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Green business cycle: an analysis on China and France

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Abstract
Business cycle analysis generated an essential impulse in stimulating and provoking interesting academic and professional debates within a growth perspective. In fact, measuring business cycles is critical in determining the stylized facts on the cyclical behavior of aggregate macroeconomic indicators over time. As green growth topics started to occupy much academic interest, the question of the co-existence of equitable and sustainable development as well as current dynamics and cyclical features of economic growth comes into foreplay. This paper aims to evaluate cyclical characteristics of green growth related variables by observing two countries that showed different green policy aspirations over time, namely China and France. Following the paper's main objective, we want to provide a detailed analysis of the extent to which Green GDP and relevant output measures are comparable in a wider 'deviation cycle' context that includes cycle correlation, cycle coherence, and cycle magnitude. Results suggest that business cycles of GDP/GNI and Green GDP are strongly connected and coherent to a high degree. However, we found that the strength of that nexus and the degree of similarity has changed considerably over time, yet in a positive way.

Keywords
business cycles, Green GDP, cycle coherence, magnitude of cycles

Introduction

The term business cycle (economic cycle) refers to changes in the economy at the level of production or economic activity over several months or years. Changes in the economy most often occur around a long-term growth trend. They usually involve changes over a period of relatively rapid economic growth (expansion) and periods of relative stagnation or decline (recession). There are a vast number of different fluctuations in economic life and external factors that affect economic processes. Any change in one of these factors directly affects changes in economic activity. If these changes are large and long-lasting and affect the economy's external determinants and thus cause disturbances in the economy for a long time, we can talk about an economic crisis. Experience and history have shown that there is a certain regularity in fluctuations in the economy that cannot be explained in any way with the help of random external disturbances. As a potentially possible solution, we seek the causes that influence these regular cycles' creation, and their explanation is sought.

This topic is inexhaustible and very complex in economic circles, and it provokes very large and exhaustive discussions that have not contributed to reaching a common position or conclusion to date. With various theories of crises and theories of cycles that have formed in the meantime, we come to an attempt to solve the problem. The first and most important issue related to business cycles is what causes them. In addressing this issue, we have many experts who have different visions of the answers that shocks cause the emergence of business cycles. In theory, we have several approaches to this problem so far, and these are through monetary, fiscal policy, and oil shocks. One of the theories of the emergence of business cycles starts from the impact of technological shocks on the economic system. Gali (1999) stimulated a discussion of the importance of technological shocks as impulses in business cycles. Gali uses structural VAR, which identifies assuming that technological shocks are the only source of long-term labor productivity changes. He revealed that there is a drop in the number of hours worked in response to the positive shocks in technology in a short period of time. The present invention is in direct contradiction with the basics of the real business cycle model. In addition to the theory of the impact of technological shocks, we also have the impact of fiscal shocks through tax rates and government spending and the impact of oil and petroleum products' price.

In addition to theories on the impact and reasons for the emergence of business cycles, we also have the problem of measuring the business cycle itself. Business cycle measurement provides a reference point against which macroeconomic theories and policies can be assessed. The business cycle measurement process takes place in several steps. First, the cycle must be defined and discovered, and second, the turning points must be located. The next step toward business cycle measurement is in determining the basic procedures of the models used to define and locate milestones in business cycles. After that, it is necessary to perform the characteristics of the measurement cycle. The next step is to define and detect business cycles using multivariate data, followed by the automatic construction of the reference cycle. As a last option, it is necessary to list the basic procedures in the model for defining the determination and extraction of the reference cycle. There are several variables we can look at to see the existence of business cycles. One of the most frequently observed and used variables is GDP. Given the large number of shortcomings that GDP contains as a measure, from not including leisure, money transfers, gifts, intermediary transactions, etc., the use of this measure to assess business cycles did not make sense.

Therefore, in this paper, we tried to use Green GDP and determine the existence of Green business cycles within certain observed economies. Green GDP is today known as a general concept that refers to a wide array of adjusted GDP measures that are corrected for social and environmental costs (for some of these commodities are not traditionally presented in monetary units). In that manner, Green GDP is just an alternative way to quantify and measure the monetary impact of social and environmental damage caused by a country's economic growth. The most common approach to measuring the Green GDP is to deduct social and environmental costs (for example, natural resources depletion and pollution damage) from the standard GDP measure. There is an interesting way to explain the (conceptual) purpose of this indicator. Suppose we consider that by adding social features / human capital and environmental features / natural capital to a standard measure of the volume of output, we are, in fact, relating it to the deterioration in social or environmental capital and reducing it by the amount of capital, thus consumed. Some say that we could look the other way around too. So that any improvement in social and/or environmental capital constitutes in itself a form of output and can be, therefore, added to the standard GDP measure.

This paper aims to evaluate the cyclical characteristics of green growth-related variables by observing two countries that showed different green policy aspirations over time, namely China and France. Following the paper's main objective, we want to provide a detailed analysis of the extent to which Green GDP and relevant output measures are comparable in a wider 'deviation cycle' context that includes cycle correlation, cycle coherence, and cycle magnitude. Results suggest that business cycles of GDP/GNI and Green GDP are strongly connected and coherent to a high degree. However, we found that the strength of that nexus and the degree of similarity has changed considerably over time, yet in a positive way.

China and France are the two countries considered in this paper. China is one of the leaders in all countries in terms of economic growth, with very high annual growth rates. China is studied in this paper because it is interesting due to the fact that it invests very little in environmental policies at the state level and has a very high consumption of natural resources. Unlike China, France is a country that has a very advanced environmental policy and has very large allocations for the environmental protection of natural resources. As such, two ideologically completely opposite countries are interesting for studying green business cycles.

Literature review

There is a very large number of scientific papers and books on the topic of business cycles, a little less on the topic of green GDP, while on the topic of green business cycles, we have very little or no work or book. One of the interesting papers on the topic of business cycles is a paper by Bergaman (2004), entitled How similar are European business cycles, where the author focuses on European economic integration and its impact on the synchronization and strength of business cycles in member states. From the paper itself, it can be concluded that there is a very high degree of synchronization within the integration. In the book by Kaiser et al. (2001), the question that arises for all economists is how to correctly separate the cyclical component from the economic time series, i.e., how to separate the elements of business cycles that arise from secular trends and rapidly growing seasonal components. One of the most difficult questions in macroeconomics is related to business cycles, i.e., the question of which shocks are the cause of business fluctuations? In theory, so far, most of the answers to this question are given through monetary policy, fiscal policy, and oil shocks. To this list, Prescott (1986) adds the impact of technological shocks. Capital utilization variables observed by Basu (1996), and Burnside, Eichenbaum, and Rebelo (1996); changes in labor utilization also studied by Burnside, Eichenbaum, and Rebelo (1993); and changes in income rates, studied by Jaimovich (2004), show important differences between TFP and actual technology shocks. These differences imply that the magnitudes of the actual technology shocks will be much smaller than the TFP shocks used by Prescott.

