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Measuring business cycles: Empirical evidence based on an unobserved component approach

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Abstract: We adopt an unobserved components time series model to track the business cycles in the G7 countries using the Industrial production index over the period from 1:1961 to 8:2017. The advantage of adopting the industrial production series frequency is that the business cycle can be investigated in terms of a higher frequency than once per quarter. The aim here is to extract the classical cycle by dating the peaks and troughs and investigating the characteristics of the business cycle through the unobserved component model, which has the capacity to model fat tails data using a driven parameter through the Kalman filter. We find that the industrial production index has medium-term cycles which have a few statistical properties in common. We show that the length and amplitude of the business cycles vary over time and across countries.

Subjects: Economics; Macroeconomics; Econometrics

Keywords: unobserved component time series model; maximum likelihood estimation; classical cycle; industrial production index; medium-term cycles
JEL classification: C410; E100; E310; E370

ABOUT THE AUTHOR

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This work is a part of a project that investigated the economic cycle issue in both developed and developing countries.

PUBLIC INTEREST STATEMENT

In this paper, I tend to advocate the literature on dating the business cycles of the G7 countries based on high frequency data, for the first time in the literature, and identify clusters among the regions showing differences business cycle behaviour.

It is striking that our analysis shows that the industrial production index captures the classical characteristics of the business cycle. Moreover, it exhibits medium-term cyclical behaviour with ample fluctuations. We find that the persistence, length and amplitude of the extracted cycles vary over time and vary across countries. In particular, we report differences in the business cycles within the considered sample, and we establish that business cycles have increased in amplitude and persistence over time.

The heterogeneity reported here shed new light on important criterion for implementing policies. That is to say, region-specific national policies should be adopted to characterise such economic features and, hence, taking into account the regional dimension.

1. Introduction

The variations in economic fortune and hence economic instability associated with business boom and bust draw much attention to the economic situation all over the world. According to Elliott and Timmermann (2013), the possible directions and events in advance of the economy will promote the process for decision makers. Studies of the business cycle, however, are still concerned to determine the cycle phases, a task made harder by the noisy data that raise mixed signals about the overall state of the economy (Alqaralleh, 2018; Borio, 2014; Hiebert, Klaus, Peltonen, Schüler, & Welz, 2014; Taylor, 2015). Put differently, the central question of business cycle analysis nowadays is how to decompose long-term trends and cyclical components.

Since the seminal work by Burns and Mitchell (1946), who defined the business cycles as fluctuations in economic activity that last between 1.5 and eight years, several studies from different points of view have tried to measure the cycle and investigate its statistical properties. Most of these studies rely mainly on three approaches: turning point analysis, frequency-based filters and model-based filters.

The study of the turning point analysis approach dates back to its origins in traditional cycle-dating methods, mainly dating the peaks and troughs to identify business cycles. This method is still used, mainly by the NBER and the Euro Area Business Cycle Dating Committees. Frequency-based filters such as the filters proposed by Hodrick and Prescott (1997) and Baxter and King (1999) have also become very popular, largely because of their relatively simple implementation (e.g. Aikman, Haldane, & Nelson, 2015). In their influential papers, Stremmel (2015), Schüler, Hiebert, and Peltonen (2015) and Igan, Kabundi, De Simone, Pinheiro, and Tamirisa (2011) use filters of this kind to filter the component of each series and then investigate the turning points. Among the univariate approaches, the unobserved components model that take into account the stochastic properties of the data are used as an alternative to the above *ad hoc* filtering procedures (e.g. Creal, Koopman, & Zivot, 2010; Valle e Azevedo et al., 2006 and the references therein).

The issue of which economic indicator should be used to investigate the business cycle has also received considerable critical attention. Given the importance of economic information for policy-makers and researchers alike, an economic indicator should contain information that can help to understand and forecast business cycles and hence provide information about a country's economy in the past, now and in the future. These indicators should be reliable and provide accurate information for all players to interpret them correctly. Moore and Shiskin (1967) present a list of criteria for evaluating an indicator before choosing it as a predictor. According to Forni, Hallin, Lippi, and Reichlin (2000) and Stock and Watson (2014), hundreds of economic time series may be used to measure the indicators of the business cycle and growth.

