_t = \left(PP_t + \tfrac{1}{2}P_t\right) - \left(\tfrac{1}{2}M_t + MM_t\right) \quad (2)$$

Table 1
Survey indicators

Industry survey
Monthly questions
INDU.1 – Production trend observed in recent months
INDU.2 – Assessment of order-book levels
INDU.3 – Assessment of export order-book levels
INDU.4 – Assessment of stocks of finished products
INDU.5 – Production expectations for the months ahead
INDU.6 – Selling price expectations for the months ahead
INDU.7 – Employment expectations for the months ahead
Consumer survey
Monthly questions
CONS.1 – Financial situation over last 12 months
CONS.2 – Financial situation over next 12 months
CONS.3 – General economic situation over last 12 months
CONS.4 – General economic situation over next 12 months
CONS.5 – Price trends over last 12 months
CONS.6 – Price trends over next 12 months
CONS.7 – Unemployment expectations over next 12 months
CONS.8 – Major purchases at present
CONS.9 – Major purchases over next 12 months
CONS.10 – Savings over next 12 months
CONS.11 – Statement on financial situation of household

Business and consumer survey data record opinions of agents, and as such, they are influenced by unpredictable economic and political events such as strikes, elections, sudden interest rate movements and other special events. This irregular component is considered important in interpreting the data, so balances are constructed using the seasonally-adjusted series instead of the trend (European Commission, 2016).

As stated by the EC, even when respondents are required indicate whether the reported change can be attributed to seasonal factors, time series often display characteristic seasonal fluctuations. As a result, the EC applies a specific method for seasonal adjustment. This method is known as Dainties, and it was originally developed by Eurostat. The main advantage of Dainties is the absence of revisions when adding data at the end of the time series.

Dainties mainly uses filters, which in turn are based on the assumption of the breakdown of the series in three components known respectively as seasonal, trend and irregular. More specifically, the Dainties approach assumes that for any term in the series there is certain 'vicinity', i.e. part of the series containing the term analysed, which can be broken down according to a specific model. This model is in turn based on three hypotheses: i) the trend can be represented by a cubic, ii) the seasonal component by a stationary periodic series and, iii) the irregular component by a random series of sum zero. By means of least squares, the method obtains an optimum breakdown that minimises the square of the irregular component.

For series whose behaviour varies over time, and can either be described by an additive model or a multiplicative model, where the seasonal component is proportional to the level of the trend, Dainties applies three additive models and three multiplicative models, weighting the various results by the inverse of the variance. The length of the moving filters is determined by the number of observations per year. Depending on the length of the series and on the presence of negative values, a set of appropriate models are selected. Then, a seasonally-adjusted series is calculated for each of the selected models, and then evaluated according to its smoothness. Weights are assigned to each series according to its variation. The final seasonally-adjusted values are obtained as a weighted average of the series from the models considered (European Commission, 2016).

As it can be seen, this procedure for obtaining the seasonally-adjusted balances depends on a set of assumptions. The applied filters are decided a priori and do not depend on the data.

To overcome these limitations, in this paper we propose a different approach based on spectral analysis that avoids making any a priori assumption regarding the structure of the components. We analyse the data directly in order detect the different periodic components, and thus for each individual series we determine how the periodic components with different periods and intensities give rise to the observed time series.

The proposed procedure also differs from the Dainties filter in that instead of filtering the series, it uses decomposition in a sum of periodic functions such as sines and cosines. The periodic components of the time series are estimated by means of a variation of the Fourier transform, where the trend component is reflected in the extreme of low frequency components. The cyclical components are separated along a frequency axis, and the noise is represented as an underlying flat component that appears at a lower level than the cyclical components.

In the next section we describe the methodological approach used for transforming the information from the time domain to the frequency domain. The proposed procedure is based on the Welch method for spectral density estimation. This approach is used for the detection of periodicities in the time domain and, allows us to gain some insight into potential hidden structures in business and consumer survey data.

3. Methodology – Spectral density estimation

Discret Fourier Transform (DFT) can be regarded as a mathematical tool that when applied to any discrete time series decomposes them into a linear combination of discrete frequencies. These frequencies determine the importance of a given cyclical component of the time series. Thus, a frequency component with a higher value in the DFT will correspond to a cyclical component with higher energy (amplitude). The statistical average of a certain signal as analysed in terms of its frequency content is called its spectrum. Fourier analysis allows converting a signal from its original domain, time in our case, to a representation in the frequency domain, and vice versa.

In signal processing, a periodogram is an estimate of the spectral density of a signal, and is computed as the square of the absolute value of the Fourier transform of the time series. The periodogram is a standard method for determining the spectral components of a time series, and it is the most common tool for examining the amplitude vs frequency characteristics. Periodograms have been used for more than one century (Gardner, 1987).

Nevertheless, one drawback of the periodogram is that it presents a very high variability in terms of the estimation at each frequency. Therefore, in non-parametric estimation methods, a smoothing is usually applied, either in the frequency direction, averaging amplitudes corresponding to adjacent frequencies, or by dividing the time series into segments and, then averaging the time sequence of periodograms corresponding to each window.

In this study, we use the Welch method for spectral density estimation. Welch's method represents an improvement on the standard periodogram spectrum estimation in that it reduces noise in the estimated power spectra in exchange for reducing the frequency resolution.

The method is based upon the usage of periodogram spectrum estimates, which are the result of converting a signal from the time domain to the frequency domain. In that sense is similar to Bartlett's method, but it differs in that: i) the signal is split up into overlapping data segments, ii) the overlapping segments are then windowed in the time domain, resulting in a modified periodogram. This is justified because a high resolution in frequency with a strong variability component is traded for a lower resolution in frequency, allowing for averaging the data segments, and therefore diminishing the estimation variability.

While most window functions afford more influence to the data at the centre of the set than to data at the edges, which implies a loss of information, Welch's method mitigates that loss by overlapping in time.

This procedure is done as follows. First, the original time series are fragmented into overlapping segments. Then, for each segment a periodogram is computed by means of DFT of business and consumer survey indicators, denoted as x_t, where $x_t = \{x_1, \ldots, x_T\}$. The DFT transforms a sequence x_t into another sequence of complex numbers $X_k = \{X_1, \ldots, X_T\}$ by means of the following expression:

$$F(x_t) = \sum_{t=1}^{T} x_t e^{-\frac{i2\pi}{T}kt} = \sum_{t=1}^{T} x_t \left[\cos\left(\frac{2\pi}{T}kt\right) - i \cdot \sin\left(\frac{2\pi}{T}kt\right) \right] \tag{3}$$

Where $F(x_t)$ denotes the Fourier component at frequency *k*; *i* denotes the the imaginary number (square root of –1); *t* is a time index of the sequence $t = 1, \ldots, T$; and the frequency component *k* indicates the inverse of the detected periodicity, i.e. *T/k*. Finally, the squared magnitude of the result is computed and the individual periodograms are averaged using the Welch method to reduce the variance of the individual power measurements.

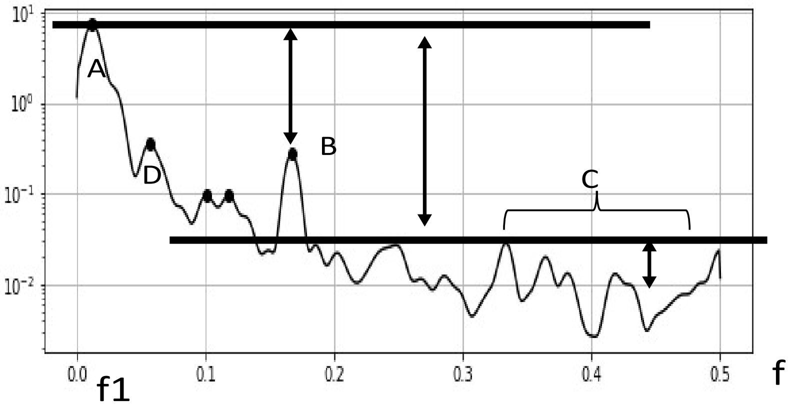
4. Spectral analysis

In this section we present the results of applying the Welch algorithm to business and consumer survey data. We compute the spectral components of time series and use the built-in method for automatic peak detection that comes with Python's scipy library (https://scipy.org/). These peaks correspond to the underlying periodic components of each survey indicator. Results are grouped by questions. In each graph of Figs 2–6, we present the estimates of the spectral density for each response category of each question. In the first subsection (4.1) we present the results for the industry survey and, in the second subsection (4.2) the results for the consumer survey.

