Technology evolution and long waves: investigating their relation with spectral and cross-spectral analysis

Eirini Ozouni, Constantinos Katrakylidis and Grigoris Zarotiadis
School of Economics, AUTH University Campus, Thessaloniki, Greece

ABSTRACT
The present paper is an empirical exercise that contributes to the debate on whether long-lasting cyclical economic development can be viewed as a deterministic phenomenon or a stochastic process. First, we search for longer lasting, periodically reappearing cycles of GDP per capita in four countries: USA, UK, Germany and France. Second, based on theoretical arguments that stress applied knowledge as a significant driving force, we test its dynamic interrelationship with these countries’ economic performance by applying spectral and cross-spectral methodologies. We confirm the existence of periodical long waves both in terms of GDP per capita as well as of applied knowledge. Moreover, we find strong interrelations between them and modest evidence for which is the leading force in the long term.

1. Introduction

There are two central questions with respect to long waves of economic development: first, if they exist and second, beyond confirming their existence, if they are the stochastic outcome of historical incidents, or the result of endogenous deterministic procedures. Therefore, some researchers try to link the time series with major political and socioeconomic events, while others, based on theoretical approaches, follow advanced simulation methods (Freeman & Louçã, 2001: 92–118).

The verification of long waves proceeds by the use of different methodologies that can be categorized as follows. First, we have the decomposition approaches with moving average smoothing techniques – for instance the analysis in Kondratieff and Oparin (1928/1984), Kuznets (1958), Van der Zwan (1980) and Van Duijn (1983), as well as the search for significant growth rate changes between longer periods (Kleinknecht, 1986). They see long waves as long cycles around a long-term trend with short-term fluctuations overlaid (such as Juglar or Kitchin cycles). These studies, although useful to reveal long wave patterns, are unable to estimate at the same time the significance of cyclical components of different duration.

Second, we have analyses in the frequency domain such as spectral analysis (Korotayev & Tsirel, 2010; Reijnders, 2009; Metz, 1992; Van Ewijk, 1981; 1982; Haustein & Neuwirth, 1982) or alternative techniques for estimating stochastic cycles.
In contrast to the first category, these techniques allow the simultaneous examination of cycles of different duration for the periodicity of the series.

The present paper is an empirical exercise that contributes to the debate on long waves in two ways. First, we proceed with spectral analysis and we search for longer lasting, periodically reappearing cycles of GDP per capita (GDP p.c.) in four countries: USA, the largest free-market economy in modern times, and three of the main European technologically leading countries since the industrial revolution, UK, Germany and France. Second, based on theoretical analyses (Mensch, 1975; Olsson, 2000, 2001, 2005; Romer, 1990; Schumpeter, 1939; Zarotiadis & Ozouni, 2017) that stress applied knowledge as a significant driving force, we apply cross-spectral methodology to test its dynamic interrelationship with the economic performance of the above countries.

In the next pages, we present briefly the data and the methodology we use, along with some indicative diagrams. Next, we proceed with the discussion of the estimations derived from spectral and cross-spectral analysis of GDP p.c. as well as of the series of a proxy for the development of applied knowledge. Finally, we conclude and we refer to shortcomings and proposals for further research.

2. Data and methodology

Our focus here is first to reveal long-lasting patterns of cyclical movement of GDP p.c. in the USA, UK, Germany and France using annual data for the period 1883–2010 from the Angus Maddison Project dataset. Second, we try to confirm the importance of applied knowledge as a significant driving force for long waves of economic activity. Therefore, we consider the number of annual patent grants as a proxy for the development of applied knowledge in each one of the four countries (data from the World Intellectual Property Organization) and we apply cross-spectral analysis with the GDP p.c. series.

As we proceeded with the specific empirical exercise, we came across methodological issues, already highlighted in the relevant literature, such as the choice of the appropriate detrending method. Spectral and cross-spectral analysis requires stationary series. Yet, the question is in which manner to achieve stationarity. This issue is highly related with the theoretical assumptions about the nature of the trend of the series. Following Nelson and Plosser’s (1982) distinction, the deterministic trend series becomes stationary by simple detrending techniques. On the other hand, series with a stochastic trend that are permanently affected by shocks become stationary by filtering techniques with the most common being the conversion of differencing (taking the differences of the series or differences of their logarithms and thus growth rate conversion). Hence, in case the long waves are seen as an endogenous movement of the trend itself, with a stochastic character, the prerequisite of stationarity creates difficulties in the analysis in the frequency domain because the researcher needs to have stationary series, yet without removing the low-frequency periodic cycles.