In their classic work "Measuring Business Cycles," Burns and Mitchell (1946) define specific cycles in the y_t series and have since used this as a milestone for depicting business cycles. This part represents the first step in measuring business cycles, i.e., it represents the definition and detection of cycles. When we talk about business cycles, Burns and Mitchell simply describe y_t as the level of aggregate economic activity, although it would be more correct to say that this series shows the logarithm of economic activity at a cycle turning point equal to the logarithm of total economic activity. Burns and Mitchell's well-known definition of business cycles has two aspects. First, it is necessary to identify aggregate economic activity, and second, it is necessary to have the synchronization of different variables during certain phases of business cycles. They considered GDP as a variable to be a good measure for displaying the index of economic activity, although others like Moore and Zarnovitz (1986) preferred to have a weighted average of several series rather than just one.

Stjepanović, Tomić, and Škare (2017 and 2019) introduce a new methodology for calculating Green GDP in their works. The authors try to estimate the potential Green GDP from the existing calculated GDP as a measure consisting of the cost of pollution and the degree of utilization of natural resources. The authors are of the opinion that economic growth, which is observed separately and does not take into account the consequences arising from it, such as pollution and the use of natural resources, cannot objectively present the business picture. Both the degree of pollution and resource utilization certainly come to fruition, if not immediately, in the same year, then after a certain period of time, and in that case, if proactive environmental policies are not pursued, real economic growth is much lower than shown. One such paper that seeks to reveal the background of the relationship between energy consumption growth and green GDP growth for China is a paper (Hongxian, 2018) entitled "Influence energy consumption has on green GDP growth in China". In this paper, the author analyzes the direct and indirect impact on the growth rate of green GDP, which affects several ratios of energy consumption as well as the relationship between different energy sources. Likewise, (Al-mulali, 2014), in his paper, describes the association of GDP growth with energy consumption.

This paper aimed to investigate the relationship between gross domestic product growth and renewable and independent energy consumption in 82 developing countries. One of the papers that analyzed the relationship between green GDP and sustainable development is the paper (Vaghefi, Siwar, and Aziz, 2015), which provides evidence of the usefulness of alternative GDP measures, i.e., green GDP. The authors calculated green GDP for Malaysia and indicated the important role of depleted natural resources and environmental damage within the country's sustainable development perspective. The problem of calculating green GDP is also studied by Wang, He, and Zheng (2014), who describe the way in which the Green GDP system was designed and developed for China. The results suggested that China has not achieved 'clean 'economic growth due to excessive pollution and too high utilization of natural resources. However, the problem of calculating green GDP is not always only in the technology and method of calculation. In Steinhardt and Jiang (2007), we see that there are two different interpretations of the impossibility of calculating green GDP in China. One interpretation is that local politiciansoppose it, and the other is that politics itself does not allow or obscure actual figures on the depletion of natural resources.

Methodology and data

Constant, both theoretical and empirical, dwellings whether business cycles can explain economic growth and/or that some relevant factors (such as the environment or technology) account for a substantial share of economic progress considering the timing and magnitude of the on-going business cycle. This leads us to the point where we wanted to explore the extent to which the national output, as an indicator that measures flows of output and income through the economy, can be related to its augmented version, the Green GDP, having in mind the coherence and magnitude of their cyclical behavior. Such business cycle analysis can serve as an important impulse in stimulating and provoking interesting 'green topic' debates for China and France as their contrast in the average bias of the Green GDP towards standard GDP measure is consistent and prevalent (Stjepanović, Tomić and Škare, 2017). Following the paper's main objective, we want to provide a detailed analysis of the extent to which Green GDP and relevant output measures are comparable in a wider 'deviation cycle' context that includes cycle correlation, cycle coherence, and cycle magnitude.

Methodological framework

Our deviation cycle framework implies that we should be concerned with phases of above and below trend growth rates. In order to evaluate cyclical components of selected variables, we opted to use an array of recognized methods for removing long-run movements from the time series.Also, we evaluated the integration properties of the data to check methodological possibilities. Empirical scrutiny of the papers such as Bergman (2003), Ruth, Schouten and Wekker (2005), Mink, Jacobs and de Haan (2012), and Tomić and Stjepanović (2018) provided relevant evidence in favor of four methods for decomposing the trend and cycle component from the real output, namely Hodrick-Prescott filter, Christiano-Fitzgerald filter, Beveridge-Nelson decomposition, and basic ARIMA modeling. After a long period in which it was held that the correct method of detrending could not be decided upon and yet was critical in effect, there seems now to be some convergence of opinion on the idea that a band pass filter is broadly optimal (Artis, 2004).

The Hodrick-Prescott filter (HP filter) popularity to detrend a time series lies in the fact that it is easy to calculate. Hodrick and Prescott's (1997) approachconsiders that we can decompose time data series into two components (long term trend and stationary cycle)thereby if the evaluation can provide estimates of growth components with errors that are small relative to the cyclical component, computing the cyclical component rests on calculating the difference between the observed value and the growth component. This approach resulted in the creation of the filter that became the common method for removing long-run movements from the time series as itwithstood the test of time and the intensity of discussion on its relevance. The HP filter focuses on removing a smooth trend τ_t from some given data y_t by solving the next equation:

$$\min_t \sum_{t=1} ((y_t - \tau_t)^2 + \lambda((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2) \tag{1}$$

so the residual $y_t - \tau_t$ is then commonly referred to as the business cycle component. This filter also requires the previous specification of a parameter lambda (λ). Hence, considering the time domain (annual, quarterly, or monthly data), this parameter tunes the smoothness of the trend. Parameter lambdais often based on the intuitive interpretation of the researcher. Thus this is considered the main weakness of the HP filter.