Spectral density analysis tools developed in the field of signal processing do not provide confidence margins (Oppenheim and Schafer, 2010). In order to discern the presence of a periodic component with respect to the background noise, the decision is based on the component's energy and its physical viability, and it is circumscribed to the type of analysis.The energy of a component can be defined as its relative amplitude with respect to the background noise level.

Consequently, the decision on whether to consider the presence of a periodic component as relevant has an interpretative factor. With the aim of facilitating the interpretation of the graphs, in Fig. 1 we simulate a potential spectral density function and illustrate its interpretation. The spectral density function in Fig. 1 shows three main frequency peaks (A, B and D) and several secondary frequency peaks denoted as C. The periods associated with each peak are the inverse of the observed discrete function 'f' multiplied by the duration of the time series. Thus, f1 is associated with the period 1/(f1) times the sample time unit.

Fig. 1. Spectral density function – Example



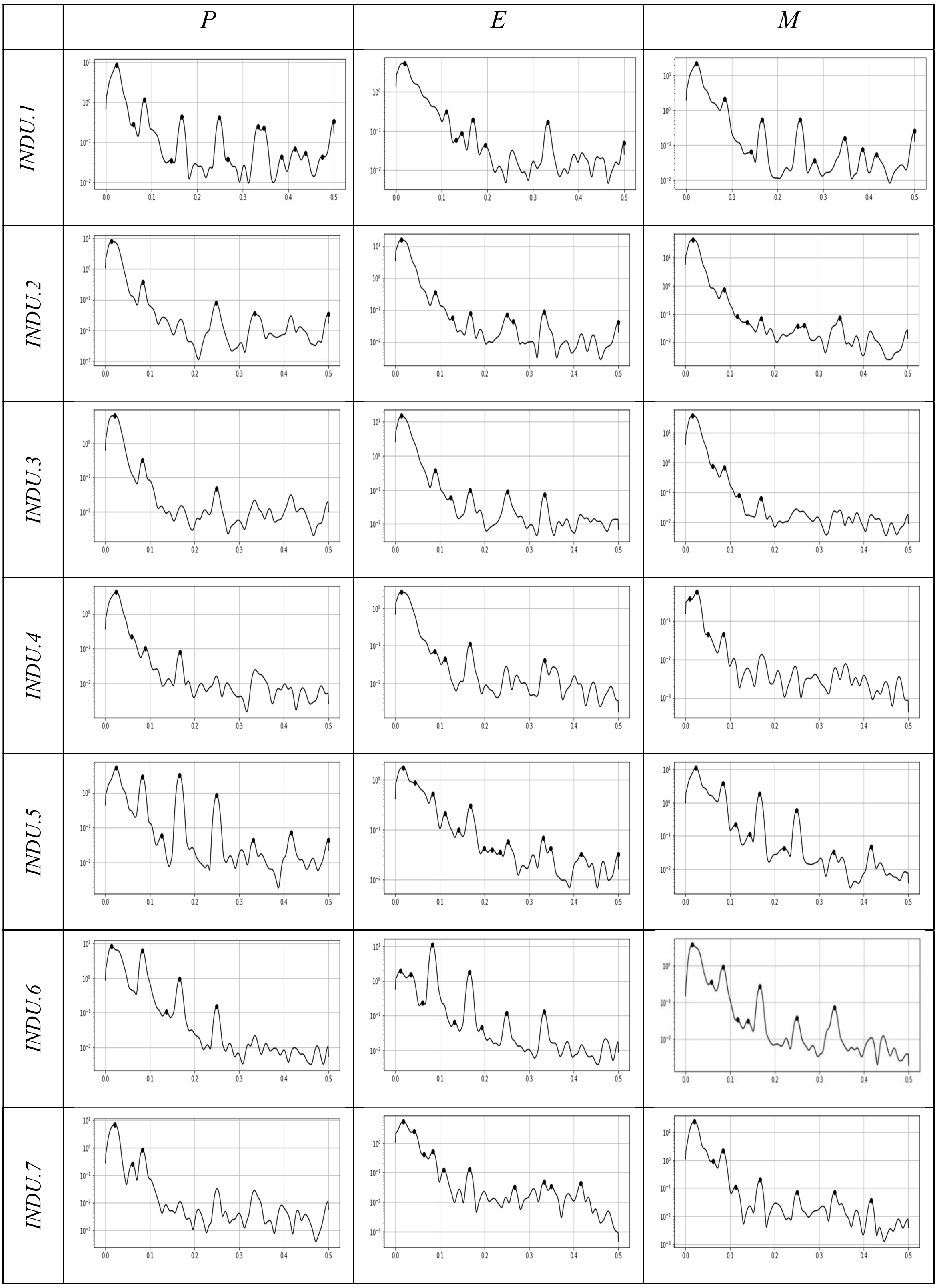
In Fig. 1 we can observe that peaks A and B are clearly above the flat level of the density spectrum. The amplitude of A is about 10, while the amplitude of B is about $5*10^{-1}$, this means that the energy associated with B is 50 times lower. As B is above the underlying flat line, we can consider that this peak will be a significant component to the time series. On the other hand, peak D is at the same height than B, but is very near to the underlying flat level and is near the high energy peak A. In this case, peak D is a candidate to be considered as a spurious peak, and may not be considered as relevant.

Peaks in C are high frequency ones, which means that they are associated with fast changes in the time series that might be considered spurious components related to noise. These peaks are also candidates to be discarded both because i) their level is very low, $2 * 10^{-2}$, which is about 1/500 times the amplitude of the peak A, and also because ii) they are near the flat underlying level of the frequency spectrum.

Figs 2–6 contain the estimation of the spectral density function for each frequency. DFTs (3) are presented in logarithmic scale. The abscissa axis represents the normalised frequencies, measured in cycles per month. The dots in each graph indicate the periodic components detected in the reference time series. As explained before, the importance of the peaks is given by their relative local variation, giving rise to peaks that cannot be considered relevant. As a result, only some of the peaks are clearly associated with the underlying periodicities. To facilitate the interpretation of the obtained results, in Tables 2 and 3 we present the relevant periodic components detected in Figs. 2- 6 , conveniently re-expressed in months. Table 2 summarises the main periodicities for the industry indicators and Table 3 the main ones for the consumer indicators.

4.1. *Industry survey*

Fig. 2. Spectral density functions of the industry survey indicators – Monthly questions



Notes: The black line represents the estimation of the spectral density function for each frequency (Y-axis). The X-axis the normalised frequencies, measured in cycles per month. The dots indicate the cycles detected in the reference time series using the built-in method for automatic peak detection that comes with Python's scipy library.