The same question arises when one asks which trend to eliminate. Series can become stationary, either by having monotone or polynomial de-trending. In case we choose a polynomial de-trending, fitting of the actual data may be better, but we lose cyclical information, starting from the longer lasting cycles. Generally, monotone trend eliminations maintain longer lasting fluctuations, while, on the contrary, polynomial trends, either being of constant or of adjustable degree, e.g., Hodrick-Prescott (1997) filter (HP-
filter), preserve only shorter cycles. According to Metz (2011), long wave analysis can be achieved with an appropriate design of the gain function (frequency response function) of the filter in order not to eliminate the low frequency cyclical components. The filters that are commonly used are the HP-filter with the appropriate choice for the smoothing parameter \( \lambda \) (Metz, 2002), the Baxter and King (1999) filter (BK-filter), the Christiano and Fitzgerald (2003) filter (CF-filter) and the Stier filter (2001) that has been used in the analysis of Metz (2011).

Figure 1 depicts the actual development of the two variables we have chosen to use through time – the diagrams on the left side show the history of GDP p.c. (Y) and those on the right the history of patent grants (P). In all four countries, GDP p.c. follows a clear exponential path; as we see, the exponential trend (FITEXP) is by far more suitable than the linear (FITLINE) one. In case of patents, the picture is different: in all countries, the evolution is clearly polynomial with an obviously increasing variance. Therefore, both linear and exponential trend estimations have the same (poor) degree of fit against the actual data.

In case of variables that follow an exponential path, as it is the case in our time series, stationarity can be achieved by simply transforming level data into change rates. Nevertheless, estimations must be discussed cautiously. The duration of the cycle of the change rates is, by definition, shorter as one of the corresponding series of level data. Ignoring this feature may result to biased conclusions, as is the case in Van Ewijk (1982).

To achieve stationarity while preserving, as much as possible, any underlying cyclical movement of all possible frequencies, we proceeded with the elimination from our time series of an exponential trend of a higher degree following Reijnders (2009). The OLS estimation of the parameters was achieved by regressing the logarithms of the series to a third-degree time variable (\( \ln(\text{series}) = a + b_1 t + b_2 t^2 + b_3 t^3 \)). After the elimination of this third-degree parabola (FITP3 trend) from all eight series, we applied spectral and cross-spectral analysis in the remaining residuals. In Figure 1, one can also see the three kinds of trend estimations as well as the evolution of the logarithms of the series.

Before conducting spectral analysis, the residuals from the elimination of the P3 trend were tested for a unit root. As depicted in Table 1, following the Augmented Dickey–Fuller test with GLS De-trending (DFGLS) proposed by Elliott, Rothenberg, and Stock (1996), all series are proven to be stationary. As for the Phillipps-Perron (1988) test, the null hypothesis of a unit root was rejected in all series as well, except the French GDP p.c., where the value of the respective statistic is very close to the critical value of a 90% confidence level.

After verifying that our time series are stationary, we proceed with the actual part of our analysis. Given stationarity, each succession of data can be expressed as a sum of cosines and sines. Thus, following a Fourier transformation of the series’ auto covariance function, each succession of data is presented as a function of frequencies from 0 to \( \pi \) (Angular Frequencies), helping us to interpret the significance of cycles of different duration. This is a density function: if we integrate the function for all possible frequencies (from 0 to \( \pi \)), the outcome is the total variance of the series.\(^1\) The sample estimation of the population spectral density is provided by the periodogram. For more consistent estimations, we proceeded with the kernel density estimation

\(^1\)For a more detailed analysis and comprehensive interpretation of the spectral methodology, see Granger and Hatanaka (1964), Hamilton (1994) and also Engle (1976).
(smoothed periodogram) choosing Parzen window and a truncation point at 20. Finally, we tested the statistical significance of the periodogram ordinate.