Real Gross Domestic Product (GDP) is undoubtedly one of the most critical variables for the economic cycle (e.g. Antolin-Diaz et al., 2017; Kim, Morley, & Piger, 2005; Neftci, 1984; Sarantis, 2001). In their seminal work, Stock and Watson (2003) state that the cyclical component of real GDP is a suitable proxy for the overall business cycle, due to the fluctuations in aggregate output which is at the core of the business cycle. However, decision-makers for economic policy need to consider this kind of business cycle indicator at a high frequency, which is usually not available at the desired frequency of the GDP series. Recently, evidence indicates that the cycles extracted from the industrial production index could act as alternative monthly business cycle indicators. For this reason, since industrial production indices are based on real activity, the data available on this may give accurate signals of economic growth and hence the business cycle. Moreover, growth rates in the indices of industries based on service actively move in the same direction as business cycles (e.g. Marczak & Gómez, 2017).

Despite these efforts in understanding the activity of the business cycle in determining economic behaviour, in the above literature real GDP typically served as a basis for constructing a business cycle indicator, but one which was only available at lower frequencies. In contrast, the framework proposed in the present paper takes on board the contribution of high frequency over an extended period to account for most of the fluctuation in the economies under consideration. In line with this picture, our aim here is, first, to extract the classical cycle by dating the peaks and troughs and investigating the characteristics of the business cycle at a higher frequency for the G7 countries.

The advantage of adopting the industrial production series frequency is that the business cycle can be formulated in terms of higher frequency instead of lower. In the business cycle literature, it is well acknowledged that short-term cycles of industrial production and GDP are closely aligned with each other (Burns & Mitchell, 1946). Therefore, we will help to evaluate the capability of the industrial production index to function as a proxy for the business cycle. We then track this cycle considered a monthly proxy for economic growth. To do so, we adapt the work presented in Galati, Hindrayanto, Koopman, and Vlekke (2016) to extract such cycles, based on an unobserved components time series model (UCTSM).

Such a decomposition technique is particularly useful in studying cyclical movement because it tends to model fat tails data using a driven parameter through the Kalman filter (Durbin & Koopman, 2012; Harvey & Trimbur, 2003). Put differently, this model estimates the cycle frequency by estimating an unobserved component model (UCM) using the maximum likelihood method. Moreover, researchers could use diagnostics to evaluate the validity and accuracy of the model.

Our results reveal that, first, there are differences in the cycle's characteristics between countries and over time, especially in respect of fluctuation and excess area. Second, the frequency and variance of the model-based filters are significantly estimated. The notation emerging here is that the cycle is centred on low-frequency components. Additionally, the cyclical components are near the estimated central frequency. Furthermore, considerable heterogeneity is observed not only across countries but also over time.

The remainder of this paper proceeds by introducing the methodology and the specifications of the procedure that was used. The third section presents the data and the classical cycle. The research results are presented in the fourth section. We conclude with a summary of the main findings.

2. Model-based filters approach

Denoted by $y_{i,t} = \log Y_{i,t}$ an industrial production index for country *i* observed at *t*, the UCM decomposes such series into unobserved cycle-trend components. Such that

$$y_{i,t} = \tau_{i,t} + \psi_{i,t} + \epsilon_{i,t}, \epsilon_{i,t} \sim \text{i.i.d}\, N\left(0, \sigma^2_{\epsilon,i}\right) \tag{1}$$

in Equation (1) (τ_t) is the long-term trend, (ψ_t) standing for short to medium-term cyclical dynamics in series (i) at time (t) and for normally distributed residuals represented by (ϵ_t). The covariance between the disturbances driving a particular component is typically non-zero and indicates a dependence structure among the dynamic characteristics of all the components (Harvey & Trimbur, 2003).

To measure the variations in the cycle components compared with the fluctuation in the trend (the appropriate smoothness of the cycle component), Harvey et al. (1997) state that the smoothness of the trend could be selected using a differencing order (m), such that

$$\begin{array}{c} \tau^{(m)}_{i,t+1} = \tau^{(m)}_{i,t} + \tau^{(m-1)}_{i,t} \\ \tau^{(m-1)}_{i,t+1} = \tau^{(m-1)}_{i,t} + \tau^{(m-2)}_{i,t} \\ \vdots \\ \tau^{(1)}_{i,t+1} = \tau^{(1)}_{i,t} + \xi_{i,t} \end{array} \quad ; \ \xi_{i,t} \sim \text{i.i.d} N\left(0, \sigma^2_{\xi,i}\right) \tag{2}$$

Where $\xi_{i,t}$ stands for the irregular components.