Table 2
Periodicities of the industry survey indicators – Monthly questions

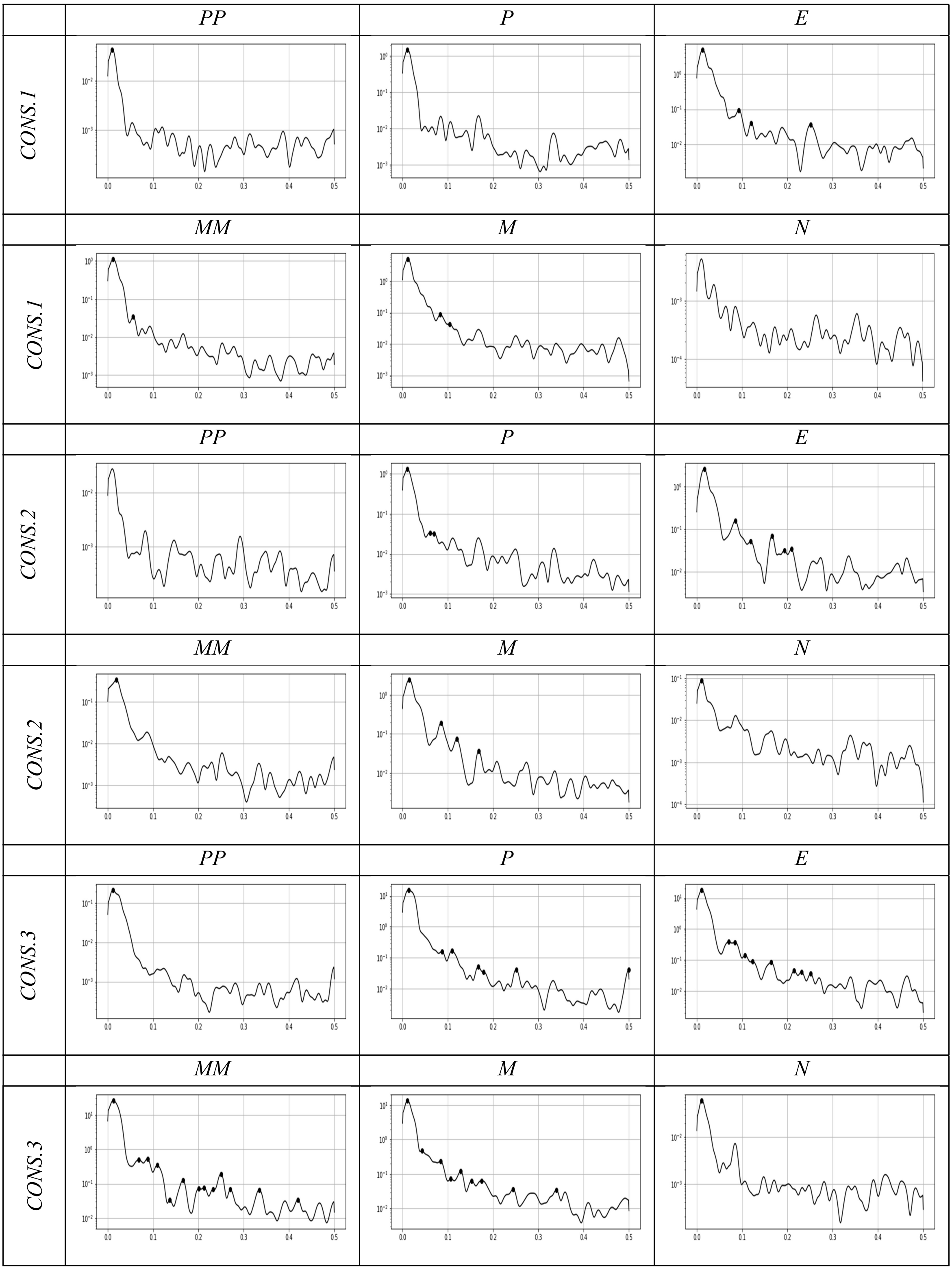
Variable	Reply option	**Periodicities** (months)
INDU.1 – Production trend observed in recent months	*P*	56.9, 11.1, 6.0, 4.0, 3.0
	E	56.9, 5.9, 3.0
	M	56.9, 6.0, 4.0
INDU.2 – Assessment of order-book levels	*P*	52.9, 12.0, 4.0, 3.0
	E	52.9, 3.0
	M	52.9, 11.4
INDU.3 – Assessment of export order-book levels	*P*	52.9, 11.4, 4.0
	E	52.9, 11.6, 6.0, 4.3
	M	52.9, 11.6, 6.0
INDU.4 – Assessment of stocks of finished products	*P*	52.9, 6.0,
	E	56.9, 6.0, 2.9
	M	50.0, 11.0
INDU.5 – Production expectations for the months ahead	*P*	52.9, 11.4, 6.0, 4.0
	E	52.9, 6.0
	M	52.9,11.4, 6.0, 4.0, 2.9
INDU.6 – Selling price expectations for the months ahead	*P*	52.9, 11.4, 6.0, 4.0
	E	11.4, 6.0, 4.0, 3.0
	M	52.9, 11.4, 6.0, 4.0, 3.0
INDU.7 – Employment expectations for the months ahead	*P*	48.8,12.1
	E	56.9, 12.2, 6.0
	M	51.2, 11.9, 5.9, 4.0, 2.9

In Table 2 we observe that most survey indicators tend to present a strong cyclical component of about 4 to 4½ years, with the exception of category *E* in the case of ‘selling price expectations for the months ahead’ (*INDU.6*).

Other common periodicities between all reply options from all questions are the ones corresponding to 11 to 12 months, half a year, a quarter of a year, and 3 months. These periodic components were clearly detected as high energy peaks in the Fourier transforms, especially for category *P* in two questions: ‘production expectations for the months ahead’ (*INDU.5*) and ‘selling price expectations for the months ahead’ (*INDU.6*).

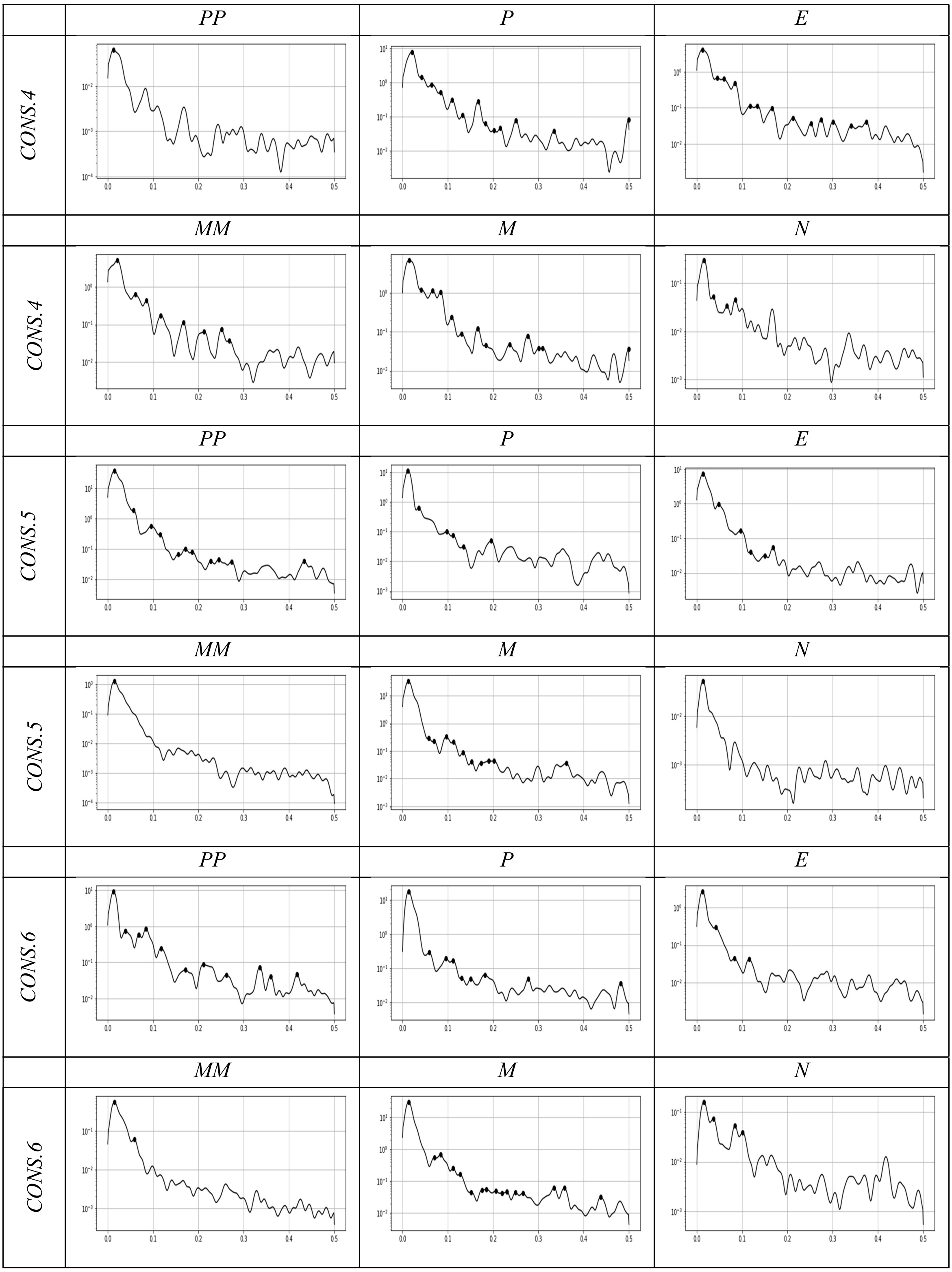
4.2. *Consumer survey*

Fig. 3. Spectral density functions of the consumer survey indicators – Monthly questions