We estimate the spectral density function for both series – GDP p.c. and patent grants – in all four countries. As we mentioned already, there is an extensive theoretical literature pointing out that long waves in economic development may result from the cyclical evolution
of applied knowledge. Therefore, after providing evidence for the existence of long waves in both variables, we proceed with cross-spectral analysis to check how the two series interact in the frequency domain. This is achieved by estimating the Fourier Transformation of the series’ cross-covariance function. The methodology is very close to that of spectral analysis. However, the presentation of the results of cross-spectral analysis differs from the above: our main focus is on two statistics: coherence (squared) that takes values from 0 to 1 depicting the correlation between two series in the frequency domain, and phase that takes values from $-1$ to $1$ showing whether one variable leads the other, or the opposite. More specifically, the phase statistic shows the lag or lead of a variable against the other in fractions of $\pi$. Therefore, the minimum lag is $-1\pi$ (a half cycle lag) and the maximum lead is $+1\pi$ (a half cycle lead).

Phase needs to be considered cautiously as it presents a “natural ambiguity” (Engle, 1976). In Figure 2, we provide a graphical explanation of this: phase measures the shorter distance between two cycles of the same durations as a proportion of a half cycle. In the first diagram of the following figure, this is clearly the distance $a$ and not $b$, which means that there is a clear lead of the blue line. But in the second diagram, where one cycle is (close to) the exact mirror image of the other ($a = b$), the specific statistic is indecisive.

This problem arises whenever phase approaches the upper and/or lower limit of its range. As we will see also in our results, in such cases the statistic jumps from $-1$ to $1$ expressing thereby in figures the difficulty of saying who is leading or lagging.

3. Results of spectral and cross-spectral analysis

Since we discussed thoroughly all the relevant methodological issues, it is time to proceed with the main part of our analysis. The pictures in Figures 3–6 provide evidence for the existence of long waves, both for GDP p.c. as well as for the number of the patent grants (the three diagrams lying aside). On the horizontal axis of the

### Table 1. Unit root tests.

| Variable Residuals of GDP p.c. (Y) and patent grant (P) series after elimination of P3 trend. | Augmented Dickey-Fuller with GLS Detrending (DFGLS) (Levels) | Phillips-Perron Test (Levels) |
|---|---|---|
| | Intercept | Intercept & trend | Intercept | Intercept & trend |
| YUSA | $-4.488^{***}$ | $-4.477^{***}$ | $-3.646^{***}$ | $-3.631^{***}$ |
| PUSA | $-3.155^{***}$ | $-3.482^{**}$ | $-3.728^{***}$ | $-3.715^{**}$ |
| YUK | $-3.970^{***}$ | $-4.489^{***}$ | $-3.248^{**}$ | $-3.199^{**}$ |
| PUK | $-3.970^{***}$ | $-4.927^{**}$ | $-3.770^{***}$ | $-3.765^{**}$ |
| YGERMANY | $-2.875^{***}$ | $-3.513^{**}$ | $-3.250^{**}$ | $-3.308^{*}$ |
| PGERMANY | $-5.771^{***}$ | $-6.010^{**}$ | $-6.214^{***}$ | $-6.190^{**}$ |
| YFRANCE | $-2.503^{**}$ | $-3.017^{*}$ | $-2.750^{*}$ | $-2.723$ |
| PFRANCE | $-3.239^{**}$ | $-3.533^{**}$ | $-3.778^{**}$ | $-3.764^{**}$ |
| Critical values (significance levels) | $-2.5833\text{ (1%)}$ | $-3.547\text{ (1%)}$ | $-3.482152\text{ (1%)}$ | $-4.031953\text{ (1%)}$ |
| | $1.9433\text{ (5%)}$ | $3.003\text{ (5%)}$ | $2.884001\text{ (5%)}$ | $3.445243\text{ (5%)}$ |
| | $-1.615\text{ (10%) }$ | $-2.713\text{ (10%) }$ | $-2.578608\text{ (10%) }$ | $-3.147253\text{ (10%) }$ |

(a) Structural change and unit roots are closely related. Conventional unit root tests are biased toward a false unit root null when the data are trend stationary with a structural break (Vogelsang and Perron 1998). Therefore, in these series we applied a unit root test with breakpoint. The critical values and corresponding significance levels of this test are: $-5.347\text{ (1%) }, -4.859\text{ (5%) }, -4.607\text{ (10%) }$. The indications ***,**, * correspond to the rejection of the null hypothesis at 1%, 5% and 10% significance level, respectively.
Figure 2. Diagrammatic discussion of phase.