Christiano-Fitzgerald filter (CF filter) random walk filter is a band pass filter similar to Baxter and King filter. Both filters are used to isolate the cyclical component of a time series by specifying a range for its duration. Roughly speaking, the band-pass filter is a linear filter that takes a two-sided weighted moving average of the data where cycles in a 'band', given by a specified lower and upper bound, are passed through (or extracted) so that the remaining cycles are filtered out. The CF filter has a steep frequency response function at the filter band's boundaries (i.e., low leakage) as it is an asymmetric filter that converges in the long run to the optimal filter (Nilsson and Gyomai, 2011). It is calculated through the procedure:

$$c_t = B_0\, y_t + B_1\, y_{t+1} + \cdots + B_{T-1-t} y_{T-1} + \tilde{B}_{T-t} y_t + B_1\, y_{t-1} + \cdots + B_{t-2}\, y_2 + \tilde{B}_{t-1}\, y_1 \tag{2}$$

so that$B_j = (\sin(jb) - \sin(ja))/\pi j$, j ≥ 1, and $B\_0 = (b - a)/\pi$,$a = 2\pi/p\_u$,
$b = 2\pi/p\_l$ (3)

and we get $B\tilde{} = -1/2\ B\_0 - \sum\_(j = 1)\char`^(k - 1) B\_j$ (4)

The parameters puand plare the cut-off cycle length in a month. Cycles longer than pland shorter than puare preserved in the cyclical term ct.

The Beveridge-Nelson procedure (hence BN filter) (Beveridge and Nelson, 1981). provides a trend/cycle decomposition because, under the assumption that the permanent component follows a random walk (with drift)and the transitory component is stationary with an unconditional mean of zero, the optimal long-horizon forecast (in a minimum–mean squared error sense) will be equal to the conditional expectation of the permanent component. Let yt be integrated of the first order so that its first differences, Δy_t, are stationary. According to Wold decomposition, then Δy_t can be written as an infinitive moving average, Δy_t = A(L)εt where εt are uncorrelated, mean zero, random disturbances with variance equal to σ2 and A(L) is the polynomial of moving average coefficients. The BN decomposition can be obtained therefore from the Wold decomposition as (Bjørnland, 2000): $\Delta y_t = \Delta g_t + \Delta c_t$, so that $\Delta g_t = \alpha_1$+A(1)εtand Δc_t=(1-L) A*(1)εt, where A(1) is the infinite sum of moving average coefficients and A*(L) = (1-L)-1 (A(L) – A(1)). Then, the trend is a random walk with drift, whereas the cyclical component is stationary:

$$gt = g0 + a1\ t + A(1)∑\_(s = 1)\^tε\_s \quad (5)$$

$$ct = A\^ *\ (L)\ ε\_t \quad (6)$$

An Autoregressive integrated moving average model (ARIMA model) is derived from a widely used group of parametric models in time series analysis called autoregressive moving average models or ARMA. We can define the general ARMA process as Sjöberg (2010) were {Xt} is an ARMA (p,q) process if {Xt} is weakly stationary and it holds for every t that:

Xt – ϕ1Xt-1 – ... – ϕpXt-p = Zt + θ1Zt-1 + ... θqZt-q (7)

and the polynomials (1– ϕ1z – ... ϕpzp) and (1– θ1z – ... θqzq) have no common factors. Then {Zt} is white noise, i.e., a sequence of uncorrelated stochastic variables with the same expected value (in this case 0) and variance σ2, which will be denoted as {Zt} ~ WN(0,σ2). A process {Xt} is, therefore, an autoregressive integrated moving average ARIMA (p,d,q) process if (Brockwell and Davis, 2002)Yt = (1 – B)dXt is an ARMA process. The operator B is the backward shift operator, and its application gives BXt = Xt-1, d as a non-negative integer. The case d = 0 gives directly Xt is an ARMA process. To simplify, assume that (invertible) ARIMA model is given by the expression:
r

∇∇4xt = θ(B)at, at ~ niid (0, Va) (8)

Components are derived, such they conform to the basic features of a trend, a seasonal and an irregular component, and aggregate into the observed model (6). Considering that ∇∇4factorizes into ∇2S, obviously∇2 represents the AR ϕp(B) polynomial for the trend component, and S represents the AR ϕs(B) polynomial for the seasonal component. The series is seen to contain non-stationary trend (or trend-cycle) and seasonal components as it can be decomposed into:

xt = pt + st + ut (9)

where pt, st and ut denote the trend-cycle, seasonal and irregular components, respectively, the latter being a stationary process (Kaiser and Maravall, 2001).

The three steps of the research process

In the *first step* of the analysis, in order to comprehend the dynamics between the cycles of the national output and the Green GDP measure, we opted to calculate their cross-correlations. According to Stock and Watson (1999) and later Napoletano, Roventini and Sapio (2005), co-movements among variables are demonstrated through the cross-correlation of the cyclical component of each series (in our case, the Green GDP variable) with the cyclical component of a reference cycle as a benchmark variable, which is thought to represent the business cycle (in our case the national output variable). That is the correlation between x_t and y_t+_k, where x_t is the filtered series and $y_t+_k$is the *k*-quarter lead of the filtered reference variable. A large positive correlation at $k = 0$ indicates the pro-cyclical behavior of one series, and a large negative correlation at $k = 0$ indicates a counter-cyclical behavior, whereas no correlation indicates the so-called acyclical behavior of the series. A maximum correlation at, for example, $k = -1$ indicates that the cyclical component of the variable tends to lag the aggregate business cycle by one year if annual data are considered. Therefore, if the absolute maximum or minimum is reached at some reference variable lead, then the variable is denoted as leading, whereas it is called lagging in the opposite case. Coincident variables usually display cross-correlations with the reference variable at lag zero.

In the *second step*, in order to reveal the nature of the cycle amplitudes, we will analyze the cycle coherence based on so-called cycle similarity. The concept of cycle coherence between the growth trend and business cycles relates to the pattern of growth between the data in regard to the magnitude of growth rates and/or the amplitude of the growth trend or business cycles (Crowley and Schultz, 2010). Mink et al. (2012)promotedthe business cycle coherence concept by estimating two related but separated, separated indicators,i.e., synchronicity and similarity indicators. When averaged over a time interval and transformed to uniform scaling, the synchronicity indicator suggests the fraction of time that the output gap of country i has the same sign as the output gap of the reference cycle, whereas averaging similarity between individual countries and the reference over all n countries in the sample yields co-movement for the whole region. Similarity measure can be obtained as:

$$(\gamma ir) = -(n\,|g(i)(t) - g(r)(t)|)/(\sum\_(i=1)^n|g(i)(t)|) \quad (10)$$

where gi(t) is the cyclical component of the analyzed output of a country i in time t and gr(t) refers to the cyclical component of the reference country r in time t.Since our analysis is not a cross-country featured and therefore is not interested in phase synchronicity, we opted to focus on the cycle similarity(γir) concept from the Mink et al. (2012) that the will help us in measuring de facto the synchronicity of the amplitudes of two cycles, namely national output and Green GDP cycles. This is an interesting alternation to the methodology that is primarily used for a cross-country analysis.

In the third step, in order to evaluate the magnitude of cycles, we will further analyze the amplitude of cycles by introducing two additional measures, mean absolute deviation - MD (suggested by Dickerson, Gibson and Tsakalotos, 1998) and absolute difference of the standard deviations - SD (suggested by Bergman, 2003) between the national output and Green GDP cycles. Mean absolute deviation or average absolute deviation is the mean of the data's absolute deviations around the data's mean and. It is a simpler measurement compared to standard deviation, hence less volatile, since it is a natural weight, whereas standard deviation uses the observation itself as its own weight, imparting large weights to large observations, thus overweighing tail events. On the other hand, the results from the absolute difference of the standard deviations in the research from Dickerson, Gibson and Tsakalotos (1998) showed relatively similar results as the mean absolute deviation. Hence, we will calculate both of them in order to achieve a more robust conclusion in general.

With a view to different dynamics across different periods and robustness of potential conclusions, we will confront two broadly accepted measures of national output against the measure of Green GDP within an aggregate period and several sub-periods related to important macroeconomic developments.

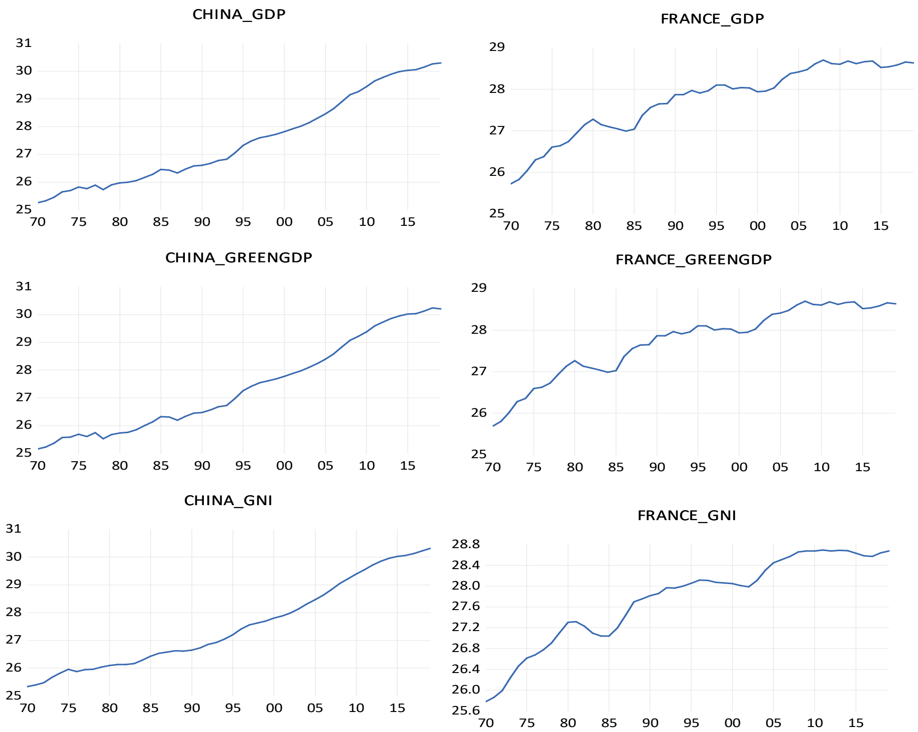
Data

Annual data for measures of national output, covering the period 1970-2019, was obtained from the World Development Indicators (2020). Gross domestic product (GDP) in current U.S. dollars was obtained as the sum of gross value added by all resident producers in one economy plus any product taxes minus any subsidies not included in the value of the products. It has been calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources, and since it is presented in PPP form, dollars for the GDP are converted from domestic currencies using single-year official exchange rates. Gross national income (GNI), also in current U.S. dollars, is presented as the sum of value added by all resident producers plus any product taxes (fewer subsidies) not included in the valuation of output plus net receipts of primary income from abroad. Data for the Green GDP are obtained by using an alternative approach in measuring the green output provided by Stjepanović, Tomić and Škare (2017). This new approach's virtue is comprehensive consideration of both quantitative (common methodological algorithm) and qualitative (opportunity costs) features of so-called green growth.

Data are transformed in their logarithmic form. In the next step, we applied four extracting procedures (HP filter, CF filter, BN filter and ARIMA modelling). To test the integration properties, we interpreted figures and applied three-unit root tests Augmented Dickey-Fuller test - ADF (1979), Phillips-Perron test - PP (1988), and Kwiatkowski-Phillips-Schmidt-Shin test (1992). In general, allfigures and tests confirmed the absence of a unit root within the variables, which is an important property of detrended variables. Results from ARIMA modeling and from unit root tests are available upon request.

The results

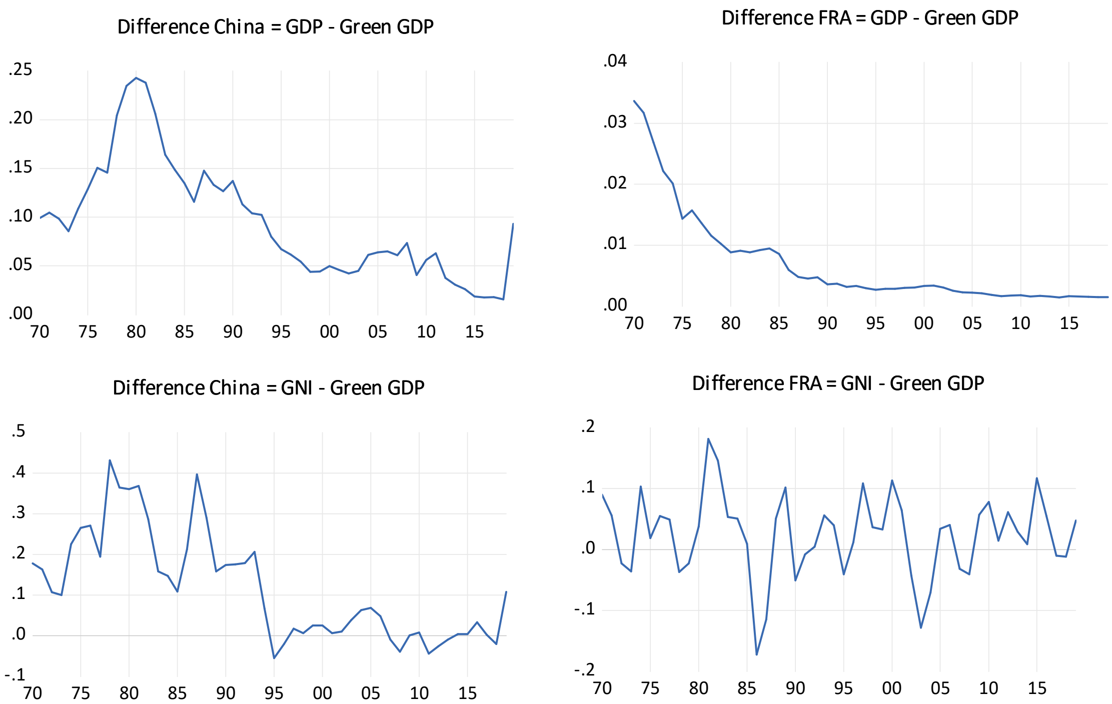
Before revealing the dynamics of cycles for both countries, we should look into the variables' real movements. In the observed period, all variables showed an increasing trend with similar fluctuations across the same country (*Graph 1*).



Graph 1. GDP, GNI, and Green GDP (in logs)

Source: Authors' analysis

When observing the difference between the variables for national output and Green GDP (*Graph 2*), we noticed that the difference between the GDP and Green GDP is decreasing rapidly as it flattens after 1980 for both countries, whereas the discrepancy between the GNI and Green GDP decreases slowly, but it also becomes less volatile over time. The smaller bias of the Green GDP variable goes in line with the pervasive thinking that economic progress should lead to more sustainable economic behavior. This position will be tested hereafter, however, from the economic cycle's perspective.



Graph 2. Difference between GDP/GNI and Green GDP (in logs)

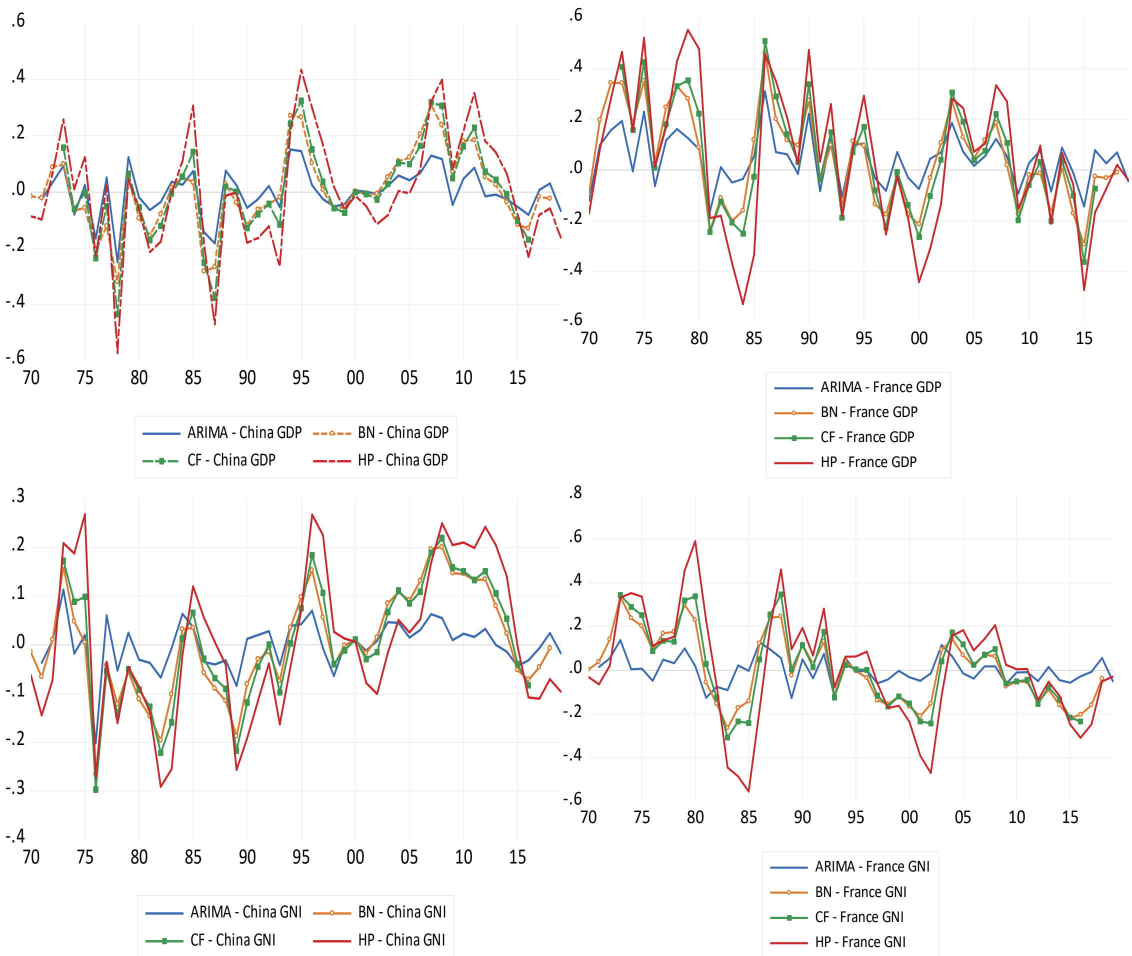
Source: Authors' analysis

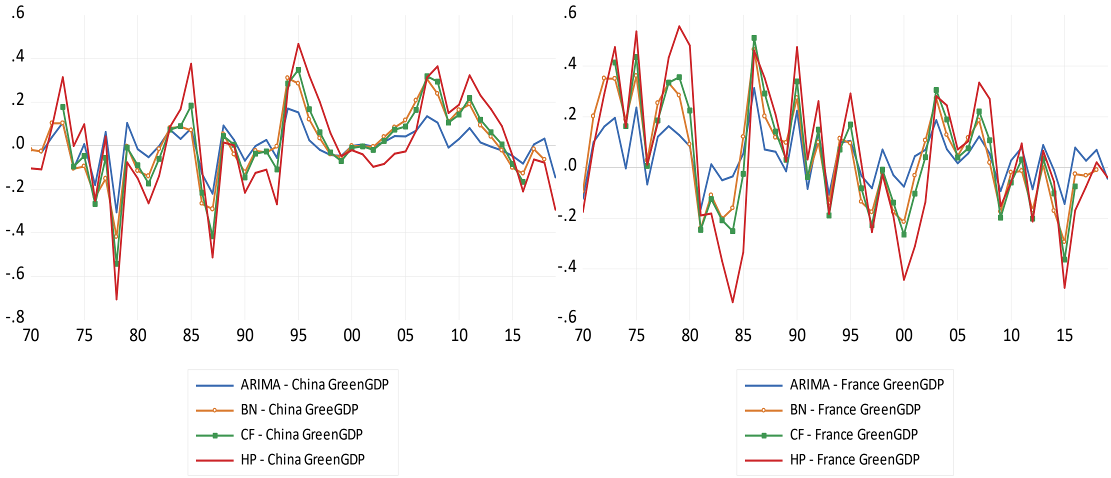
In order to comprehend the cyclical characteristics of the variables, we applied the previously explained four-cycle extraction methods. The cyclical behavior of all three variables and for each country seems to be consistent across the period and across all four-cycle extraction procedures (*Graph 3*), meaning that we can use any method in explaining the cycle dynamic.

After the reforms of 1978, China's growth was remarkable (Keidel, 2007). However, we can easily notice, within all three variables, some troughs, for example, in 1980-1982 (budget deficit and balance of payments corrections), 1985-1987 (industrial overheating corrections), 1997-2000 (rural household consumption slump), 2001 (SARS) and 2015-2016 (Chinese stock market turbulence), as well as some peaks such as 1983-1985 (rural reform boom), 1991-1996 (urban price reform and rural enterprise boom), 2008-2009 (quick and aggressive fiscal and monetary response to world's crisis).

Similarly, for France, our figures discover economic slumps at the end of the 1970s and the beginning of 1980s with austerity and inflation problems, 1992-1993 (oil shocks and the tension in the monetary union), 2000 (internet bubble crisis), the recession of the 2008), economic slowdown in 2015 (dual economy, high unemployment, low demand). Some peaks are noticeable in 1970, as well as through the whole periods of economic progress (Doz and Petronevich, 2015).

Finally, if we observe the fluctuations of the cycles for both countries, we can find very similar, almost synchronized, movements between the GDP, GNI, and Green GDP for each country, suggesting their cycles could be strongly bounded. In what way we will see through the analysis of correlation, similarity, and amplitude of those cycles.





Graph 3. The cyclical behavior of GDP, GNI, and Green GDP

Source: Authors' analysis

Cross-correlation analysis

By interpreting cross-correlations with lags/leads between the GDP and Green GDP as well as GNI and Green GDP for the whole period, we can notice positive, i.e., pro-cyclical and coincident behavior (with some lagging features of Green GDP towards the GNI only with BN filter method in table 1). This is an important feature since it suggests that Green GDP cycle movements are generally synchronized with China and France's macroeconomic developments.Another interesting point (*Table 2*) is that when we observe average cross-correlations in t_0 in three different sub-periods (1970-1985, 1986-2000, 2001-2019), we find a constantly high correlation between the GDP/GNI variables and Green GDP for France across all three sub-periods, but with an increasing cross-correlation coefficient over three periods for China. The analogous conclusion can be drawn when we also observe average cross-correlations in $t_{+/-1}$ across sub-periods. There is a quite constant average correlation between the variables across all three sub-periods for France, but a strong increase in the nexus between China's variables, especially for the relationship GDP – Green GDP from the second sub-period.

Table 1. Cross-correlations between GDP/GNI and Green GDP

China	t_{-2}	t_{-1}	t_0	t_{+1}	t_{+2}
ARIMA - GDP andGreenGDP	0.10	-0.06	**0.98**	-0.02	0.08
ARIMA - GNI andGreenGDP	0.36	0.10	0.64	-0.13	0.24
BN - GDP andGreenGDP	0.60	**0.76**	**0.98**	**0.78**	0.62
BN - GNI and GreenGDP	**0.84**	**0.86**	0.78	0.59	0.45
CF - GDP and GreenGDP	-0.22	-0.08	**0.98**	-0.02	-0.25
CF - GNI and GreenGDP	0.34	0.28	0.37	-0.13	-0.07
HP - GDP and GreenGDP	0.24	0.56	**0.98**	0.60	0.30
HP - GNI and GreenGDP	0.57	0.73	0.74	0.38	0.12
France	t_{-2}	t_{-1}	t_0	t_{+1}	t_{+2}
ARIMA - GDP and GreenGDP	0.06	-0.09	**1.00**	-0.10	0.06
ARIMA - GNI andGreenGDP	0.27	0.17	**0.77**	-0.08	0.15
BN - GDP and GreenGDP	0.54	**0.82**	**1.00**	**0.82**	0.54
BN - GNI and GreenGDP	**0.90**	**0.96**	**0.77**	0.50	0.25
CF - GDP and GreenGDP	-0.40	0.09	**1.00**	0.09	-0.40
CF - GNI and GreenGDP	0.26	0.70	0.05	-0.17	-0.27
HP - GDP and GreenGDP	0.24	0.66	**1.00**	0.66	0.24
HP - GNI and GreenGDP	0.62	**0.92**	**0.84**	0.44	0.07

Source: Authors' analysis

As cross-correlation coefficients suggest, the bond between the business cycles of the variables of national output and Green GDP for both countries is strong and increasing over time, meaning that cycles are starting to fluctuate alike. Hence cycles are becoming more and more similar in their behavior. Are they really getting more synchronized, hence more coherent? We will try to answer it through the analysis of cycle similarity.

Table 2. Cross-correlations between GDP/GNI and Green GDP in sub-periods

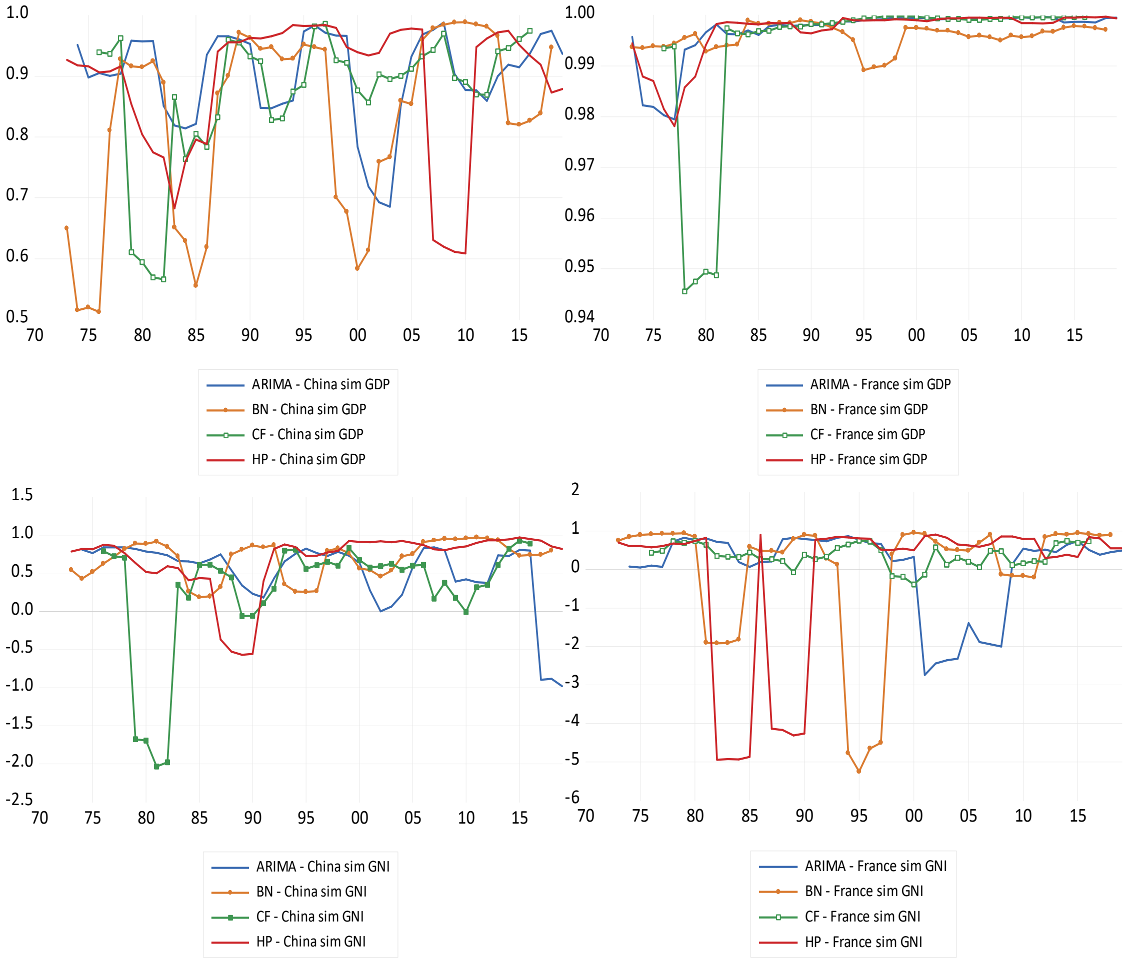
China	t_0			$t_{+/-1}$		
	1970-1985	1986-2000	2001-2019	1970-1985	1986-2000	2001-2019
ARIMA - GDP and GreenGDP	0.99	0.99	0.94	0.03	0.50	0.55
ARIMA - GNI and GreenGDP	0.69	0.46	0.80	0.02	0.31	0.56
BN - GDP and GreenGDP	0.97	1.00	0.97	0.63	0.80	0.86
BN - GNI and GreenGDP	0.49	0.67	0.95	0.54	0.65	0.85
CF - GDP and GreenGDP	0.98	0.99	0.97	0.15	0.33	0.45
CF - GNI and GreenGDP	0.43	0.17	0.70	0.13	0.07	0.47
HP - GDP and GreenGDP	0.98	1.00	0.98	0.53	0.72	0.83
HP - GNI and GreenGDP	0.61	0.69	0.93	0.39	0.70	0.63
France	t_0			$t_{+/-1}$		
	1970-1985	1986-2000	2001-2019	1970-1985	1986-2000	2001-2019
ARIMA - GDP and GreenGDP	1.00	1.00	1.00	0.32	0.17	0.30
ARIMA - GNI and GreenGDP	0.78	0.76	0.77	0.43	0.13	0.29
BN - GDP and GreenGDP	1.00	1.00	1.00	0.85	0.81	0.84
BN - GNI and GreenGDP	0.74	0.78	0.68	0.69	0.75	0.64
CF - GDP and GreenGDP	1.00	1.00	1.00	0.52	0.23	0.35
CF - GNI and GreenGDP	0.75	0.01	0.50	0.54	-0.08	0.27
HP - GDP and GreenGDP	1.00	1.00	1.00	0.79	0.51	0.69
HP - GNI and GreenGDP	0.92	0.62	0.84	0.78	0.37	0.69

Source: Authors' analysis

Coherence analysis

Following the methodology presented in the third section, we calculated the measure of cycle similarity (across four different cycle extraction methods) that will help us in explaining cycle coherence in between the observed variables(similarity between the business cycle of a variable and the reference cycle ranges between 1 and 1 –n, soas the value is closer to 1, the similarity is higher).

Results and displayed figures (*Graph 4*) suggested that similarity levels (of variables for national output and Green GDP) fluctuated substantially over time for China for both GDP and GNI (fluctuations that can be traced to explanations from *Graph 3*). However, in general, there was a higher similarity in movements (between 0.5 and 1) between the GDP and Green GDP cycles, compared to the similarity between the GNI and Green GDP that showed much stronger fluctuations. On the other hand, for France, we found very little fluctuations and a consistently very high degree of similarity of GDP and Green GDP cycles (close to 1) and relatively strong fluctuations in similarity levels between the GNI and Green GDP cycles.



Graph 4. Similarity levels between GDP/GNI and Green GDP

Source: Authors' analysis

By observing the degree of similarity between the cycles, we can conclude that over time Green GDP cycles have fluctuated highly similar to GDP movements for both countries, however for the GNI variable, we found a relatively consistent degree of similarity with the Green GDP, but with strong set off in similarity, related to macroeconomic shocks in each country. After 2000, we can trace consistently high degrees of similarity for each variable and for both countries, suggesting higher coherence of cycles. Let's see if the argument of increasing coherence of business cycles over time stands the test of the amplitudes in cycles.

Magnitude analysis

In *Table 3*, we report estimates of the mean absolute deviation (MD) and the absolute difference between the standard deviations (SD) between the GDP/GNI and Green GDP for the whole period and for the sub-periods. According to these estimates, amplitudes of cycles between these variables (especially within relationship GDP to Green GDP) have decreased considerably across all cycle extraction methods and for both countries. This implies that the magnitudes of cycles were less similar in the past but are become more similar as the awareness about green policies grew. By observing amplitudes of cycles across three distinct periods (similar to the cross-correlation analysis), we are, in fact, testing if the magnitude of the business cycle is equal across sub-periods. Since we can reject the hypothesis of equal magnitudes when comparing the whole sample with other sub-periods, we come to the conclusion that the bilateral differences in the magnitude are smaller in the most recent sub-periods. Amplitudes of cycles are decreasing; thus, their similarity is increasing.

It is not surprising that the relative magnitude of business cycles between the variables of national output and Green GDP for both countries tends to decrease over time, since two previous analyses suggested an increase in the correlation coefficients, an increase in similarity, and hence a decrease in fluctuations of business cycles, meaning that some developing (China) and high-income (France) countries appear to support more sustainable growth, development, and lifestyle, even though in practice they consume more resource per capita than the other countries. Finally, we can state that our results suggest that business cycles of GDP/GNI and Green GDP are strongly connected and coherent to a high degree, but we also found that the strength of that nexus and the degree of similarity has changed considerably over time, yet in a positive way.

Table 3. Mean absolute deviation (MD) vs. absolute difference between the standard deviations (SD) between the GDP/GNI and Green GDP

	MD				***SD***			
China	**1970-2019**	1970-1985	1986-2000	2001-2019	**1970-2019**	1970-1985	1986-2000	2001-2019
ARIMA - GDP and GreenGDP	**0,013610**	0,017469	0,010692	0,012610	**0,009327**	0,012710	0,011070	0,004929
ARIMA - GNI and GreenGDP	**0,047764**	0,053266	0,062131	0,030901	**0,041333**	0,042721	0,051666	0,036454
BN - GDP and GreenGDP	**0,013040**	0,020965	0,010908	0,008049	**0,007105**	0,016642	0,004285	0,003454
BN - GNI and GreenGDP	**0,038101**	0,053246	0,043415	0,021152	**0,010529**	0,016305	0,022719	0,012945
CF - GDP and GreenGDP	**0,006272**	0,008627	0,006086	0,004435	**0,003619**	0,006555	0,005771	0,003446
CF - GNI and GreenGDP	**0,027852**	0,037175	0,035912	0,013637	**0,020888**	0,025415	0,025955	0,009774
HP - GDP and GreenGDP	**0,016017**	0,025183	0,008754	0,014032	**0,010739**	0,022425	0,008352	0,002775
HP - GNI and GreenGDP	**0,045759**	0,066451	0,049495	0,025385	**0,027298**	0,033926	0,032465	0,018440
	MD				***SD***			
France	**1970-2019**	1970-1985	1986-2000	2001-2019	**1970-2019**	1970-1985	1986-2000	2001-2019
ARIMA - GDP and GreenGDP	**0,000780**	0,001781	0,000489	0,000167	**0,000901**	0,001764	0,000665	0,000152
ARIMA - GNI and GreenGDP	**0,065870**	0,075343	0,067901	0,056290	**0,041342**	0,047739	0,046277	0,032616
BN - GDP and GreenGDP	**0,001173**	0,001905	0,000715	0,000904	**0,001171**	0,001593	0,000537	0,000076
BN - GNI and GreenGDP	**0,056840**	0,073744	0,044645	0,051977	**0,016120**	0,024743	0,000581	0,014228
CF - GDP and GreenGDP	**0,000267**	0,000541	0,000210	0,000082	**0,000349**	0,000693	0,000231	0,000110
CF - GNI and GreenGDP	**0,040960**	0,035731	0,053962	0,035098	**0,015648**	0,014896	0,014720	0,018938
HP - GDP and GreenGDP	**0,000594**	0,001447	0,000259	0,000140	**0,000717**	0,001405	0,000264	0,000205
HP - GNI and GreenGDP	**0,049115**	0,047417	0,057217	0,044148	**0,000315**	0,002625	0,007909	0,000337

Source: Authors' analysis

Concluding remarks

Business cycle analysis generated an important impulse in stimulating and provoking interesting academic and professional debates within a growth perspective. In fact, measuring business cycles is critical in determining the stylized facts on aggregate macroeconomic indicators' cyclical behavior over time. In this paper, we have analyzed two countries that are oppositely diametrical in environmental policies. The paper's very idea was to show and determine the existence of green business cycles and compare them with classic business cycles and see if there is mutual equality.What we saw from the analysis itself is that by observing the degree of similarity between the cycles, we can conclude that over time Green GDP cycles have fluctuated highly similar to GDP movements for both countries. However, for the GNI variable, we found a relatively consistent degree of similarity with the Green GDP, but with a strong set-off in similarity, related to macroeconomic shocks in each country. After 2000, we can trace consistently high degrees of similarity for each variable and for both countries, suggesting higher coherence of cycles. The analysis showed that the correlation between the business cycles of GDP and green business cycles is very large and coherent, but the strength of the correlation and similarity in the cycles changes over the observed time.

This paper's contribution reveals itself in the existence of green business cycles and its comparison with classical business cycles where similarity is established. This similarity between the observed business cycles changes over time because there are different economic environmental policies that significantly affect GDP, and when we take them into account, we come to a green GDP that is significantly different. If we compare the observed countries, we see that in France, unlike China, there is a very large connection and similarity between classical GDP and green GDP because French environmental policy is very proactive and effective with a very high investment in a green economy and environmental protection from pollution and excessive resource depletion. As opposed to France, China deals very little with environmental issues, and their very large annual economic growth goes at the expense of the detriment of pollution and overexploitation of resources that are highlighted at the moment when we compare the classic business cycle with green business cycles for China. We can conclude based on the observed that green business cycles more accurately show the country's economic movement than the classic business cycles and have a much more significant role in observing the quality of economic growth rates of a particular economy.

For future research on this topic, it would be necessary to calculate green business cycles for a larger number of countries over a much longer period of time and compare them with classical calculations. One of the directions of the calculation would be to change or upgrade the green GDP with new variables that would add, in addition to the environmental component, other components that represent a shortcoming in the classical GDP.

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