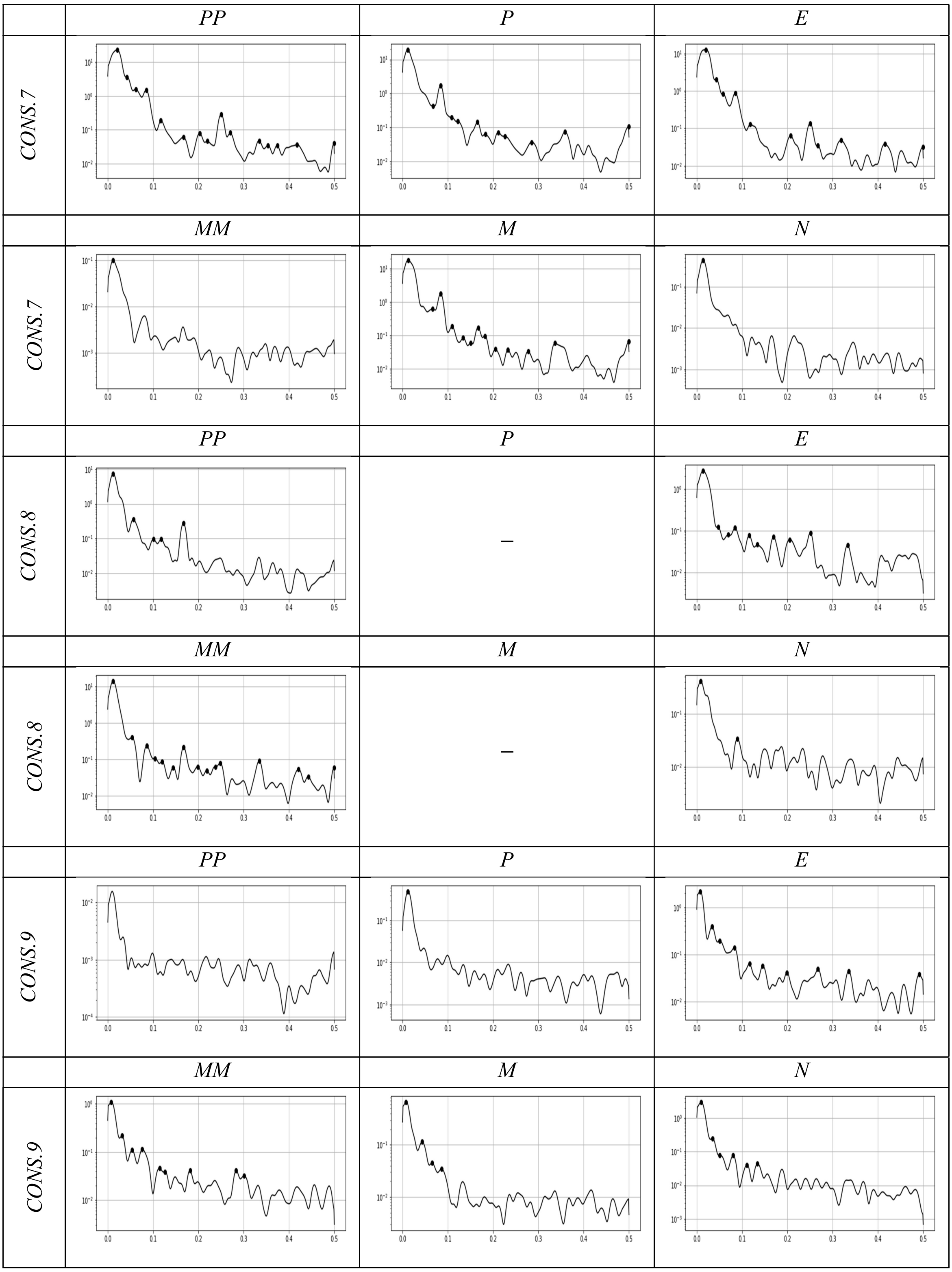
Notes: The black line represents the estimation of the spectral density function for each frequency (Y-axis). The X-axis the normalised frequencies, measured in cycles per month. The dots indicate the cycles detected in the reference time series using the built-in method for automatic peak detection that comes with Python's scipy library.

Fig. 4. Spectral density functions of the consumer survey indicators – Monthly questions



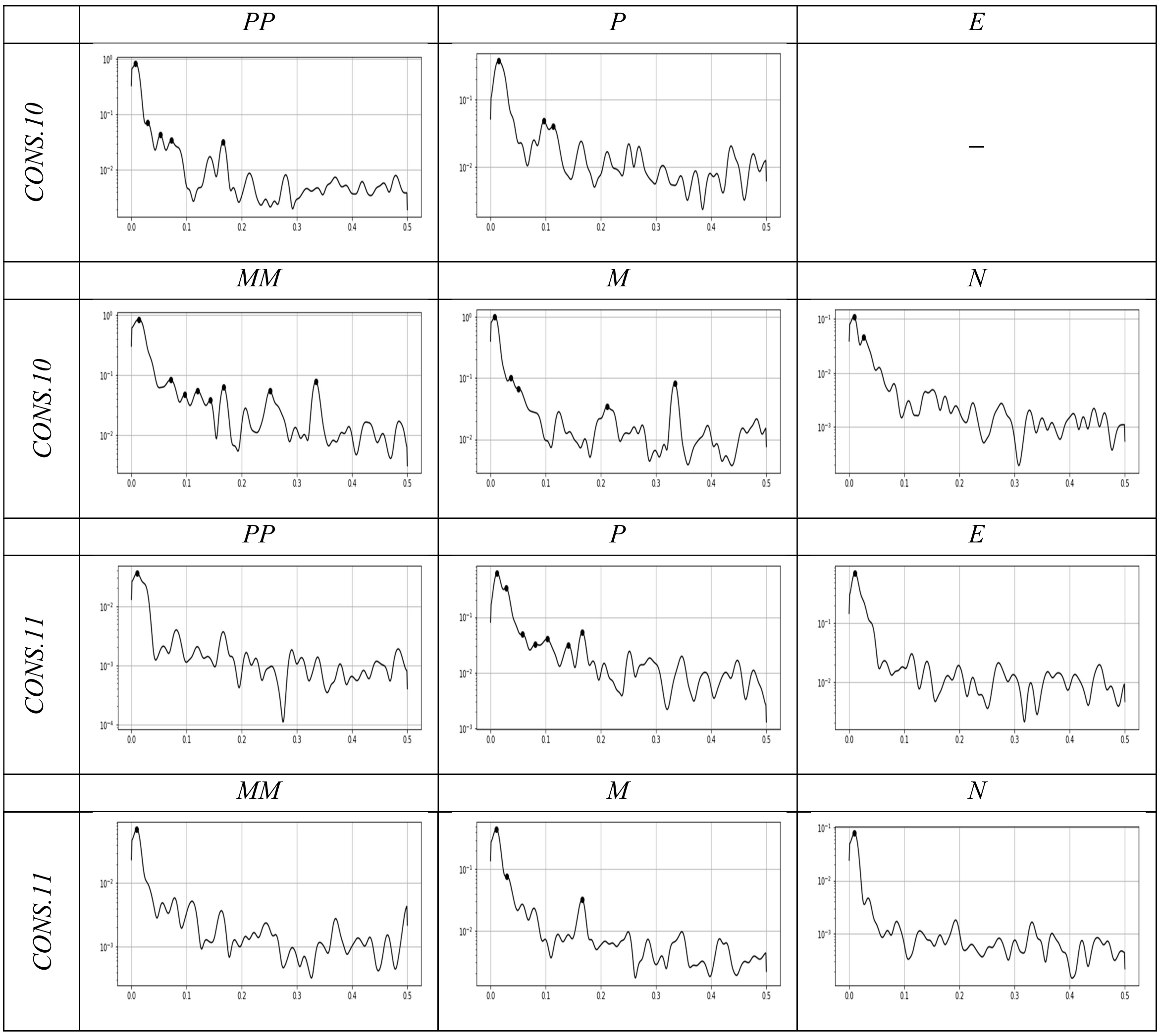
Notes: The black line represents the estimation of the spectral density function for each frequency (Y-axis). The X-axis the normalised frequencies, measured in cycles per month. The dots indicate the cycles detected in the reference time series using the built-in method for automatic peak detection that comes with Python's scipy library.