Figure 3. Spectral and cross-spectral analysis of level data in the UK.
diagrams (Periodogram and Parzen smooth), we have the frequencies (cycle/time unit) on the range from 0.01 to 0.5 that correspond to cycles of different duration, starting from around a century till the smallest cycle of 2 years. On the vertical axis, we have the respected values of the periodogram and smoothed periodogram, respectively. Therefore, when the line of the diagram indicates higher values, it means that cycles of the corresponding duration are the important component of the series’ variance.

Along with the diagrams, Table 2 shows the key figures of spectral estimations in the USA, UK, Germany and France. Based upon the estimations given in the periodogram and smoothed periodogram, we sum up the percentages (%) of contribution of each interval to the total variance explained due to the periodical cycles of the series such as Kondratieff’s (1935) cycles lasting 40–60 years (angular frequencies interval 0.20 – 0.10), Kuznets’ (1930) fluctuations of 15–25 years (angular frequencies interval 0.04–0.25), Juglar’s (1862) cycles of 7–11 years (angular frequencies interval 0.93–0.54) and finally the shorter business cycles of Kitchin (1923) lasting from 3 to 5 years (angular frequencies interval 2.11–1.28). The total sum of all intervals is the 100% of the variance of the series explained due to cycles.

Figure 4. Spectral and cross-spectral analysis of level data in Germany.
There is a clear message from the above: long waves are present both for the economic activity as well as for its possibly underlying cause, namely applied technological evolution. Especially in terms of GDP p.c., Kondratieff and Kuznets periodicity seems to explain the biggest share of overall variability of the series in all countries. Moreover, opposite to shorter cycles, spectral estimations for long waves appear to be statistically significant. In the Figures 3–6, one can also see that the coefficient periodogram estimations for the intervals that correspond to long cycles are statistically significant since the $p$-value is almost zero.\textsuperscript{2}

\textsuperscript{2}In the Graphs 3–6, we present the estimations of the Fisher (1929) g statistic test. We test the H0: The periodogram ordinate is not significant enough. In the diagrams, we present the estimations of the g statistic (level of significance 5\%) and the $p$-value.
The relevant literature consists of several empirical confirmations of long waves (Bieshaar & Kleinknecht, 1983; Kleinknecht, 1986; Korotayev & Tsirel, 2010; Metz, 1992; Reijnders, 1992, 2009; Van Duijn, 1977, 1983). There are also many contributions questioning the existence of long waves (Garvy, 1943; Solomou, 1998, 1990; Van der Zwan, 1980; Van Ewijk, 1981, 1982). In that sense, an additional evidence as the present one is useful and contributes to the discussion. Yet, as we argued in the first paragraphs, since the discovery of long waves in the nineteenth century (Jevons, 1884; Parvus, 1901; Van Gelderen, 1913; De Wolff, 1924; Kondratieff, 1935), analysts searched further to specify if the long waves are the stochastic outcome of historical incidents, or the result of endogenous deterministic procedures. For the same reason, we proceed with cross-spectral analysis to examine the interaction between GDP p.c. and applied knowledge.

Figure 6. Spectral and cross-spectral analysis of level data in the USA.
Table 2. The significance of different cycles for the levels of GDP p.c. and patent grants.

| Angular frequency (omega) | Frequency (cycle/time unit) | Cycle duration in years (years/cycle) | Relevant type(s) of economic cycle | Share of GDP p.c. series' residual variance (%) | Share of patent grants series' residual variance (%) |
|--------------------------|-----------------------------|--------------------------------------|-----------------------------------|-----------------------------------------------|--------------------------------------------------|
| USA                      | 0.20–0.10                   | 0.04–0.02                            | 32–64                             | 15.828                                        | 13.474                                           |
|                          | 0.44–0.25                   | 0.07–0.04                            | 14 (14.22) – 25 (25.60)           | 8.826                                         | 13.041                                           |
|                          | 0.93–0.54                   | 0.15–0.09                            | 7 (6.74)-11 (11.64)              | 21.093                                        | 23.581                                           |
|                          | 2.11–1.28                   | 0.34–0.20                            | 3–5                               | 12.47                                         | 12.794                                           |
| UK                       | 0.20–0.10                   | 0.04–0.02                            | 32–64                             | 19.128                                        | 14.125                                           |
|                          | 0.44–0.25                   | 0.07–0.04                            | 14 (14.22) – 25 (25.60)           | 21.863                                        | 22.386                                           |
|                          | 0.93–0.54                   | 0.15–0.09                            | 7 (6.74)-11 (11.64)              | 18.741                                        | 23.337                                           |
|                          | 2.11–1.28                   | 0.34–0.20                            | 3–5                               | 12.150                                        | 12.401                                           |
| GER                      | 0.20–0.10                   | 0.04–0.02                            | 32–64                             | 22.789                                        | 20.59                                            |
|                          | 0.44–0.25                   | 0.07–0.04                            | 14 (14.22) – 25 (25.60)           | 22.733                                        | 23.088                                           |
|                          | 0.93–0.54                   | 0.15–0.09                            | 7 (6.74)-11 (11.64)              | 17.847                                        | 20.336                                           |
|                          | 2.11–1.28                   | 0.34–0.20                            | 3–5                               | 13.727                                        | 14.208                                           |
| FR                       | 0.20–0.10                   | 0.04–0.02                            | 32–64                             | 28.4                                          | 20.59                                            |
|                          | 0.44–0.25                   | 0.07–0.04                            | 14 (14.22) – 25 (25.60)           | 20.172                                        | 24.392                                           |
|                          | 0.93–0.54                   | 0.15–0.09                            | 7 (6.74)-11 (11.64)              | 17.49                                         | 18.98                                            |
|                          | 2.11–1.28                   | 0.34–0.20                            | 3–5                               | 14.557                                        | 13.77                                            |

The sum of total variance for all categories of cycles is less than 100%. This is because we do not present in our table the outlier cycles with the duration of 2 years as well as the category of cycles covering 100 years (Hegemonic cycles).

Figure 7. Cross-spectral analysis of level data.
Figure 7 depicts the results of the cross-spectral analysis: coherence is represented by the black line, measured on the left-hand axis and phase is represented by the blue line, measured on the right-hand axis. Note that in the horizontal axis of the cross-spectral diagrams the frequencies are presented as fractions (1 corresponds to $1 \times \pi$) corresponding similarly to cycles of the same duration with the spectral diagrams, starting from around a century till the smallest cycle of 2 years. In this manner, we can see whether the economic activity is related with applied knowledge, but also which one of the two leads the other.

When coherence is low, phase statistic has no meaning: even if it provides clear evidence for the lead/lag of any variable, this would not make any sense since coherence is insignificant. Thus, similarly to Reijnders (2009), we chose one critical value as a benchmark level of coherence at 0.45.

Our main focus is on lower frequencies, hence, for longer lasting cycles. Table 3 presents the results of cross-spectral analysis between GDP p.c. level series and the residuals of patent grants for cycles 33.5–65 years. In USA, the estimations sustain our theoretical argument: more specifically, coherence is above 0.45 for cycles lasting more than 33 and 43 years, with the cycles of patent grant series being ahead of those of GDP series by approximately a half cycle. Estimated correlations (coherence) in the series of the UK may be below the chosen benchmark, but in France and Germany coherence is very high – more than 0.80 and around 0.70, respectively. As for the phase statistic, in France 65-year cycles of patent grants appear to be simultaneous with the GDP p.c. cycles of the same length. On the contrary, French 33.5- and 43.5-year lasting cycles of the patents are marginally lagging compared with the analogue GDP p.c. cycles. The same applies for Germany for all the frequencies.

Although we focus on the left-hand side of diagrams with the lower frequencies (and the longer cycles), in Germany and France, we have high correlation (coherence of more than 0.5) and persisting positive values of phase, meaning that there is a clear lead of technological activity for shorter lasting cycles (lasting from 5–7 and 2 years for Germany and 10–26 and 2 years for France).

Note that in the diagrams, at some points, the picture we get from the statistic phase is not that clear. In fact, the behavior of phase is indicative for the case we outlined in the methodological discussion: it fluctuates from −1 to 1 providing an undefined picture.

4. Conclusions

The present paper is an empirical exercise that contributes to the debate on long waves in two ways. First, we provide strong evidence for the existence of longer lasting fluctuations of GDP p.c. in four countries: USA, UK, Germany and France. Using data from the Angus Maddison Project dataset and the World Intellectual Property Organization, we proceed with spectral and cross-spectral analysis after removing a third-degree parabola – the P3 trend, as named by Reijnders (2009). Recall that our aim is not to estimate the best-fitting functional illustration of the real-time series, but to achieve stationarity, while preserving, as much as possible, any underlying cyclical movement of all possible frequencies.

Our results confirm that long waves are present, explaining a significant share of overall variability of the actual data, both for economic activity as well as for the possibly underlying cause of applied technological evolution.
Table 3. Results of cross-spectral analysis.

|                        | GDP p.c. USA | GDP p.c. UK | GDP p.c. Germany | GDP p.c. France |
|------------------------|--------------|-------------|------------------|-----------------|
|                        | Cycle years  |            |                  |                 |
|                        | 33.5  | 43.3 | 65.0 | 33.5  | 43.3 | 65.0 | 33.5  | 43.3 | 65.0 |
| **Patents grants USA** | Coherence   | 0.48 | 0.45 | 0.26 | 0.27 | 0.25 | 0.35 | 0.75 | 0.74 | 0.61 |
|                        | Phase value | 0.80 | 0.75 | 0.72 | −0.34 | −0.30 | −0.17 | −0.16 | −0.16 | −0.01 |
| **Patents grants UK**  | Coherence   | 0.83 | 0.81 | 0.84 | 0.83 | 0.81 | 0.84 | 0.75 | 0.74 | 0.61 |
|                        | Phase value | −0.10 | −0.12 | −0.10 | −0.10 | −0.12 | −0.10 | −0.16 | −0.16 | −0.01 |
| **Patents grants Germany** | Coherence | 0.75 | 0.74 | 0.61 | 0.75 | 0.74 | 0.61 | 0.75 | 0.74 | 0.61 |
|                        | Phase value | −0.16 | −0.16 | −0.01 | −0.16 | −0.16 | −0.01 | −0.16 | −0.16 | −0.01 |
Second, we check the validity of the theoretical argument that stresses applied knowledge as a significant driving force. According to our cross-spectral estimations in the USA, coherence and phase statistics support our hypothesis, as there is a significant correlation between GDP p.c. and patent grants in time, while the cyclical movement of patent grants is leading. The UK does not provide us with significant estimations, while in case of Germany and France, coherence is also significant (as in the USA) but the estimated values of phase do not provide a clear picture.

If anything, our analysis gives specific answers for the existence of long waves. However, the lack of robust results with respect to the causality (lag or lead) reveals the necessity for further, thorough investigations, considering the methodological weaknesses of cross-spectral analysis. Moreover, the modest evidence regarding the leading force between economic development and applied knowledge could be attributed to other two reasons. First, the fact that patents are a poor proxy of innovation (Boldrin & Levine, 2013). Second, the changes in how that proxy is measured over long-time periods (Lerner, 2002) such as in our case study. The above discussion suggests the need for further research in exploiting not only alternative empirical methodologies but more sophisticated proxies for applied research and extended data as well.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

**Notes on contributors**

**Dr. Eirini Ozouni** Eirini Ozouni has obtained her doctoral degree in International Economy and Economic Growth from the School of Economics and Political Sciences of AUTH and her bachelor and master degree in Economic Theory and Policy from the Department of Economics of University of Ioannina. Currently she is a Research Fellow at the Alexander Technological Educational Institute of Thessaloniki (A.T.E.I.TH) as well as a Research Associate at the Career Services Office of AUTH. Dr. Ozouni has participated in many international scientific conferences and has extensive experience in research activities which she gained during her studies as well as her professional activities. Her research covers the fields of international economics, economic development and economic growth, having already many international academic publications.

**Prof. Constantinos Katrakilidis** Constantinos Katrakilidis is currently Professor of Econometrics at the Aristotle University of Thessaloniki, Faculty of Economics. His recent research and teaching focuses on Applied Econometrics and Statistics as well as on Environmental and Energy Economics. He has published over 80 journal papers in recognized international journals.