This process helps to show how much dynamic fluctuation in the variable (y_t) is assigned to the cycle, as opposed to the trend. Moreover, in the frequency domain, the resulting trend is positively related to the (m). In this case, a higher value for mentails that the low-pass gain function will have a sharper cutoff.[1]

A cyclical component (ψ_t)in the time series can be specified as an autoregressive of the order 2 model with complex coefficient roots that is as follows:

$$\begin{pmatrix} \Psi_{i,t+1} \\ \Psi^*_{i,t+1} \end{pmatrix} = \varphi_i \begin{bmatrix} \cos(\lambda_i) & \sin(\lambda_i) \\ -\sin(\lambda_i) & \cos(\lambda_i) \end{bmatrix} \begin{pmatrix} \Psi_{i,t} \\ \Psi^*_{i,t} \end{pmatrix} + \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon^*_{i,t} \end{pmatrix}, \text{s.t} \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon^*_{i,t} \end{pmatrix} \sim \text{i.i.d } N(0, \sigma^2_{i,\varepsilon}) \tag{3}$$

The damping parameter (φ_i) signifies the spread around the estimated central frequency (λ_i) which is measured in radians. We bear in mind that the cycle should model as a stationary stochastic process, so the damping should be $(0<\varphi<1)$. Moreover, these components are mutually and serially uncorrelated at all times and with all lags, but separately they may be correlated with their corresponding item of the other two variables (see e.g. Harvey, 1990).

The UCM can then be formulated in the general state space form (see Durbin & Koopman, 2012; Harvey, 1990):

$$y_t = A_t\alpha_t + \varepsilon_t \tag{4}$$

$$\alpha_{t+1} = B_t\alpha_t + \mu_t \tag{5}$$

Equations (4) and (5) state the observation equation with the state vector (α_t), and state-equation, respectively. The two matrices (A_t), (B_t) contain the objective parameters. Once the model is represented in the state space form, the Kalman filter and related state space methods can be applied. The unknown static parameters are estimated by the maximum likelihood method.[2] Given these estimates, the prediction residuals are obtained for diagnostic checking and model evaluation from the Kalman filter. Moreover, the smoothed estimates of the unobserved trend, cycle and residuals components are obtained from a smoothing method (Durbin & Koopman, 2012).

3. Data and empirical results

3.1. Data and sample chosen

This paper used monthly data for all G7 economies over the sample period from 1:1961 to 8:2017 to extract business cycles from a time series of the Industrial production index. The sample of studies was carefully chosen with the aim of evaluating the industrial sector in countries that provided examples of unsustainable asymmetric cycles where booms were followed by prolonged recession and financial instability.

The time series were taken from the macroeconomic database of the World Bank; they are seasonally adjusted, deflated by the consumer price index and the logarithms were taken to remove (potentially) exponential growth patterns and to linearize the series approximately. For more robust results, we first extracted the classical cyclical properties to report the features of the movement in the business cycle between the turning points.

3.2. Classical business cycle

To measure the classical cycle, we dated the peaks and troughs in the log-level of aggregate economic activity, using the turning point procedure (see Bry & Boschan, 1971; Harding & Pagan, 2002). As highlighted before, such algorithm is used here as a simple statistical analysis to report the movement's features in industrial production index between the turning points.

This algorithm recognises local maxima (minima) to disentangle the expansion (contraction) phase of a time series (Bry & Boschan, 1971).

$$\text{Trough at } t = \{X_{t-k} > X_t < X_{t+k}\}, \forall k = 1, \dots, 5 \quad (6)$$

$$\text{Peak at } t = \{X_{t-k} \langle X_t \rangle X_{t+k}\} \quad (7)$$

With monthly data, a complete cycle must be at least 15 months long and each of its contraction (expansion) phases should last at least 6 months. Moreover, the turning point was chosen so that they should alternate. In other words, each peak (trough) must be higher (lower) than the previous one. Moreover, to ensure that we do not identify spurious phases, this "growth cycle" approach have been analysed with trend adjustments (see e.g Morley & Piger, 2012; Zarnowitz & Ozyildirim, 2006). Further, we smooth the data to remove the influences of outliers, structural break and to determine how the end points are to be treated (see e.g. Abuhommous, 2017; Hall and McDermott; 2011; King & Plosser, 1994). Finally, we bear in mind that doing so does not influence results is further tested in Section 3.3.