Fig. 5. Spectral density functions of the consumer survey indicators – Monthly questions



Notes: The black line represents the estimation of the spectral density function for each frequency (Y-axis). The X-axis the normalised frequencies, measured in cycles per month. The dots indicate the cycles detected in the reference time series using the built-in method for automatic peak detection that comes with Python's scipy library. Survey question *CONS.8* only has four reply options; N/A categories (*P* and *M*) are marked with a – sign.

Fig. 6. Spectral density functions of the consumer survey indicators – Monthly questions



Notes: The black line represents the estimation of the spectral density function for each frequency (Y-axis). The X-axis the normalised frequencies, measured in cycles per month. The dots indicate the cycles detected in the reference time series using the built-in method for automatic peak detection that comes with Python's scipy library. Survey question *CONS.10* only has five reply options; N/A categories (*E*) are marked with a – sign.

Table 3
Periodicities of the consumer survey indicators – Monthly questions

Variable	Reply option	Periodicities
CONS.1 – Financial situation over last 12 months	*PP*	–
	P	–
	E	10.8, 8.3, 4.0
	M	12.0
	MM	18.0
	N	–
CONS.2 – Financial situation over next 12 months	*PP*	–
	P	–
	E	11.8, 6.0
	M	11.8, 8.3, 6.0
	MM	–
	N	–
CONS.3 – General economic situation over last 12 months	*PP*	–
	P	–
	E	11.9, 8.1, 6.1
	M	–
	MM	11.4, 6.0, 4.3
	N	12.0
CONS.4 – General economic situation over next 12 months	*PP*	12.0
	P	48.7, 6.0, 3.0
	E	–
	M	68.3, 12.0, 9.2, 6.0, 4.2, 3.6
	MM	46.6, 16.5, 11.8, 8.5, 6.0, 4.7, 4.0
	N	64.0, 11.8
CONS.5 – Price trends over last 12 months	*PP*	–
	P	–
	E	73.1, 21.0, 10.3, 6.0
	M	–
	MM	–
	N	–
CONS.6 – Price trends over next 12 months	*PP*	11.2, 8.4
	P	–
	E	51.2, 8.5
	M	12.0
	MM	–
	N	64.0, 27.7, 12.0, 10.0

Notes: Sign – denotes that no cyclical components have been detected or that the detected peaks are of very low energy so as to be considered relevant.

Table 3 (Cont.1)
Periodicities of the consumer survey indicators – Monthly questions

Variable	Reply option	**Periodicities**
CONS.7 – Unemployment expectations over next 12 months	*PP*	48.8, 11.8, 6.0
	P	85.3, 12.0
	E	51.2, 11.8, 4.8
	M	78.8, 12.0
	MM	–
	N	–
CONS.8 – Major purchases at present	*PP*	17.7, 6.0
	E	12.0, 8.7, 4.9, 4.0
	MM	11.6, 6.0, 3.0, 2.0
	N	11.1
CONS.9 – Major purchases over next 12 months	*PP*	–
	P	–
	E	–
	M	23.3
	MM	32.0, 18.6, 13.1, 8.7, 5.5, 3.5
	N	–
CONS.10 – Savings over next 12 months	*PP*	6.0
	P	10.3
	M	4.7, 3.0
	MM	14.0, 8.3, 7.0, 6.0, 3.0
	N	–
CONS.11 – Statement on financial situation of household	*PP*	–
	P	–
	E	–
	M	6.0
	MM	–
	N	–

Notes: Sign – denotes that no cyclical components have been detected or that the detected peaks are of very low energy so as to be considered relevant.

Results in Table 3 show that for consumer survey indicators the intensity of the cycles heavily varies across questions and reply options. In most cases we do not detect any cyclical components, and when we do, these peaks are of very low energy so as to be considered relevant. In certain questions we find a component of 12 months but it tends to be of very low energy. One of the questions for which we obtain clearly marked peaks is the one regarding the 'financial situation over next 12 months' (*CONS.2*), especially for reply option *M*. Curiously, when the question is stated in the past, regarding the last 12 months (*CONS.2*), the result is opposite: the detected peaks are of very little energy in all categories. This difference between forward-looking questions (expectations) and those referring to the past (perceptions), is repeated in some other cases. For example, prospective questions such as the one referring to the 'general economic situation over the next 12 months' (*CONS.4*) tend to show more relevant lower frequency periodicities than when they are referred to the past (*CONS.3*).

In summary, we find that the detected lower frequency periodicities for consumer survey indicators show a very irregular pattern across questions and reply options. This pattern notably differs from the results obtained for industry survey indicators (Table 2). Business survey indicators showed a common cyclical component of low frequency that corresponds to about 4 to 4½ years which was present across reply options from all questions.

It should be highlighted that to a certain extent these findings may be conditioned by several biases derived from the fact that the wording of the questions differs between both surveys. While business survey indicators mostly refer to the evolution of the variables 'in the recent months' or 'for the months ahead', consumer survey indicators refer to the situation 'over the last twelve months' or 'over the next twelve months'. Furthermore, as opposed to firms, which are faced with three reply options, consumers have three additional response categories: two at each end ("a lot better/much higher/sharp increase", and "a lot worse/much lower/sharp decrease"), and a "don't know" option. Additionally, we want to point out the different nature between the questions of both surveys, since the questions of the consumer survey refer to objective variables, while the questions of the business survey refer to specific factors of the firm. Finally, as suggested by Kahneman and Tversky (1971), there may be additional biases attributable to the agents themselves. Phenomena such as loss aversion or anchoring may be affecting respondents when they answer the questionnaires, and should not be neglected.

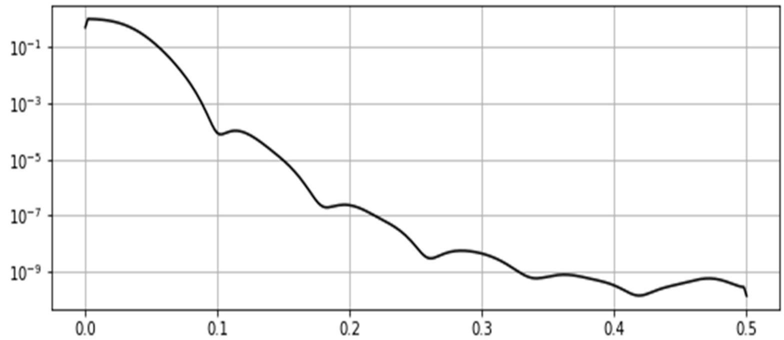
5. Design of a filter for survey indicators

In this section we design a filter for business and consumer survey indicators. The selection criterion of the filtering process is based on the results of the previous section. Our objective is to tailor make a filter to extract the components of the survey indicators with periodicities similar to those that can be found in the dynamics of economic activity. With this aim, we first conduct the spectral analysis of seasonally-adjusted GDP growth in the EA. We use GDP data from the OECD.Stat (Organisation for Economic Co-operation and Development, 2020).