**Assoc. Professor Grigoris Zarotiadis** Grigoris Zarotiadis studied economics in Johannes Kepler University of Linz – Austria. During his PhD he spent a year in UMIST (University of Manchester – Institute for Science and Technology). Currently, he is Assoc. Professor and Dean of the Faculty of Economic and Political Sciences in Aristotle University of Thessaloniki. He is the Vice-President in the Association of Economic Universities of South and Eastern Europe and the Black Sea Region, as well as in the Institute for Social Research Dimitris Mpatsis. His research covers the fields of international economics, economic development and economic growth, having a plentiful record of international academic publications and references.
References

Baxter, M., & King, R. G. (1999). Measuring business cycles: Approximate band-pass filters for economic time series. Review of Economics and Statistics, 81(4), 575–593.

Bieshaar, H., & Kleinknecht, A. (1983, October 26–29). Kondratieff long waves in aggregate output. In Serie Researchmemorandum 1983-12. Vrije Universitat Ekonomische Fakulteit Amsterdam. Paper for the Meeting of Long Waves, Depression and Innovation: Implication for National and Regional Economic Policy, IIASA and IRPE, Florence, Italy.

Boldrin, M., & Levine, D. K. (2013). The case against patents. The Journal of Economic Perspectives, 27(1), 3–22.

Christiano, L. J., & Fitzgerald, T. J. (2003). The band pass filter. International Economic Review, 44(2), 435–465.

De Wolff, S. (1924). Prosperitats-und Depressionsperioden. In O. Jensen (Ed.), Der Lebendige Marxismus. Festgabe zum 70. Geburtstage von Karl Kautsky (pp. 13–43). Jena: Thüringer Verlagsanstalt und Druckerei.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. Econometrica, 64(4), 813–836.

Engle, R. F. (1976). Interpreting spectral analyses in terms of time-domain models. Annals of Economic and Social Measurement, 5(1), 89–109.

Fisher, R. A. (1929). Tests of significance in harmonic analysis. Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character, 125(796), 54–59.

Freeman, C., & Louçã, F. (2001). As time goes by: From the industrial revolutions to the information revolution. USA: Oxford University Press.

Garvy, G. (1943). Kondratieff's theory of long cycles. The Review of Economic Statistics, 25(4), 203–220.

Gil-Alana, L. A. (2001). Testing stochastic cycles in macroeconomic time series. Journal of Time Series Analysis, 22(4), 411–430.

Granger, C., John, W., & Hatanaka, M. (1964). Spectral analysis of economic time series. Princeton, NJ: Princeton University Press.

Hamilton, J. D. (1994). Time series analysis. Princeton, NJ: Princeton University Press.

Haustein, H.-D., & Neuwirth, E. (1982). Long waves in world industrial production, energy consumption, inventions, and patents and their identification by spectral analysis. Technological Forecasting and Social Change, 22(1), 53–89.

Hodrick, R. J., & Prescott, E. C. (1997). Postwar US business cycles: An empirical investigation. Journal of Money, Credit, and Banking, 29, 1–16.

Jevons, W. S. (1884). Investigations in currency and finance. London: Macmillan.

Juglar, C. (1862). Des crises commerciales et de leur retour périodique en France, en Angle-terre et aux Etats-Unis. Paris: Guillaumin.

Kitchin, J. (1923). Cycles and trends in economic factors. The Review of Economic Statistics, 5(1), 10–16.

Kleinknecht, A. (1986). Long Waves, Depression and Innovation. De Economist, 134(1), 84–108.

Kondratieff, N. D. (1935). The long waves in economic life. The Review of Economic Statistics, 17(6), 105–115.

Kondratieff, N. D., & Oparin, D. (1928/1984). The “long wave cycle” and “The theses of N.D. Kondratieff’s paper: Long cycles in economic conditions”. In N. Kondratieff & J. M. Snyder (Eds.), The long wave cycle (pp. 25–99, 101–105, 108–137). New York: Richardson & Snyder.

Korotayev, A. V., & Tsirel, S. V. (2010). A spectral analysis of world GDP dynamics: Kondratieff waves, Kuznets swings, Juglar and Kitchin cycles in global economic development, and the 2008–2009 economic crisis. Structure and Dynamics, 4(1), 1–57.

Kuznets, S. S. (1930). Secular movements in prices and production (Ph. D, Doctoral dissertation, Thesis under Prof. Wesley Clair Mitchell). Columbia University, New York.

Kuznets, S. S. (1958). Long swings in the growth of population and in related economic variables. Proceedings of the American Philosophical Society, 102(1), 25–52.

Lerner, J. (2002). 150 Years of Patent Protection, American Economic Review, 2002, 92, 221–225.
Mensch, G. (1975). *Stalemate in technology: Innovations overcome the depression*. New York: Ballinger.

Metz, R. (1992). A re-examination of long waves in aggregate production series. In A. Kleinknecht, E. Mandel, & E. Wallerstein (Eds.), *New findings in long-wave research* (pp. 80–119). New York: St. Martin’s Press.

Metz, R. (2002). *Trend, Zyklus und Zufall: Bestimmungsgründe und Verlaufsformen langfristiger Wachstumsschwankungen*. Wiesbaden, Stuttgart.

Metz, R. (2011). Do Kondratieff waves exist? How time series techniques can help to solve the problem. *Climetrika*, 5(3), 205–238.

Nelson, C. R., & Plosser, C. R. (1982). Trends and random walks in macroeconomic time series. *Journal of Monetary Economics*, 10, 139–162.

Olsson, O. (2000). Knowledge as a set in idea space: An epistemological view on growth. *Journal of Economic Growth*, 5(3), 253–275.

Olsson, O. (2001). Why does technology advance in cycles? *Working Papers in Economics*. Retrieved from https://gupea.ub.gu.se/bitstream/2077/2882/1/gunwpe0038.pdf.

Olsson, O. (2005). Technological opportunity and growth. *Journal of Economic Growth*, 10(1), 31–53.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in the time series regression. *Biometrika*, 75(2), 335–346.

Reijnders, J. P. G. (1992). Between trends and trade cycles: Kondratieff long waves revisited. In A. Kleinknecht, E. Mandel, & E. Wallerstein (Eds.), *New findings in long-wave research* (pp. 15–44). London: Palgrave Macmillan.

Reijnders, J. P. G. (2009). Trend movements and inverted Kondratieff waves in the Dutch economy, 1800–1913. *Structural Change and Economic Dynamics*, 20(2), 90–113.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5), 71–102.

Schumpeter, J. A. (1939). *Business cycles. A theoretical, historical and statistical analysis of the capitalist process, abridged, with an introduction, by Rendigs Fels*. New York: McGraw-Hill.

Solomou, S. (1990). *Phases of economic growth, 1850–1973: Kondratieff waves and Kuznets swings*. Cambridge: Cambridge University Press.

Solomou, S. (1998). *Economic cycles: Long cycles and business cycles since 1870*. New York: St. Martin’s Press.

Stier, W. (2001). *Methoden der Zeitreihenanalyse*. Berlin, Heidelberg: Springer.

Van der Zwan, A. (1980). On the assessment of the Kondratieff cycle and related issues. In S. K. Kuipers and G. J. Lanjouw (eds.), *Prospects of economic growth* (pp. 183–222). Amsterdam.

Van Duijn, J. (1977). The long wave in economic life. *De Economist*, 125(4), 544–576.

Van Duijn, J. (1983). *The long wave in economic life*. Shaftesbury, Dorset: George Allen & Unwin Ltd.

Van Ewijk, C. (1981). The long wave–A real phenomenon? *De Economist*, 129(3), 324–372.

Van Ewijk, C. (1982). A spectral analysis of the Kondratieff cycle. *Kyklos*, 35(3), 468–499.

Van Gelderen, J. (ps. J.Fedder) (1913). *Springvoed: Beschouwingen over industriële ontwikkeling en prijsbeweging*. In *De Nieuwe Tijd*, XVIII, 4, 5 and 6, April, May, and June, 254–77, 370–84, 446–64.

Zarotiadis, G., & Ozouni, E. (2017). *Standing-on-shoulder and fishing-out synergies: A model for endogenous long-waves*. Research Paper presented in the 13th Annual International Scientific Conference EEFS, Thessaloniki, Greece.