Another two major features of a cyclical phase, namely, duration and amplitude, can be investigated, in which the duration of a contraction (expansion) period refers to the number of months between troughs (peaks) to the next one in a completed cycle. Amplitude relates to the change in the series of interest from a peak (trough) to the next peak (trough).

Following the work by Engel, Haugh, and Pagan (2005), suppose the dates of the turning point produce N expansions and contractions; the average duration of expansion $\left(D^E\right)$ and contraction (D^C) are given by:

$$D^E = \frac{1}{N}\sum_{i=1}^{N} D_i^E, D^C = \frac{1}{N}\sum_{i=1}^{N} D_i^C \quad (8)$$

The total gain (loss) in the Industrial index over the phase can be estimated through cumulative movement, which is given by

$$C.M = \sum_{j=1}^{D}(y_j - y_0) - \frac{A}{2} \quad (9)$$

whereDandArefer respectively to the duration and amplitude of an expansion (contraction).

By combining the duration, amplitude, and cumulative movement, we can calculate the total rise (fall) in economic output.

$$\text{excess area} = \frac{C.M - AD}{AD}, \text{ s.t; } AD = \frac{D * A}{2} \quad (10)$$

For the purpose of analysis, we apply the BB-algorithm to explore the classic cycle characteristics. Table 1 report the dates when the peaks (troughs) of the business cycle occurred. It is apparent from the table that the business cycle behaved very differently across regions. It is also apparent from the table that the Industrial production index highly fluctuates over the time. Moreover, the time to reach the turning point within the same phase also varies to quite an extent. For instance, before the present century industrial production in the sample experienced the most prolonged period of expansion for more than 4 years. Moreover, these countries needed less than 18 months to hit the contraction phase. By contrast, the length of contraction was greater over the last two decades. In specific, the cases of Italy, Canada and France show that the depression in the economy continued for more than 3 years. However, the remaining countries needed less than 18 months to hit the decline phase.

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Table 1. Dating of peaks (troughs) in real business cycle

UK				GERMANY				France				USA			
trough Index	Duration of down-swing	peak Index	Duration of up-swing	trough Index	Duration of down-swing	peak Index	Duration of up-swing	trough Index	Duration of down-swing	peak Index	Duration of up-swing	trough Index	Duration of down-swing	peak Index	Duration of up-swing
1962–01	13	1966–07	54	1963–12	16	1962–08	20	1963–03	19	1961–08	8	1967–07	9	1966–10	70
1967–08	13	1969–06	22	1967–05	14	1966–03	27	1964–12	7	1964–05	14	1970–11	15	1969–08	25
1970–01	7	1971–01	12	1975–07	23	1973–08	75	1968–05	20	1966–09	21	1975–04	16	1973–12	37
1972–02	13	1974–06	28	1980–09	9	1979–12	53	1975–05	9	1974–08	75	1980–07	16	1979–03	47
1975–08	14	1977–01	17	1984–06	25	1982–05	20	1987–01	89	1979–08	51	1982–12	19	1981–05	10
1981–05	52	1981–12	7	1993–07	17	1992–02	92	1991–05	15	1990–02	37	1989–07	6	1989–01	73
1982–11	11	1990–03	88	1995–10	10	1994–12	17	1993–12	25	1991–11	6	1991–03	7	1990–08	13
1992–05	26	1994–12	31	2001–11	9	2001–02	64	1996–07	12	1995–07	19	2001–11	16	2000–07	112
1996–05	17	1998–03	22	2003–09	13	2002–08	9	1999–02	9	1998–05	22	2009–06	18	2007–12	73
1999–04	13	2000–11	19	2006–03	16	2004–07	10	2003–06	30	2000–12	22	2014–01	11	2013–02	44
2002–06	19	2004–03	21	2009–04	15	2008–01	22	2009–04	20	2007–08	50	2016–08	21	2014–11	10
2005–03	12	2007–01	22	2013–01	18	2011–07	27	2014–05	36	2011–05	25			2017–08	12
2009–08	31	2012–01	29			2017–08	55			2017–08	39				
2013–02	13	2014–11	21												
2015–07	8	2016–12	17												
2017–08	8														

JAPAN				ITALY				CANADA			
trough Index	**Duration of downswing**	**peak Index**	**Duration of upswing**	**trough Index**	**Duration of downswing**	**peak Index**	**Duration of upswing**	**trough Index**	**Duration of downswing**	**peak Index**	**Duration of upswing**
1965–12	12	1964–12	48	1975–04	10	1974–06	162	1970–09	14	1969–07	103
1975–03	13	1974–02	98	1979–07	7	1978–12	44	1975–05	16	1974–01	40
1980–08	6	1980–02	59	1983–05	38	1980–03	8	1980–06	13	1979–05	48
1982–10	11	1981–11	15	1993–07	27	1989–12	79	1982–12	20	1981–04	10
1986–08	15	1985–05	31	1996–12	12	1995–12	29	1991–12	34	1989–02	74
1994–01	32	1991–05	57	1998–12	12	1997–12	12	1995–12	11	1995–01	37
1998–08	15	1997–05	40	2005–05	53	2000–12	24	2003–08	34	2000–10	58
2001–11	11	2000–12	28	2009–03	19	2007–08	27	2009–06	41	2006–01	29
2009–02	12	2008–02	75	2013–04	24	2011–04	25	2011–12	13	2010–06	12
2012–11	21	2011–02	24	2014–10	9	2014–01	9	2012–12	12	2017–08	56
2016–02	25	2014–01	14			2017–08	37				
		2017–08	18								

The results of the average duration and amplitude are presented in Table 2. We found a notable variation in the pattern of the cycle's duration over two phases. In specific and in line with the classical definition of Burn and Mitchell (1946), the expansion stage is longer than that of the contraction. Moreover, the industrial index seems highly to fluctuate in the downturn phase. That is to say, the duration of the expansions in the industrial index is about two to four years while the contractions seem on average to last less than two years.

The average of amplitude was also discovered to be entirely different in both phases. Another significant finding was that a downswing, in all cases in this study, qualified as "major" since the cumulative real index decline (increase) exceeded 15%. However, over the expansion period, the increase in the real cumulative index was only about 10%. These results are likely to be related to asymmetry in the cycle. Indeed, another sign of such asymmetry was that the upturn phases were longer than the decline phases. The impression of these results is that cyclical differences may not relate to differences in the structure of economic systems and nations' industrial production.[3]

Table 2 also reveals that there are notable differences in the characteristics of the cycle in different countries. On the one hand, during the upturn phase the US, Japan and Canada have higher results (with less fluctuation) than the remaining G7 countries. On the other, the findings suggest that the decline phase in Germany, the US and Japan came to an immediate halt in less than 15 months.

Moving toward the excess area, we consider the total extra economic output that is gained (lost) during an expansion (contraction). Interestingly, the ratio of the excess area is positive during the expansion phase. In addition, during the contraction phase, we find a negative impact on the total gain in industrial production. However, it seems to be relatively small.

3.3. Estimation results

Following Galati et al. (2016), we first extracted cycles from the time series based on a univariate UCM (Equation (1)), and then we verified whether the characteristics of the cycle component of UCM were close to those of the classical filter and checked whether the model had any common characteristics with those of the classical cycle. Statistical diagnostic and test procedures were adopted to establish whether "similar" cycles exist in the industrial sector that is under consideration for the entire sample.

A preliminary analysis of the time series using UCM reveals several impressive results. First, Table 3 provided the most extensive set of significant clusters of the UCM variables, namely; the frequency, damping factor and variance of the stochastic cycle. One interesting point is that we found evidence of the existence of medium-term business cycles in the countries in question. To illustrate, most of the estimated series lasted from two to four years since the frequency was centred on 16%. Business cycles of such length are consistent with the findings of previous research in this field. Further, the high damping factor shows that the cyclical components were close to the estimated central frequency.

Another significant finding is that the damping factor between phases was estimated to operate on around 97% of the sample. This result reveals that the cycle component of a series is first order. Put differently, the countries under consideration confirmed only one medium cycle in the sample period.[4]

The amplitude of these cycles can be measured by the range of medium-term fluctuations which are also presented in the damping factors. As presented in Figure 1, the amplitudes of our extracted business cycles range around 15%, except in Canada (see also the discussion in McGuckin, Ozyildirim, & Zarnowitz, 2007). Hence, we can conclude that business cycles are distinct among phases.

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Table 2. Classical characteristics in business cycle

	Contraction				Expansion			
	Duration	Amplitude	Cumulative	Excess area	Duration	Amplitude	Cumulative	excess area
CANADA	**16.8**	**−0.044**	**−0.436**	**0.179**	**36.7**	**0.089**	**2.380**	**0.453**
FRANCE	19.1	−0.041	−0.408	0.041	24.5	0.060	1.838	1.509
GERMANY	13.1	−0.036	−0.255	0.073	33.0	0.068	1.760	0.573
ITALY	17.8	−0.045	−0.470	0.176	31.9	0.075	2.912	1.426
JAPAN	14.3	−0.053	−0.395	0.045	39.1	0.115	3.817	0.702
UK	15.1	−0.028	−0.253	0.194	24.0	0.042	0.734	0.446
USA	14.0	−0.024	−0.234	0.393	43.8	0.088	3.089	0.603

Duration and amplitude refer to the average of the duration and amplitude of the cyclical component by the country.
Amplitude, cumulative and excess area are are expressed in percent.

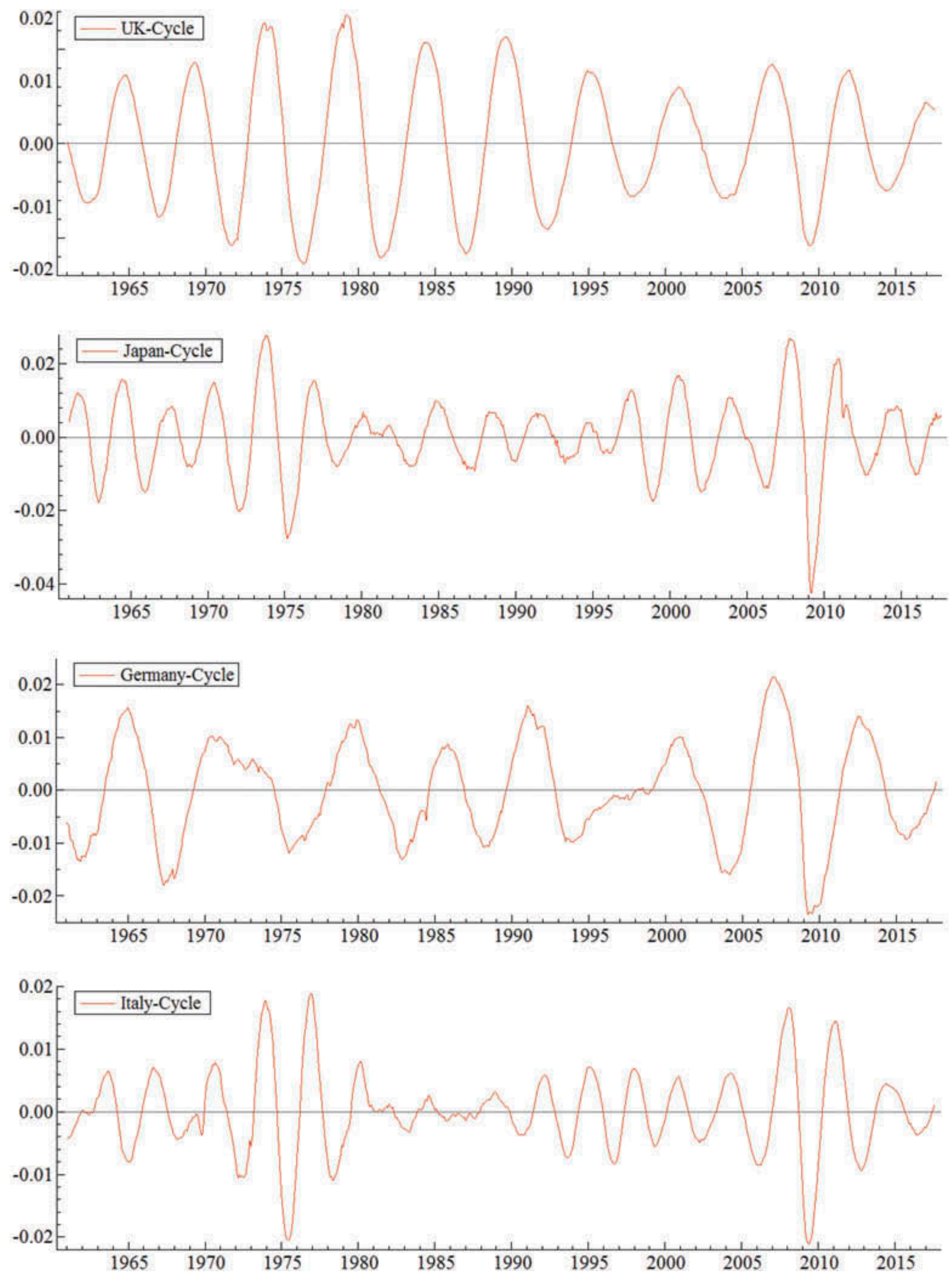
Table 3. Estimation results for a complete cycle.

	CANADA	FRANCE	GERMANY	ITALY	JAPAN	UK	USA
Main statistics							
frequency	0.209	0.148	0.147	0.160	0.158	0.152	0.166
damping	0.981	0.975	0.988	0.981	0.981	0.969	0.975
period	30.0	42.6	42.9	39.3	39.7	41.3	37.9
Variance (level)	[0.001]	[0.026]	[0.016]	[0.026]	[0.001]	[0.049]	[0.069]
Variance (cycle)	[0.037]	[0.015]	[0.013]	[0.002]	[0.007]	[0.003]	[0.012]
Model Goodness of Fit							
R_D^2	0.47	0.60	0.63	0.65	0.68	0.58	0.59
Prediction error variance	0.003	0.013	0.008	0.011	0.005	0.044	0.025
Prediction error mean deviation	0.020	0.002	0.027	0.021	0.020	0.003	0.017
correlation up to p lags	1.225	1.07845	1.291	3.113	2.673	2.439	1.025

The probability value in brackets.

R_D^2: is the coefficient of determination based on differences, which compare the Prediction error variance with the variance of first differences.

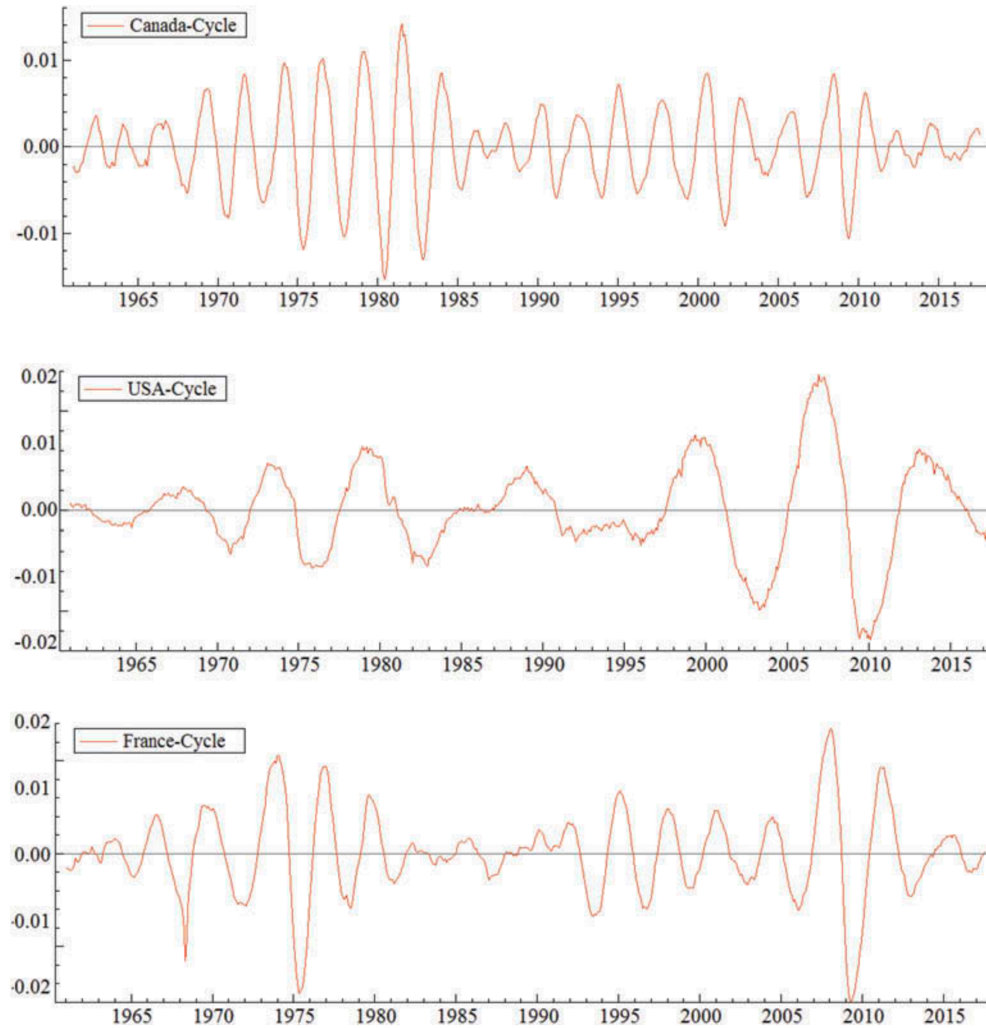
Figure 1. Extracted cycle through UCTSM.



Furthermore, it is interesting to find after the 2008 crisis evidence of significant heterogeneity between countries. The business cycle in the US appears to have been the longest and deepest of any in the sample, while the cycle in Canada fluctuated greatly. Indeed, we observe this heterogeneity not only across countries, but also over time. This result may be explained by the fact that the industrial sectors are operated in different ways by different countries.

To evaluate the goodness of the model, misspecification tests related to the residuals were applied. These tests included the prediction error variance and prediction error mean deviation (see, e.g., Durbin & Koopman, 2012; Harvey, 1990). The p-value of the mentioned tests verifies that the estimated models did not have any misspecification problems. In addition, the portmanteau Q-

Figure 1. (Continued).



statistics in Panel B in Table 3 Show that the null hypothesis of no autocorrelation was accepted against the q-order autoregressive for all estimated models. Finally, the coefficient of determination (R_D^2) indicates that the model was reasonably capable of explaining cyclical behaviour.

4. Conclusions

In this paper, we date the business cycles of the G7 countries, for the first time in the literature, and identify clusters among the regions showing differences business cycle behaviour. Moreover, we explore a model-based methodology to examine trends and business cycles. The capability of the mentioned technique was tested against properties of the classical cycle as well as the stationarity of a simulated cycle.

Our analysis shows that the industrial production index captures the classical characteristics of the business cycle. Moreover, it exhibits medium-term cyclical behaviour with ample fluctuations. We find that the persistence, length and amplitude of the extracted cycles vary over time and vary across countries. In particular, we report differences in the business cycles within the considered sample, and we establish that business cycles have increased in amplitude and persistence over time. The heterogeneity reported here shed new light on important criterion for implementing policies. That is to say, region-specific national policies should be adopted to characterise such economic features and, hence, taking into account the regional dimension.

Notes

1. Further, the series is assumed to be stationary if m = 0. In addition, it has a random walk if m = 1. However, most of the macro and financial variables are supposed to use m = 2 as an optimum choice.
2. numerical maximization requires the Kalman filter to compute the log likelihood function.
3. The literature suggests that due to a country's financial structure, an asymmetric cycle occurs when the expansion phase lasts twice as long as the contraction phase (Igan et al., 2011; Taylor, 2015).
4. According to Durbin and Koopman (2012), the cycle component of a series is first order if the damping factor is close to unity. Otherwise, we should test for a cycle of the second order.

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Conflict of Interest
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