Second, we present the filter, describing its properties. Third, we apply the filter to all business and consumer survey indicators (Table 1). Then, we apply expression (1) to the smoothed industry survey indicators and expression (2) to the smoothed consumer survey indicators in order to compute the balance statistic of the filtered time series. Finally, we assess the performance of the resulting filtered balance statistic (*BF*) by comparing it to the seasonally-adjusted balance (*BS*) published by the EC according to the procedure described in Section 2.

The selection criterion of the filter is based on the spectral analysis of economic activity. We start by computing the spectral density function of seasonally-adjusted monthly GDP growth in the EA. The obtained result is presented in Fig. 6.

Fig. 6. Spectral density function of seasonally-adjusted GDP growth



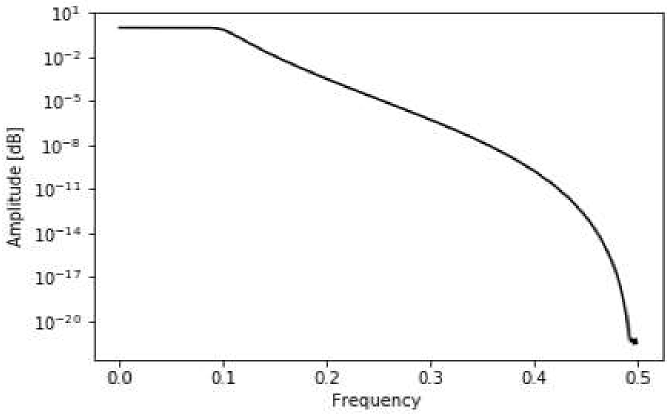
In order to extract the components of the survey responses that are closest to those observed in seasonally-adjusted GDP growth (Fig. 6), we have opted for a zero-phase low-pass filter. More specifically, we have chosen a Butterworth filter, which is a type of signal processing filter designed to have a frequency response as flat as possible in the pass band (Butterworth, 1930). As a result, the Butterworth filter is also referred to as a maximally flat magnitude filter (Bianchi and Sorrentino, 2007).

In a n-th order Butterworth filter, the frequency response $H(i\omega)$ is given by:

$$H(i\omega) = \frac{1}{\sqrt{1+\varepsilon^2\left(\frac{\omega}{\omega_p}\right)^{2n}}} \qquad \text{where } \omega = 2\pi f \tag{4}$$

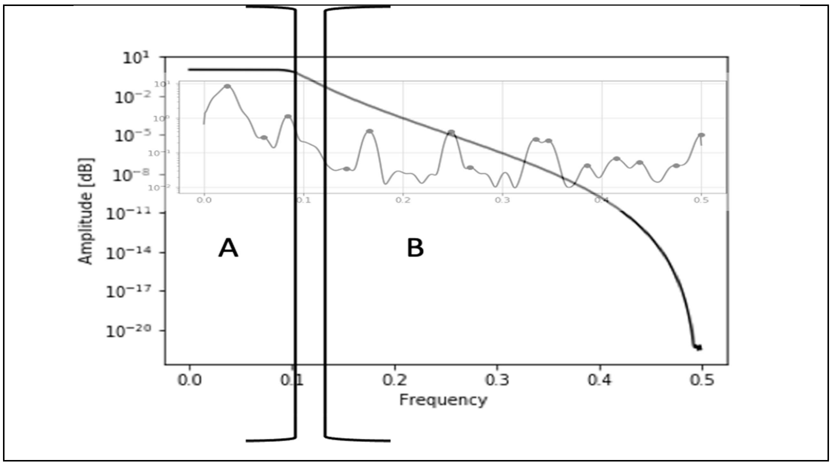
Where n represents the filter order, ω is the radian frequency, ε denotes the maximum pass band gain, and i the the imaginary number corresponding to $\sqrt{-1}$. In our case, we have applied a Butterworth filter of order 10. According to the spectral analysis of GDP growth shown in Fig. 6, the cut-off frequency was fixed at 0.1, i.e. 10 months, as the spectral density function shows a sharp decrease in energy around this normalized frequency. Note that at frequency 0.1, the energy associated with the higher frequency components is attenuated by a factor bigger than 10^{-4}. The frequency response of the resulting filter is shown in Fig. 7.

Fig. 7. Frequency response of the low-pass zero-phase filter



In order to illustrate the properties of the selected filter and its effect on survey indicators, in Fig. 8 we superimpose the frequency response of the filter with with the spectral density function of a consumer survey indicator chosen as an example. We divide the graph into two areas: section A and section B. On the one hand, section A corresponds to the area selected for the output, and coincides with the region of the frequencies of the GDP signal with maximum energy. Section B, on the other hand, corresponds to the region where the components outside the section of the GDP spectral density function that accumulates most of the energy are attenuated. Therefore, we are filtering, i.e. rejecting, the frequency components of the survey indicators that do not have a counterpart in the GDP time series.

Fig. 8. Overlap of the frequency response of the filter and a spectral density function



Notes: Section A contains the preserved frequencies, while section B, the frequencies that are attenuated by a factor greater than 100.

The filtering procedure is performed by a finite difference equation of the form:

$$y(t) = \sum_{n=1}^{N} a_n y(t-n) + \sum_{m=0}^{M} b_m x(t-m) \tag{5}$$

Where $y(t)$ refers to the output of the filter and, $x(t)$ to the time sequence to be filtered. $\{a_n, b_m\}$ are the coeffitiens of the filter. The order of the filter is computed as the $Max(N, M)$. The coefficients of the filter are computed by means of the scipy library in Python (https://scipy.org/).

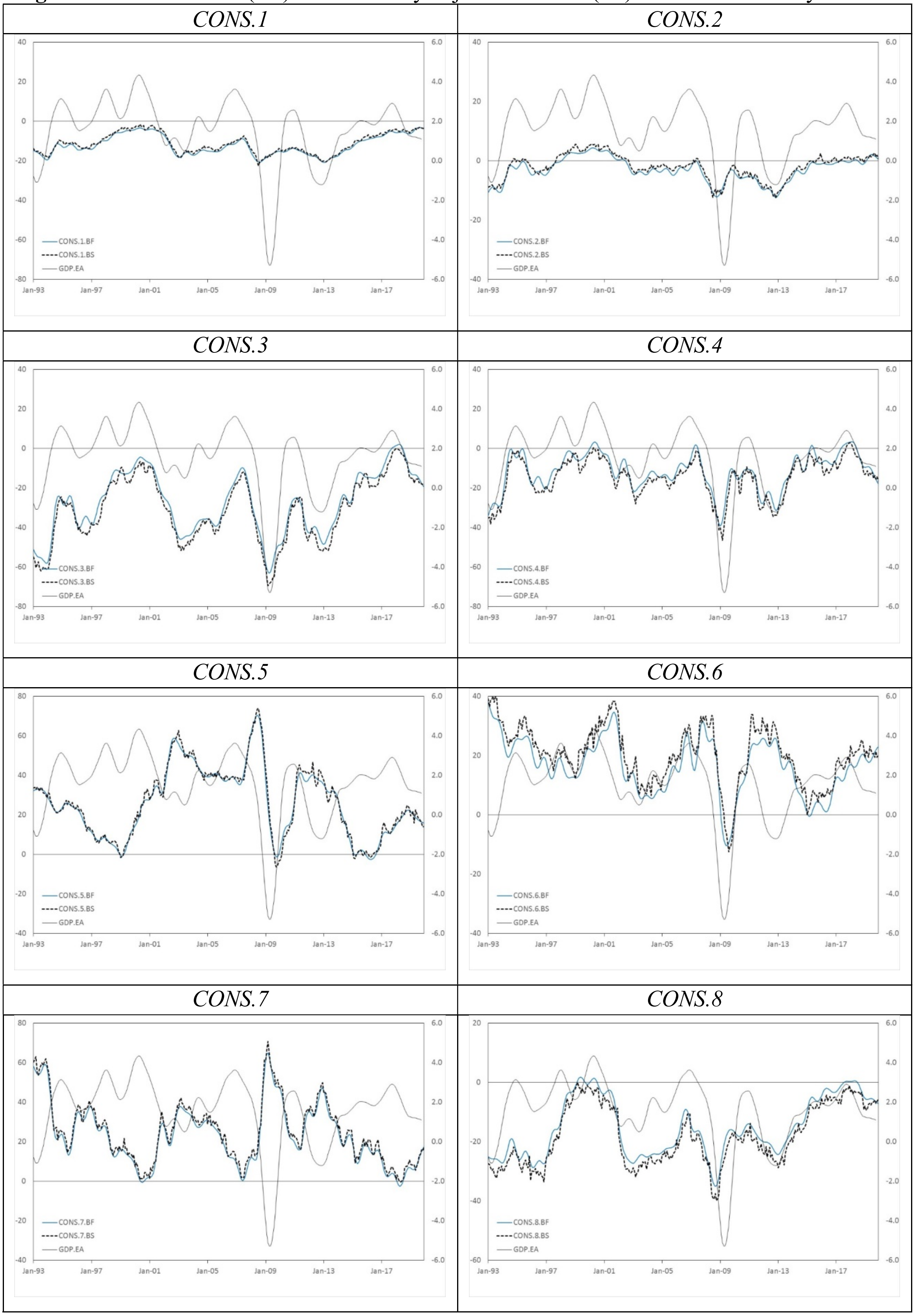
The zero-phase is obtained by filtering the time series twice: first, from the past values of the series to the future ones, and then, from the future values to the past values. This process allows compensating for the delays introduced by the filtering process. As a result, the resulting filtered survey indicators are temporally aligned with the original time series. Note that this procedure can only be done retrospectively. See Hamming (1998) and Proakis and Manolakis (1996) for detailed information on the properties of low-pass filtering.

Next, we proceed to apply the low-pass filter to all survey indicators (Table 1). Then, we compute the balance statistic of the filtered series. By applying expression (1) to the smoothed industry survey indicators and, expression (2) to the smoothed consumer survey indicators, we obtain a filtered balance statistic (*BF*) for all survey indicators. In order to assess its performance, in Figs 9 to 11 we compare them to the seasonally-adjusted balances (*BS*) published by the EC according to the Dainties method described in Section 2. In all graphs we include the year-on-year growth rates of seasonally-adjusted monthly GDP in the EA.

Fig. 9. Filtered balance (*BF*) vs. seasonally-adjusted balance (*BS*) – Industry survey

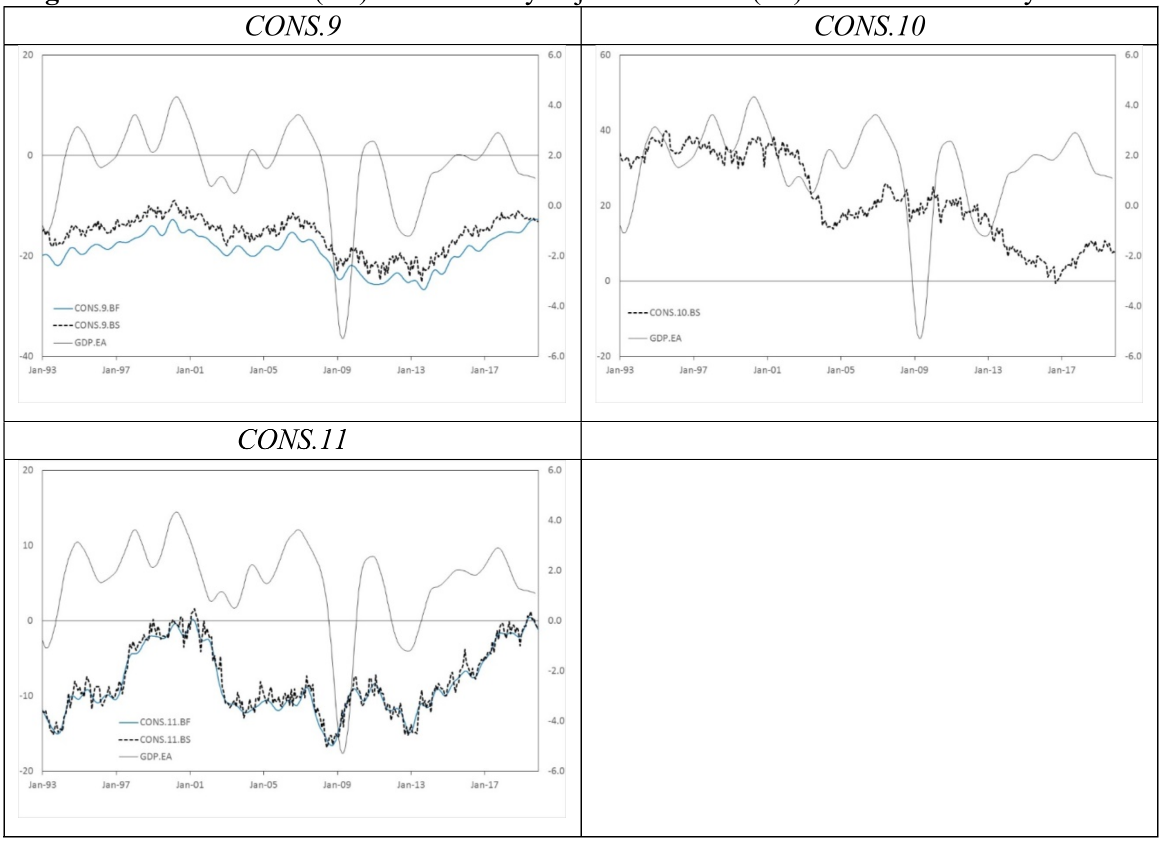
Notes: The blue line represents the evolution of the filtered balance (BF), the black dotted line the evolution of the seasonally-adjusted balance (BS) and, the grey line the year-on-year growth rates of seasonally-adjusted monthly GDP for the EA.

Fig. 10. Filtered balance (*BF*) vs. seasonally-adjusted balance (*BS*) – Consumer survey



Notes: The blue line represents the evolution of the filtered balance (BF), the black dotted line the evolution of the seasonally-adjusted balance (BS) and, the grey line the year-on-year growth rates of seasonally-adjusted monthly GDP for the EA.

Fig. 11. Filtered balance (*BF*) vs. seasonally-adjusted balance (*BS*) – Consumer survey



Notes: The blue line represents the evolution of the filtered balance (BF), the black dotted line the evolution of the seasonally-adjusted balance (BS) and, the grey line the year-on-year growth rates of seasonally-adjusted monthly GDP for the EA.

Apart from the fact that survey indicators, regardless of how they are processed, show a strong and positive relation to economic growth[2], in Figs. 9 to 26 it can be seen that both the filtered balance (*BF*) and the seasonally-adjusted balance (*BS*) are highly correlated. Notwithstanding, the evolution of *BF* tends to be smoother than that of the *BS*, especially for the consumer survey indicators.

[2] There is strong evidence in the literature regarding the predictive power of survey expectations. Acuña, Echevarría, and Pinto-Gutiérrez (2020) recently found that consumer confidence indicators were positively related to consumption growth in Chile. Altug and Çakmakli (2016), obtained superior forecasts of inflation when incorporating survey expectations for Brazil and Turkey. Similarly, Juhro and Iyke (2019) showed that accounting for consumer and business sentiments improved forecast accuracy of consumption in Indonesia. Gayer, and Reuter (2015) and Sorić et al. (2019) obtained similar results for the EA. Claveria, Monte and Torra (2017a,b; 2018, 2019a,b) have used the survey expectations from the World Economic Survey carried out by the Ifo Institute to show their good forecasting performance when used to construct economic indicators. Lanzilotta, Brida and Rosich (2019) have recently found a nonlinear cointegration relationship between producers' expectations and Uruguayan GDP growth.

6. Concluding remarks

The main objective of the paper is two-fold. On the one hand, we aim to detect the underlying existing periodicities in business and consumer survey data. On the other hand, we aim to provide researchers with a filter especially designed for survey indicators that allows circumventing the application of filters based on a priori assumptions regarding the structure of the components.

First, with the objective of giving some insight into the hidden periodicities of business and consumer survey data, we use the Welch algorithm to compute the specific periodic components of each question and their respective reply options.

We find remarkable differences between business survey indicators and consumer survey indicators. The former, present stronger cyclical components than the indicators form the consumer survey. In the case of the industry survey indicators, we detect a common cyclical component among reply options, corresponding to approximately four to five years, as well as other higher frequency periodicities: twelve, six, four and three months. The cyclical component corresponding to four years is absent in the case of the neutral category of response for the question regarding 'selling price expectations for the months ahead'. For the higher frequency periodicities, the neutral category of response of the industry survey tends to show less marked peaks and of smaller amplitude than the other two extreme response categories. On the contrary, for consumer survey indicators the intensity of the cycles varies across questions and reply options. In most cases we do not detect any cyclical components, and when we do, these peaks are of very low energy so as to be considered relevant. We also observe that the detected lower frequency periodicities show a very irregular pattern across questions and reply options.

To a certain extent, these findings could be in part derived from the fact that the wording of the questions differs between both surveys. While business survey indicators mostly refer to the evolution of the variables 'in the recent months' or 'for the months ahead', consumer survey indicators refer to the situation 'over the last twelve months' or 'over the next twelve months'. Additionally, we want to point out the different nature between the questions of both surveys, since the questions of the consumer survey refer to objective variables, while the questions of the business survey refer to specific factors of the firm.

Second, we design a filter for business and consumer survey data. The selection criterion of the filtering process is based on the objective of extracting the components of the survey indicators with periodicities similar to those that can be found in the dynamics of economic activity. With this aim, we opt for a low-pass filter that does not need a sharp cut-off frequency and that does not distort the wave form. Specifically, we we use a Butterworth filter and apply a zero-phase filtering process to preserve the time alignment of the time series.

To assess the performance of the filtered series, we computed the balance statistic and compared its evolution to that of the seasonally-adjusted balances obtained with the Dainties methodology used by the European Commission. We observed that both statistics are highly correlated, although filtered balances tend to be smoother than the seasonally-adjusted ones, especially for the consumer survey indicators.

Finally, we want to note that this is a preliminary examination of the periodicities of business and consumer survey indicators by means of spectral analysis. The analysis focuses solely on monthly survey data for the Euro Area. One issue left for further research is the extension of the analysis to quarterly data and to the rest of the countries included in the surveys. We also want to point out that one drawback of the proposed approach for the detection of periodicities is its lack of accuracy for components of extremely low frequency. Regarding the filtering of survey indicators, another issue left for further research is the evaluation of alternative filters.

References

Acuña, G., Echevarría, C., & Pinto-Gutiérrez, C. A. (2020). Consumer confidence and consumption: Empirical evidence from Chile. *International Review of Applied Economics*, 34(1), 75–93.

Altug, S., & Çakmakli, C. (2016). Forecasting inflation using survey expectations and target inflation: Evidence from Brazil and Turkey. *International Journal of Forecasting*, 32(1), 138–153.

Bianchi, G., & Sorrentino, R. (2007). *Electronic filter simulation & design*. New York, N.Y.: McGraw Hill Professional.

Butterworth, S. (1930). On the theory of filter amplifiers. *Wireless Engineer*, 7, 536–541.

Claveria, O. (2019). A new consensus-based unemployment indicator. *Applied Economics Letters*, 26 (10), 812–817.

Claveria, O. (2019). Forecasting the unemployment rate using the degree of agreement in consumer unemployment expectations. *Journal for Labour Market Research*, 53(3), 1–10.

Claveria, O. (2020). Uncertainty indicators based on expectations of business and consumer surveys. *Empirica*. Forthcoming.

Claveria, O., Monte, E., & Torra, S. (2017). A new approach for the quantification of qualitative measures of economic expectations. *Quality & Quantity*, 51(6), 2685–2706.

Claveria, O., Monte, E., & Torra, S. (2017). Using survey data to forecast real activity with evolutionary algorithms. A cross-country analysis. *Journal of Applied Economics*, 20(2), 329–349.
Claveria, O., Monte, E., & Torra, S. (2018). A data-driven approach to construct survey-based indicators by means of evolutionary algorithms. *Social Indicators Research*, 135(1), 1–14.
Claveria, O., Monte, E., & Torra, S. (2019). Empirical modelling of survey-based expectations for the design of economic indicators in five European regions. *Empirica*, 23 (6), 428–431
Claveria, O., Monte, E., & Torra, S. (2019). Evolutionary computation for macroeconomic forecasting. *Computational Economics*, 23(6), 428–431.
Claveria, O., Pons, E., & Ramos, R. (2007). Business and consumer expectations and macroeconomic forecasts. *International Journal of Forecasting*, 23(1), 47–69.
European Commission (2016). *The Joint Harmonized EU Programme of Business and Consumer Surveys*. User Guide.
European Commission (2019). *Business and consumer surveys*. Available at: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en. Last accessed on January 6, 2020.
Gardner, W. (1987). Introduction to Einstein's contribution to time-series analysis. *IEEE ASSP Magazine*, 4(4), 4–5.
Gelper, S., & Croux, C. (2017). On the construction of the European economic sentiment indicator. *Oxford Bulletin of Economics and Statistics*, 72(1), 47–62.
Girardi, A., Gayer, C., & Reuter, A. (2015). The role of survey data in nowcasting euro area GDP growth. *Journal of Forecasting*, 35(5), 400–418.
Gottman, J. M. (1981). *Time-series analysis. A comprehensive introduction for social scientists*. New York: Cambridge University Press.
Hamming, R. W. (1998). *Digital Filters* (3rd Edition). Mineola, N.Y.: Dover Publications.
Juhro, S. M., & Iyke, B. N. (2019). Consumer confidence and consumption in Indonesia. *Economic Modelling*. Forthcoming.
Kahneman, D., & Tversky, A. (1971). Belief in the law of small numbers. *Psychological Bulletin*, 76(2), 105–110.
Lanzilotta, B., Brida, J. G., & Rosich, L. (2019). Common trends in producers' expectations, the nonlinear linkage with Uruguayan GDP and its implications in economic growth forecasting. *Serie Documentos de Trabajo, DT 28/19*. Instituto de Economía *IECON*, Universidad de la República, Uruguay.
Oppenheim, A. V., & Schafer, R. W. (2010). *Discrete-time signal processing* (3rd Edition). Upper Saddle River, N.J.: Prentice Hall.
Organisation for Economic Co-operation and Development (2020). OECD.Stat. Available at: https://doi.org/10.1787/data-00900-en. Last accessed on January 9, 2020.
Proakis, J. G., & Manolakis, D. G. (1996). *Digital signal processing* (3rd Edition). Upper Saddle River, N.J.: Prentice Hall.
Sorić, P., Lolić, I., Claveria, O., Monte, E., & Torra, S. (2019). Unemployment expectations: A socio-demographic analysis of the effect of news. Labour Economics, 60, 64–74.
Welch, P. D. (1967). The use of Fast Fourier Transform for the estimation of power spectra: A method based on time averaging over short, modified periodogram. *IEEE Transactions on Audio and Electroacoustics,* 15(2), 70–73.

UBIREA

Institut de Recerca en Economia Aplicada Regional i Públic
Research Institute of Applied Economics

WEBSITE: www.ub-irea.com • **CONTACT:** irea@ub.edu

AQR

Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group

WEBSITE: www.ub.edu/aqr/ • **CONTACT:** aqr@ub.edu

Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona