OECONOMIA
COPERNICANA

VOLUME 14 ISSUE 3 SEPTEMBER 2023

p-ISSN 2083-1277, e-ISSN 2353-1827
www.oeconomia.pl

REVIEW ARTICLE

Citation: Pu, Z., Fan, X., Xu, Z., & Skare, M. (2023). A systematic literature review on business cycle approaches: Measurement, nature, duration. *Oeconomia Copernicana, 14*(3), 935–976. doi: 10.24136/oc.2023.028

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Article history: Received: 22.06.2023; Accepted: 10.09.2023; Published online: 30.09.2023

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A systematic literature review on business cycle approaches: Measurement, nature, duration

JEL Classification: *B15; B22; B41; C50*

Keywords: *business cycle; business cycle approach; business cycle model; business cycle measurement; literature review*

Abstract

Research background: The business cycle (BC) approaches have found extensive use in economic analysis and forecasting. Especially in the last 40 years, various modern BC models have been proposed and have experienced rapid development. However, there are no recent studies that provide a systematic review of the publications on this topic.
Purpose of the article: This paper aims to comprehensively review publications of BC approaches based on the cause, nature and methods of measurement BC, with the goal of identifying the current research states, research gaps and future trends of BC approaches.
Methods: A systematic literature review of BC approaches is conducted by qualitatively introducing the cause and the nature of BCs and quantitatively analyzing the methods of measurement BCs. We selected 206 articles related to BC approaches from the WoS Core Collection and Google Scholar database, spanning the years 1946 to 2022, for comprehensive statistical and content analysis. The statistical analysis presents the distribution of publication years, the most popular journals and the highly cited publications. The content analysis classifies the selected publications into 6 categories based on methods of measurement BCs, and the theory, technique and applications of each category are analyzed in detail.
Findings & value added: The analysis results indicate that BC approaches have progressively evolved in sophistication and have found widespread application in decomposing trends within economic time series, quantifying the nature of business cycles, and elucidating the causes and transmission mechanisms underlying them. This review paper provides current states, research challenges and future directions in effectively employing BC approaches for empirical study.

Introduction

The business cycle (BC) is a critical area of research in macroeconomics (Morley & Piger, 2012). The study of BCs necessarily begins with the measurement of BCs (Baxter & King, 1999). Since Burns and Mitchell (1946) systematically proposed a book called *Measuring business cycles*, this subject has garnered widespread attention across various sectors of society. In their book, BCs were defined as a type of fluctuation in aggregate economic activities characterized by cyclic movements through four stages: expansions, recessions, contractions, and revivals. They employed statistical methods to analyze and measure the nature of U.S. BCs, providing effective tools that later researchers could employ in different economic contexts and sample periods. Subsequently, scholars have conducted extensive quantitative research on BCs, leading to the development of numerous influential measurement methods (Sims, 1980; Smets & Wouters, 2007; Tian & Shen, 2019).

The National Bureau of Economic Research (NBER) is considered the authority for dating U.S. BC fluctuations (Boldin, 1994). NBER established

the BC chronology and used turning points, duration, amplitude, etc., to measure BCs (Chauvet & Piger, 2008). Today, the NBER chronology is still used as a baseline to test the performances of other BC methods. However, some scholars believed that the traditional NBER methods relied too much on personal experience rather than economic theory (Koopmans, 1947). Instead, some modern BC models such as Dynamic factor (DF) model and Markov switching (MS) model, Real business cycle (RBC) model were proposed to detect BCs. For example, Stock and Watson (1989) established DF model to distinguish and analyze the fluctuation of BCs. Hamilton (1989) extended MS regression to the time series model and proposed the Hamilton filter method to uncover optimal statistical estimates. Kydland and Prescott (1982) proposed RBC model to account for observed economic fluctuations. Compared with the NBER dating methods, these modern BC models are based on rigorous mathematical theory, which can effectively explain the transmission mechanism of BCs and capture the dynamic change in economic variables. As a result, these models are widely applied to BC analysis and economic forecasting (Born & Pfeifer, 2014; Kim & Loungani, 1992; Neumeyer & Perri, 2005).

In addition, the results of business cycle measuring greatly depend on the detrending methods of economic time series (Canova, 1998). There are various detrending methods adopted in the previous literature. For example, considering the non-stationary characteristics of time series, Hodrick and Prescott (1997) proposed a filtering method (HP filter) to separate the long-term trend and short-term economic fluctuations of economic time series. This method was simpler and more effective than the classical detrending method (BN method) employed by Beveridge and Nelson (1981). Subsequently, other frequency-based methods proposed by Baxter and King (1999) (BK filter) and Christiano and Fitzgerald (2003) (CF filter) were regarded as substitutes for HP filtering.

Overall, BC approaches have drawn wide attention since Burns and Mitchell (1946) published their BC measuring book in 1946. There are some reviews of BC literature such as Boldin (1994) and Massmann *et al*. (2003). However, few of them conducted a review of related articles on BCs from a methodological perspective. Especially in the last 40 years, modern BC approaches have undergone significant and rapid development. These BC approaches are applied widely in detrending economic time series, finding the cause and transmission mechanisms research of BCs and measuring BC nature. Therefore, this study attempts to systematically review publications

of BC approaches based on the cause, nature and methods of measurement BC to identify the current research states, research gaps and future trends of BC approaches. We mainly focus on the following questions:

1. What are the cause and the nature of BCs?
2. What are the statistical features of current publications about BC approaches?
3. What methodological approaches have been adopted for measuring BCs and how did they work?
4. What are the research challenges and future directions of BC approaches?

The rest of the study is organized as follows: Theoretical overview section introduces the cause and the nature of BCs. Research methodology section illustrates the method and data source of this research. In results section, based on the methods of measurement BCs, a statistical analysis of the selected articles is presented, and the selected articles are classified into 6 categories for content analysis. Discussion section analyzes the research challenges and future trends of BC approaches. The final section provides the conclusion with major findings and research limitations.

Theoretical overview

This section introduces the cause of BCs and the nature of BCs. This analysis not only offers a theoretical overview of the key concepts related to BCs, but also establishes a research foundation for the measurement of BCs.

The cause of BCs

The first question in studying BCs is: what causes BCs? Early BC theories were simplistic, attributing economic fluctuations to a single factor, such as the sunspot cycle, inventory cycle, fixed investment cycle and political cycle, among others. These BC theories were based on Say's Law, which posited that supply would create demand by itself, thereby considering economic stability as the norm.

After the Great Depression in the 1930s, economists began to reassess the cyclical phenomenon occurring in the economic process. In this regard, Mitchell and Burns provided a new definition of BC (Burns & Mitchell, 1946), marking the beginning of extensive studies on BC as a complete eco-

nomic object. Different schools of economics put forward different theories to explain the phenomenon of BC, and gradually evolved into five main schools, including Keynesian cycle theory, Monetarist cycle theory, Rational expectation school, RBC theory and new Keynesian cycle theory. The BC theories from different schools of thought provide multidimensional perspectives for the measurement methods of BCs. These theoretical viewpoints have influenced the development of measurement methods, aiding researchers in gaining a more comprehensive understanding and interpretation of various aspects of BCs, thus facilitating better responses to and management of BCs.

(1) Keynesian cycle theory

The Keynesian school believed that the emergence of BCs was rooted in endogenous factors (Keynes, 1937). Under the action of the three psychological laws, the effective demand would be lower than the total supply level, resulting in unstable spontaneous consumption and investment spending. Additionally, this school placed particular emphasis on effective demand, asserting that its inadequacy was the underlying cause of economic recessions and BCs.

(2) Monetarist cycle theory

The modern monetarism school represented by Friedman believed that cyclical fluctuations in the economy were primarily a result of shifts in aggregate demand triggered by unanticipated changes in the money supply (Friedman & Schwartz, 2008). Changes in aggregate demand had real effects on output and unemployment due to expected adaptations. When the money supply changed, the money demand remained unchanged in the short term, which would lead to changes in the relative prices of general commodities. Since economic agents' expectations were adaptive, they would make targeted adjustments to their resource allocation in response to these price fluctuations, further contributing to cyclical fluctuations in the real economy.

(3) Rational expectations theory

The rational expectations school inherited classical assumptions such as market clearing and the pursuit of self-interest by economic agents. Building upon these foundations, they introduced the concept of rational expectations. According to their theory, the economy forms expectations about economic variables based on all currently available information. In the understanding of the nature of BCs, Lucas proposed the monetary illusion theory with incomplete information, which regarded changes in money supply as the source of exogenous demand shocks (Lucas & Robert, 1972). This school of thought posited that unforeseen fluctuations in the money supply were the root cause of price changes and the catalyst for fluctuations in production.

(4) RBC theory

Kydland and Prescott (1982) tried to use technical shocks to explain the cyclical fluctuations of the real economy, which provided a standard paradigm for the study of BCs and was also the pioneering work of the RBC school. RBC theory held that economic fluctuations were caused by actual factors represented by technological changes, rather than nominal factors such as currency. The RBC theory emphasized the dominant role of supply and argued that the economic system was frequently subject to exogenous shocks that affected output. In terms of economic policy, the RBC school believed that monetary policy was ineffective, so the government did not need to use monetary policy to intervene in the macroeconomy.

(5) New Keynesian Cycle Theory

Similar to the RBC theory, the new Keynesian BC school also focused on micro-foundations. They amalgamated the strengths of the Keynesian, rational expectations, and RBC schools, integrating imperfections in product markets, labor markets, and financial markets into their model analysis. Subsequently, they developed a new Keynesian DSGE (NK-DSGE) model. Based on this paradigm, the new Keynesian school had achieved a good fit for real-world data, and they believed that both supply shocks and demand shocks played pivotal roles in economic cyclical fluctuations. Furthermore,

they contended that both fiscal and monetary policies exerted substantial influence on these economic cyclic variations (Wang *et al*., 2022).

In general, the formation of business cycles (BCs) is influenced by a multitude of factors. The exploration of various BC theories has revealed that there is no single, exclusive driving force behind BCs. Different schools offer diverse perspectives on understanding economic cycles. After extensive debates and empirical testing, consensus has emerged on several key aspects. For example, it is recognized that both aggregate demand and aggregate supply play crucial roles in BCs, and the instability of aggregate demand may come from many factors such as consumption, investment spending and money supply. Therefore, a comprehensive understanding of BCs requires considering a broad spectrum of economic, financial, and policy-related factors, each contributing to the complex dynamics of business cycles.

The nature of BCs

BC fluctuations emphasize the alternating changes of rising and falling economic growth rates (Burns & Mitchell, 1946). Generally speaking, a complete BC mainly includes boom, recession, depression and recovery stages, as shown in Figure 1. In this section, we introduce the nature of BC from its phase, duration, turning point, asymmetry and co-movement. These basic concepts of BC help provide context and a theoretical foundation for introducing methods of measuring BCs.

(1) Phase

In terms of the stages of BCs, it can be broadly categorized into four stages. The four-stage classification method considers a complete BC as comprising the following stages: boom, recession, depression, and recovery. During the boom stage, both investment and consumption continue to expand. Prices of goods and services experiencing high demand rise rapidly to elevated levels, and the employment rate tends to be relatively high. Following a period of boom, the market often experiences oversupply, weakening corporate profitability, declining commodity prices, and a slowdown in economic growth. The depression phase leaves supply and demand at a low level and unemployment at a high level. The final stage is the recovery stage, during which the government employs policies to stim-

ulate economic development, and the stimulus effect begins to manifest. Demand gradually recovers, production becomes more active, and prices enter an upward trajectory.

(2) Duration

Many economists have studied the duration of BC expansions and contractions (Castro, 2013). Based on cycle length, BCs can be categorized into Kitchen cycle, Jurag cycle, Kondratiev cycle and Kuznets cycle. Kitchen cycle comprises two BC types, namely large and small cycles. The major cycle includes about 2 or 3 small cycles, with an average length of about 40 months for the small cycles. Jurag cycle is the repeated occurrence of three stages of prosperity, crisis and depression, resulting in a cyclical pattern with fluctuations occurring every 9 to 10 years. Kondratiev cycle indicates that there may be three long waves in the process of capitalist economic development, which are manifested as long-term fluctuations of an average of 50–60 years of economic development (Jakimowicz & Rzeczkowski, 2019). Kuznets cycle signifies prolonged economic fluctuations occurring over 15 to 25 years. These fluctuations are particularly pronounced in various economic activities in the U.S., notably in the construction sector, so it is also known as the construction cycle.

(3) Turning point

The central focus of measuring and analyzing BC revolves around pinpointing the cyclical fluctuations' turning points, encompassing peak and trough dates. Consequently, BC can be divided into two different stages of alternating expansion and contraction, laying the groundwork for the analysis of BC's characteristics. The traditional method of identifying and determining turning points is a nonparametric method based on some identification criteria or algorithms, the typical representative of which is the BB method developed by the NBER. With the innovation of statistics and econometric techniques, parameter methods based on statistical models have been widely used such as MS model, DF model and Probit model. These methods provide powerful tools for studying the nonlinear characteristics of BC fluctuations.

(4) Asymmetry

Asymmetry is one of the typical characteristics of BC. Essentially, it entails that the dynamic changes of macroeconomic variables, such as GDP, employment rate and price level, differ across various phases of growth. These transitions exhibit distinct dynamic attributes, including variations in the speed of ascent or descent and differences in duration. The MS model with fixed transition probabilities (MS-FTP) model proposed by Hamilton (1989). Lam (1990) describes the dynamic transformation process of BC in the form of a probability distribution. This model effectively identifies economic cycle asymmetry and has emerged as a foundational framework for describing BC. Subsequently, scholars successively proposed the MS model with the time-varying transitional probabilities (MS-TVTP) model (Filardo, 1994) and the Markov switching component ARCH (MS-ARCH) model (Hamilton & Susmel, 1994). The above models have gradually become the mainstream research method for the asymmetry analysis of BC.

(5) Co-movement

Co-movements denote the simultaneous movements between the cycle indicator and the cyclical component of other variables (Lucas, 1977). With the development of economic globalization and regional integration, this linkage has grown increasingly prominent. A country's economic fluctuations can be transmitted through international commodity markets, financial markets and collaborative mechanisms (Lv *et al*., 2023). Lucas has emphasized that, in terms of the nature of the linkage behavior between economic time series, the BCs exhibit similarities. The usual description methods include positive or negative correlations, leading or lagging indicators and volatility (Padilla & Quintero Otero, 2022).

Research methods

In this study, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement is used for data collection and further analysis. PRISMA, initially introduced by Liberati *et al*. (2009), serves as a comprehensive framework for transparently reporting literature reviews. It encompasses both systematic review and meta-analysis (Page *et al*., 2021).

The systematic review aims at collecting and analyzing all relevant studies that meet pre-specified eligibility criteria to answer a specific research question. The meta-analysis employs statistical tools to combine the findings from the included studies. There are three main steps for conducting PRISMA, including searching current publications, selecting the eligible articles and extracting the details of information and summarization.

Step 1: Search in current publications. Web of Science (WoS) Core Collection and Google Scholar are used as databases to identify the studies of BC approaches. The keywords include: 1) "business cycle*" and "measure*"; 2) "business cycle*" and "assess*"; 3) "business cycle*" and "method*"; 4) "business cycle*" and "approach*"; 5) "business cycle*" and "model*"; 6) "business cycle*" and "framework*". After removing the duplicate articles, there remain 7,396 articles. An average of 97 articles are published each year, indicating that the field is one of the most important research areas.

Step 2: Select the eligible articles. To get more valuable findings, we select core and representative articles from the 7,396 articles for in-depth analysis. The period is set as 1946 to 31st March 2022. We set 1946 as the initial year, because it was when Burns and Mitchell (1946) published their book on measuring business cycles. The search field is title, keywords and abstract in WoS Core Collection and Google Scholar. We include document types such as article, meeting paper and early access paper. Non-English published articles, on the other hand, are excluded. After filtering the above criteria, 4,878 papers remain. Subsequently, we conduct a preliminary screening of titles and abstracts to eliminate unrelated articles. To exclude papers that mention business cycles without a specific focus on a measurement approach, we meticulously review the full text of each article. In addition, when reading these full articles, we add articles that had been mentioned many times in these articles and had made outstanding contributions to the development of BC approaches, such as Burns and Mitchell (1946), Solow (1956) and Diebold and Rudebusch (1996). Finally, 206 eligible articles are selected for statistical analysis and content analysis.

Step 3: Extract the details of the information and summarization. Firstly, the statistical characteristics of 206 articles are analyzed, including the distribution of publication year, the most popular journals and the highly cited articles. Then, we classify these articles according to BC measurement methods and divide them into 6 categories. The comprehensive literature review process is shown in Figure 2.

Results

Based on the 206 eligible publications related to BC approaches, the statistical analysis of these publications and content analysis of BC approaches are employed to discern prevailing research trends and hotspots.

Statistical analysis of publications

(1) The distribution of publication years

BC is a classical topic that has captured public attention for more than 100 years. In this paper, we focus on its methodological approaches since the well-known book was published in 1946. As shown in Figure 3, 11 classical publications related to BC approaches were released between 1946 and 1986. Since 1988, research on BC approaches has garnered increasing attention from scholars, leading to a gradual rise in the annual number of publications. Between 2001 and 2011, the published articles remain at a relatively high level. Especially in 2007, the annual number of publications is up to 11. In the last decade, the number experienced a downtrend with some fluctuations. This is because we mainly focus on the influential publications of BC approaches and there aren't many popular articles in recent years. It needs to be mentioned that the application of BC approaches increased dramatically during the last few years. For example, there are more than 300 articles related to BC approaches in WoS Core Collection database.

(2) The most popular journals

The selected 206 publications in this paper are chosen from among 68 different journals. Table 1 displays the 10 most prominent journals, listing their names, the number of publications, and the corresponding percentages. Leading the list is the *Journal of Monetary Economics*, boasting 19 articles, followed by *Review of Economics and Statistics* with 13 articles. This signifies that these two journals have the greatest contribution to the publication of BC approaches. Other noteworthy journals in this field include *International Journal of Forecasting*, *Journal of Business Economic Statistics* and *Journal of Economic Dynamics Control*.

(3) The highly cited publications

By considering the number of citations, Table 2 shows the top 10 highly cited publications in the WoS Core Collection database according to their title, source, published year, total citation (TC) and annual citation (AC). five of these articles were published in the 1980s, which demonstrates that BC approaches experienced rapid growth during these years. Remarkably, the most cited article in the WoS Core Collection database is the work by Solow (1956), with 7397 TC times and 110.4 AC times. This study proposed a Neoclassical Monetary Growth Model for the first time. The article written by Christiano *et al.* (2005) receives the highest AC, with 121.33 times. In addition, three publications from Google Scholar also receive wide recognition, there are *Measuring business cycles* (Burns & Mitchell, 1946), *An estimated dynamic stochastic general equilibrium model of the euro area* (Smets & Wouters, 2003) and *Production, growth and business cycles: I. The basic neoclassical model* (King *et al*., 1988). Their TC are 5746, 5224 and 2942 times, respectively.

Content analysis of BC approaches

There are different ways of classifying BC approaches. For example, Massmann *et al*. (2003) divided BC methods into three categories: official releases, non-parametric methods and parametric methods. Harding and Pagan (2002) introduced this topic with linear models and non-linear models. Based on the methods of measurement BC, this paper classifies the selected 206 publications into 6 categories including Detrending methods, DF models, MS models, VAR-based models, DSGE models and other BC methods. Table 3 presents the classifications with the number of publications and the percentage of publications.

(1) Detrending methods

Most empirical studies of BCs adopt detrending techniques to capture cycle components of economic variables for further analysis. There are various detrending methods used in the previous literature such as BN procedure, unobserved components model, HP filter, BK filter, CF filter and so on. In this section, we mainly introduce 3 widely used detrending methods

in the selected papers and their applications in measuring BCs, including HP filter, BK filter and CF filter.

1) HP filter

Hodrick and Prescott (1997) [1] were the first to introduce the HP filter for analyzing the post-war U.S. BCs, which was used to decompose the long-term trend of economic time series. At the same time, the HP filter can be regarded as an approximate High-Pass filter, which can filter out low-frequency sequences and separate high-frequency components within a period of fewer than 8 years (Christiano & Fitzgerald, 2003). In the study about the HP filter, a very important issue is the choice of the smoothing parameter's value. Ravn and Uhlig (2002) compared images of the HP-filtered transfer equation in the frequency domain and found that the 4th power adjustment worked best. Subsequent research by Iacobucci and Noullez (2005) provided additional validation of this conclusion.

Baxter and King (1999) emphasized that the HP filter, due to its non-inducing phase drift and detrending properties, has found extensive application in the decomposition of BCs. For example, Ben (2009) extracted the BC component of output by using the HP filter to deal with the synchronization of BCs between the euro area and acceding countries. Artis and Okubo (2011) applied HP filter to identify cycles in Japan from 1955 to 1995 and found fairly high cross-correlations of prefectural GDPs for all pairs of prefectures. Stanisic (2013) used a double HP filter method to extract BCs from Central and Eastern European countries' GDP data series and the results showed that there was no common BC. Costa *et al.* (2020) separated the cycle and trend for Germany and Portugal using the HP filter. Their findings demonstrated that the amplitude of BC and persistence of shocks were greater in Portugal than in Germany.

2) BK filter

The BK filter method was first proposed by Baxter and King (1999) [2], who employed a band-pass filter instead of HP filter to separate trend elements and cyclic elements. This allows for the isolation of BC fluctuation components at specific frequencies (Murray, 2003). Compared with HP

[1] Note: 1980 Carnegie-Mellon University working paper; 1997 published.
[2] Note: 1995 NBER working paper NO:5022; 1999 published.

filtering, the advantages of BK filtering are obvious in a quarter or higher frequency data (Restrepo-Ochoa & Vazquez, 2004). Being a band-pass filter, BK decomposition divides time series into three distinct parts: high-frequency irregular disturbances, low-frequency growth trends and intermediate-frequency economic cycle fluctuations. In contrast, HP filtering, functioning as an approximate high-pass filter, may overlook high-frequency irregular disturbances. BK filtering is extensively employed in various research contexts, including the measurement of BCs in developed economies such as the U.S. (Ince & Papell, 2013) and OECD countries (Konstantakopoulou & Tsionas, 2014).

3) CF filter

The CF filter, initially introduced by Christiano and Fitzgerald (2003) , can be regarded as CF filter's special case to some extent. In comparison to the BK filter, the CF filter has two significant advancements Konstantakopoulou and Tsionas (2014). First, CF filter is necessary to examine the time series representation of the filtered sequence. secondly, although the CF filter is also linear, it abandons the stationarity and symmetry assumptions of BK filtering (Pandey *et al*., 2017). Therefore, since the CF filter was proposed, it has been widely used in the measurement of BC. For example, Drake and Mills (2010) employed the CF filter to identify a Eurozone BC. Gossel and Biekpe (2012) used CF filter to investigate the cyclical relationships between South Africa's post-liberalized capital flows and domestic BC fluctuations. Klarl (2020) applied CF filter to investigate the response of CO2 emissions to BC for the U.S.

In general, HP filter is similar to a high-pass filter, while BK and CF filters are both band-pass filters. The theoretical underpinning for these three filtering methods is rooted in the spectral analysis of time series data. High-Pass filtering is employed to dissect economic time series into components with wavelengths shorter than 8 years, while Band-Pass filtering serves the purpose of isolating economic cycle fluctuations characterized by wavelengths spanning 6 to 32 quarters. HP filtering, BP filtering and CF filtering are all considered forms of frequency selective filtering, designed to separate components of a specific frequency band from the original sequence. Table 4 presents 10 popular findings of detrending methods based on source, approach, data, time duration and major findings.

(2) Markov switching models

Markov switching (MS) is a typical nonlinear approach for modeling BC dynamics. Markov switching regression was first proposed by Goldfeld and Quandt in 1973. Hamilton (1989) extended this state-dependent approach to the time series model and proposed the Hamilton filter method to uncover optimal statistical estimates. The nonlinear characteristics of the model can capture the dynamic change in economic variables. By analyzing the U.S. real GNP growth rate, this model succeeded in identifying asymmetries and turning points in BC. Results derived from the MS model are characterized by reproducibility, method clarity, relative timeliness validity of predictions, etc. (Boldin, 1994). Therefore, this method is widely used in the identification of BC turning points, asymmetry and duration dependence (Cologni & Manera, 2009; Leiva-Leon, 2017; Owyang *et al*., 2005). For example, Goodwin (1993) used Hamilton's MS model to measure the turning points of BC and justified the asymmetry hypothesis in eight developed countries.

However, this model is only suitable for univariate time series data analysis, so it can only describe the nonlinear characteristics of BC and ignore the characteristics of coordinated changes in BC. To address this problem, Diebold and Rudebusch (1996) and Kim and Nelson (1999) applied DF-switching model and VAR-switching model to capture the nonlinear and synergistic characteristics of BCs at the same time. Besides, Filardo (1994) incorporated TVTP into Hamilton's MS model and he found that the postwar U.S. Industrial Production experienced a positive growth rate and a negative growth rate. Table 5 illustrates 10 popular articles on MS models by their source, approach, data, time duration and major findings.

(3) Dynamic factor models

Sargent and Sims (1977) first proposed the DF model in the field of economics, which was an extension of the classical factor model on time series data. Subsequently, Stock and Watson (1989) used a static near-factor model to construct consistent index, leading index and lagging index reflecting the fluctuation of BC. The fundamental concept of DF model is that the BC fluctuations are transmitted and diffused through a series of economic activities. Consequently, the fluctuation of any economic variable itself is

not enough to represent the overall fluctuation of the macroeconomy. For this reason, estimating and interpreting the common dynamic factors is one of the effective tools to distinguish and analyze the fluctuations of BC (Chauvet, 1998). DF model not only permits observed variables to be influenced by the factor lag term but also allows the factor itself to undergo an independent dynamic evolution process.

This method has attracted extensive attention within academic circles and has been widely employed to analyze the economic cycles of various countries. Researchers such as Gregory *et al.* (1997), Kim and Nelson (1998) and Camacho *et al*. (2018) respectively estimated BC for G7 countries and U.S. using DF model. Kabundi and Loots (2007) used a novel DF model to investigate the nature and extent of co-movement of the South African BC with eleven of the Southern African Development Community countries. Owyang *et al.* (2009) found that the extent to each state's economy was related to America BC using DF model. Gadea *et al.* (2012) and Camacho and Domenech (2012) used DF models to identify regional BCs within Spain.

In the study of international BCs, Berger and Wortmann (2022) estimated a DF model for a sample of 106 countries, considering output, consumption, and investment data spanning the period from 1960 to 2014. Their findings highlighted that output, consumption and investment significantly more substantial roles in shaping national business cycles than previously recognized. Table 6 illustrates 10 noteworthy publications derived from the use of DF models, categorized by source, approach, data, time duration and major findings.

(4) VAR-based models

Koopmans (1947) critiqued many of the BC models lacked both theoretical foundation and empirical support, which led to a practice of measurement without a solid theoretical framework. Rejecting the common practice, Sargent and Sims (1977) and Sims (1980) proposed a VAR model to improve the credibility of the theoretical content of macro-econometric models. The VAR model offered several advantages compared to early structural models. First, it does not rely on strict economic theory but allows data relationships to explain outcomes comprehensively. Second, the explanatory variables do not include any current variables, as long as the sample is large enough, the model can be identified no matter how many

parameters. Third, there is no need to pre-distinguish the homogeneity and endogeneity of variables.

However, the VAR model, due to its lack of consideration for ex-ante structural economic shocks, may struggle to align with the actual economic situation. To address this, Blanchard and Quah (1989) revised the VAR model and proposed a structural VAR (SVAR). The SVAR model tries to add several structural constraints to obtain a unique structural relationship, resolving the identification problem and providing economic significance to impulse responses. Besides, Simkins (1995) explored the Bayesian VAR models that presented more accurate out-of-sample forecasts than unrestricted or BC-restricted VAR models. Canova *et al.* (2007) constructed a multi-country Bayesian panel VAR model to examine the features of G-7 BCs. Buckle *et al.* (2007) proposed a four-block SVAR model to dissect the New Zealand BC fluctuations and found that international trade price and climate shocks were more significant sources of BCs fluctuations than international or domestic financial shocks. Nevertheless, some concerns have arisen regarding the relative importance of technology and other shocks identified by SVAR models, as suggested by Cooley and Dwyer (1998). In addition, Dees *et al.* (2007) used a global VAR approach to deal with the common factor interdependencies and international co-movements of BCs. Nyberg (2018) introduced a regime-switching VAR that generated superior out-of-sample forecasts of the US short-term interest rate and the term spread. Table 7 illustrates 10 popular articles on VAR-based models by their source, approach, data, time duration and major findings.

(5) Dynamic stochastic general equilibrium models

DSGE models are widely applied frameworks for quantitative BC analysis. Many economists use DSGE approach to study the economic fluctuations, sources of shocks and transmission mechanism of BC. DSGE models are constructed by integrating intertemporal optimal choices and exogenous random shocks within general equilibrium framework of some agents, such as representative households, intermediate goods manufacturers, final goods manufacturers, the central government and other economic activity entities. The specific model-building process can be found in seminal works such as Kydland and Prescott (1982), Frank Smets and Wouters (2003), Christiano *et al.* (2005), and Smets and Wouters (2007).

The earliest DSGE model is RBC, which stems from Kydland and Prescott (1982) for studying the characteristics of macroeconomic variables in the U.S. They employed stochastic technology and rational expectations to produce an approach that adhered to the Lucas micro-foundations research, which also opened the application of the RBC theory. Since then, this model has seen widespread utilization and development. For example, Long and Plosser (1983) used some ordinary economic principles to construct RBC models for explaining the characteristics of BCs. Backus *et al*. (1992) extended the RBC model to open economies to account for the domestic and international aspects of BCs. Pichler (2011) proposed a monomial rule Galerkin method for solving the multi-country RBC model with many state variables. Fiorito and Kollintzas (1994) applied the RBC methodology based on Kydland and Prescott (1990) to account for several major stylized facts of BCs in the G7 countries.

Subsequently, a large number of studies have formed the New Keynesian DSGE model by adding more realistic factors to the theoretical framework of RBC. This evolution involved replacing the assumption of perfect market competition with notions of imperfect market competition and incorporating nominal frictions, such as sticky prices and wages, into the RBC analysis framework. Therefore, the new Keynesian DSGE model demonstrated superior capacity to align with real economic phenomena compared to the RBC model. One notable study in the development of the New Keynesian DSGE model was conducted by Christiano *et al*. (2005). They integrated several friction factors such as variable capital utilization, investment adjustment costs and habit formation in consumption into the DSGE model, and found that the model accounted well for the estimation of the dynamic response of the U.S. economy to a monetary policy shock. Their model was regarded as the benchmark framework for the New Keynesian DSGE. Smets and Wouters (2003) proposed and estimated a DSGE model that incorporates sticky prices and wages for measuring the business fluctuation of the euro area. Smets and Wouters (2007) considered seven types of structural shocks and many types of real and nominal frictions to measure a U.S. BC using a Bayesian DSGE approach. They found that this approach had a fit comparable to the Bayesian VAR approach. In addition, many methods have been proposed to parameterize and evaluate DSGE models, such as calibration, moment estimation, minimum distance estimation and likelihood-based estimation. Among them, likelihood-

based methods, especially the Bayesian method, have been very popular for empirical work with DSGE models (An & Schorfheide, 2007).

In recent years, the theory and practice of DSGE models have been constantly improved and more frictions and shocks could be considered in these models, such as financial market frictions, labor and employment market frictions, open economy and uncertainty shock. For example, Merola (2015) investigated the role of financial frictions during the crisis using an estimated DSGE model and found that the role of financial channels was important in transmitting functions from financial markets to the real economy. Bloom *et al.* (2018) explored the role of uncertainty in BCs using a DSGE model with heterogeneous firms and found that uncertainty was strongly countercyclical and played an important role in driving BCs. With the help of sophisticated algorithms and high-powered computers, the latest DSGE model models have been sophisticated enough to match plenty of additional aspects of the microdata. Table 8 illustrates 10 popular articles on DSGE models by their source, approach, data, time duration and major findings.

(6) Other BC methods

In addition to the previously discussed methods, there exist various other prominent approaches for measuring BCs. These include Probit method, Smooth transition regression, Business cycle accounting and so on.

Probit method

Unlike most econometric models, the Probit model is a kind of discrete choice model. It can be used to classify BC phases and predict BC turning points. Earlier studies focused on predicting BC phases and turning points in the static Probit model (Estrella & Mishkin, 1998). For example, Bernard and Gerlach (1998) used this model to forecast future recessions in eight countries. However, the static Probit model cannot capture how the probabilities of recession or expansion may be influenced by the current or past state of BC. Kauppi and Saikkonen (2008) developed new dynamic extensions to the conventional static model, where the response probability was a function of the explanatory variables. Hao and Ng (2011) compared the predicting performance of 4 models, including traditional static, dynamic, autoregressive and dynamic autoregressive Probit models. The finding

revealed that the dynamic and dynamic autoregressive Probit models were better at predicting the duration of the recession while another two models were better at forecasting the peaks of BCs. Recently, Proano (2017) proposed a three-regime dynamic ordered Probit model to detect economic accelerations, recessions and normal growth periods for the German economy.

Smooth Transition Regression (STR)

In econometrics, mechanism transition models are mainly used to describe transition relationships, leading to the development of numerous nonlinear time series models. Given the continuity of mechanism switching, the test based on small samples is more effective. These models can effectively characterize the asynchrony of industries in BC (Sarantis, 1999). The identification of BC turning points using STR has gained increasing attention. Terasvirta and Anderson (1992) used a univariate time series smooth transition model to characterize the U.S. industrial cycle. Ocal and Osborn (2000) applied it to the study of U.K. consumption and industrial production cycles. Skalin and Terasvirta (1999) used a smooth transition model to analyze the Swedish economic cycle. In addition, some extensions of STR model such as Vector STR model (Camacho, 2004), Panel STR model (Ameer, 2014) and multiple-regime STR model (Zhang, 2017) were proposed and used to analyze BC dynamics.

Business cycle accounting

Business cycle accounting (BCA) method was aimed at accounting for BC fluctuations by 4 wide-used wedges: efficiency, labor, investment and government consumption wedges. Chari *et al.* (2007) applied this method to study the Great Depression and the 1982 recession, revealing that the efficiency and labor wedges accounted for essentially all BC decline and recovery. Kobayashi and Inaba (2006) also regarded labor wedges as a major contributor to the decade-long recession in the 1990s in Japan. However, when they used the capital wedge instead of the investment wedge in BCA method, the results implied that financial frictions may have had a large depressive effect during the 1930s in the United States. Jiang and Weder (2021) employed BCA to quantitatively investigate U.S. BC between 1889 and 1913. He *et al.* (2009) used a standard neoclassical open economy mod-

el and BCA procedure to explore the sources of economic fluctuations in China during the reform period.

Moreover, various other methods have been used for dating properties of BC. For measuring BC phases, according to ways of stages division (two, three and four stages), there were some methods including two regime MS model (Clements & Krolzig, 2003), floor and ceiling model (Pesaran & Potter, 1997) and multiple regimes smooth transition autoregressive model (Van Dijk & Franses, 1999). For predicting the turning points, except the widely used method (BB algorithm, MS model, SWI model, probit model and STR approach), some scholars also developed other methods that can be found in Kim and Nelson (1998), He and Liao (2012), Davig and Hall (2019) and Chauvet and Senyuz (2016). Regarding the dating of business cycle asymmetry and duration dependence, the main methods include MS and its extensions, such as MS-FTP, MS-TVTP and MS-ARCH. For detecting BC co-movement and synchronization among different countries or regions, there were complex networks (Caraiani, 2013), wavelet-based method (Caraiani, 2012) and multilevel structural factor model (He & Liao, 2012).

Discussion

Since Burns and Mitchell (1946) published the book *Measuring business cycles* in the journal of NBER, BC approaches have witnessed significant developments. The NBER dating method is usually regarded as a benchmark with other BC methods. However, two primary drawbacks are associated with the NBER dating method: It depended too much on experts' evaluation and there was a time lag in calculating the turning points. To address these limitations of NBER dating method and further analyze the source and nature of BC fluctuations, some quantitative approaches, such as VAR model, DSGE model, DF model and MS model have been put forward and applied successively. They are valuable tools for modeling aggregative economic observations. Over the last two decades, technological advancements have led to increased complexity and enhanced validity in BC models, so that more economic variables, shocks and frictions can be considered by BC models, such as NK DSGE model and SVAR model. These modes can quantitatively explore the driving factors of BC and forecast economic fluctuations (Kehoe *et al*., 2018). In addition, current BC models can also be

used to solve a variety of other problems, including investment under uncertainty, asset pricing, econometric policy evaluation, optimal financial and monetary policy and dynamic taxation policy.

Despite the long history of BC approaches and applications research, there are at least 5 challenges that remain for further study:

1. Continuously improving existing BC approaches and developing new ones remain open areas of research in a changing economic environment. Take the development of DSGE model as an example, the early DSGE models could only address a single source of the disturbance. Current DSGE models are capable of handling various economic time series, multiple shocks, heterogeneous agents, wage and price rigidities and monetary and fiscal policies (Kehoe *et al*., 2018). Nevertheless, economic fluctuations are complicated and volatile, indicating that there is still significant progress to be made. In addition, according to the comprehensive review of BC approaches, we found that many creative methods were proposed before the year 2000. In recent years, scholars paid more attention to elaborating on the existing methods rather than proposing new ones. It is unlikely that the best approach for dating BCs can ever be developed. Therefore, some new techniques are expected to be created to better capture and forecast BC dynamics.
2. Assessing the performance of BC approaches in capturing the characteristics of economic fluctuations remains a challenging task. Watson (1993) provided a procedure for measuring the fit of RBC models related to the familiar R^2 statistic. Chauvet and Piger (2008) compared the real-time performance of a nonparametric algorithm and a parametric MS-DF model. Siliverstovs (2019) evaluated the forecasting accuracy of the Bayesian mixed-frequency model. However, there are so many BC approaches that the forecasting performance of different approaches is hard to compare (Simkins, 1994). To address this challenge, it is necessary to employ both qualitative evaluation criteria and quantitative measures of model fit to identify the most suitable approach for empirical BC research.
3. The research on the cause and transmission mechanism of economic cycle is still challenging. In recent years, a growing number of studies have focused on this topic and tried to find the driving factors by using complex models. These articles indicated that the causes were multiple and the dominant factor varies among different economies (Schirwitz, 2009). At present, there is no unified conclusion on the cause of BCs.

Identifying and quantifying BC sources are challenging, but it is important for authorities while designing policies.

4. The necessity of removing the long-term trend from economic time series remains a topic of debate. Trend elimination methods are widely applied to decompose an economic variable into trend and cycle components for further analysis. However, some scholars suggested that there is no need to do this. Harding and Pagan (2002) proposed that the major driving forces of BC may be eliminated when removing a stochastic trend of economic time series. Massmann *et al.* (2003) utilized 8 trend extraction methods to identify growth cycles and suggested that different detrend methods can affect the conclusion of the characteristics of BCs. It is important to test the validity of detrending methods of BC detection before we use them.
5. The majority of BC research is concentrated on developed countries, with limited attention given to some developing nations, particularly emerging economies. Simultaneously, there are significant differences in economic fluctuations among different countries. Therefore, it is necessary to promote the application of BC approaches in different countries or different areas, so as to provide more useful information for government policy-making and enterprise operation practice.

Conclusions

This paper systematically conducts a literature review of BC approaches by qualitative analysis of the BC cause and nature and quantitative analysis of BC measurement methods. The selected 206 articles from WoS Core Collection and Google Scholar database are classified into 6 categories based on the methods of measurement BCs, and the theory, technique and application of each category are analyzed in detail. In response to the questions raised in the Introduction section, the main findings are as follows:

1. The earliest publication of BC approaches was released by Burns and Mitchell (1946). In the 1980s, modern BC approaches experienced rapid development with 5 of the 10 most popular journals published during this period. In the 21st century, BC models have become more and more sophisticated and have been utilized in various areas. According to the statistical analysis results, the highly cited papers include Solow (1956), Sims (1980) and Hamilton (1989). The highly cited journals include *Jour-*

nal of Monetary Economics, Review of Economics and Statistics and *International Journal of Forecasting*.

2. Based on the methods of measurement BCs, we have found that BC approaches can be classified into 6 categories: Detrending methods, MS models, DF models, VAR-based models, DSGE models and other BC methods. They are widely used to separate trends of economic time series, measure the nature of BCs and explain the cause and transmission mechanisms of BCs. The frequency selective filters are commonly used detrending methods, such as HP filter, BP filter and CF filter. MS models and DF models are popular approaches to identify the nature of BCs. DSGE models and SVAR models excel in revealing the sources and transmission mechanisms of BCs.
3. The causes of BCs exhibit diversity across different time periods and economies. BC schools have developed theories to explain the driving forces behind BCs. Modern BC models, on the other hand, tend to quantitatively analyze the driving forces for BC booms and recessions. The main factors causing economic fluctuations may not only be the components of total demand, such as consumption and investment, but also be technological progress and other aggregate supply shock factors.
4. Identifying the nature of BCs is a classical topic and the focus has changed over time. Early articles paid a lot of attention to measuring BC phases, turning points, amplitude and duration. In recent decades, there have been a great number of studies focusing on BC asymmetry, comovement, synchronization and duration dependence. While different BC methods may yield varying results, some studies have identified common factors (Boldin, 1994).
5. There are 5 main challenges four further BC approaches to study: Elaborating on existing methods and proposing new ones to better capture and forecast BC fluctuations, employing quantitative measures of models' fit and comparing forecasting performances of different models, identifying and quantifying BC sources in different economies and times, testing the validity of detrending methods, promoting the application of BC approaches in developing countries and emerging markets.

The main contribution of this review paper is to provide current states, research challenges and future directions in effectively employing BC approaches for empirical study. However, there are still some limitations. Due to the long history of BC research, some influential articles may not be included in the two databases selected in this paper. In addition, the data

source excludes non-English articles and reviews, potentially excluding some relevant publications. Besides, this paper provides an insightful review and characterization of BC methods, while the comparison and evaluation of the different methods by empirical analysis are not examined. Thus, future research can employ more empirical examinations and performance comparisons of these methods. Finally, the use of sophisticated software such as CiteSpace and VoS Viewer could provide additional levels of analysis, including co-authorship, co-occurrence, co-citation, and bibliographic coupling analysis. We plan to employ such software in future research to uncover more interesting insights into BC approaches.

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Acknowledgments

The work was supported by the National Natural Science Foundation of China (No. 72071135).

Ministry of Education and Science
Republic of Poland

The journal is co-financed in the years 2022–2024 by the Ministry of Education and Science of the Republic of Poland in the framework of the ministerial programme "Development of Scientific Journals" (RCN) on the basis of contract no. RCN/SN/0697/2021/1 concluded on 29 September 2022 and being in force until 28 September 2024.

Annex

Table 1. The 12 most popular journals

Name of the journal	Numbers	Percentage
Journal of Monetary Economics	19	9.22%
Review of Economics and Statistics	13	6.31%
International Journal of Forecasting	12	5.83%
Journal of Business Economic Statistics	11	5.34%
Journal of Economic Dynamics Control	11	5.34%
American Economic Review	8	3.88%
Econometrica	8	3.88%
Journal of Applied Econometrics	8	3.88%
Economic Modelling	8	3.88%
Journal of Monetary Economics	7	3.40%

Table 2. The 10 highly cited publications

Rank	Title	Source	Year	TC	AC
1	A contribution to the theory of economic growth	Quarterly Journal of Economics	1956	7397	110.4
2	Macroeconomics and reality	Econometrica	1980	4645	108.02
3	A new approach to the economic-analysis of nonstationary time series and the BC	Econometrica	1989	4037	118.74
4	Postwar U.S. business cycles: an empirical investigation	Journal of money credit and banking	1997	2652	102
5	Time to build and aggregate fluctuations	Econometrica	1982	2221	54.17
6	Nominal rigidities and the dynamic effects of a shock to monetary policy	Journal of political economy	2005	2184	121.33
7	Shocks and frictions in U.S. business cycles: a Bayesian DSGE approach	American economic review	2007	1776	111
8	The dynamic effects of aggregate demand and supply disturbances	American economic review	1989	1564	46
9	Measuring business cycles: approximate band-pass filters for economic time series	Review of economics and statistics	1999	983	40.96
10	A new approach to decomposition of economic time-series into permanent and transitory components with particular attention to measurement of the BC	Journal of monetary economics	1981	866	20.62

Table 3. The distribution of publications based on methods of measurement BC

Approach	Numbers	Percentage
Detrending methods	17	8.25%
DF models	19	9.22%
MS models	34	16.51%
VAR-based models	21	10.20%
DSGE models	52	25.24%
Other BC methods	63	30.58%
Total number	206	1

Table 4. 10 popular articles on detrending methods

Source	Approach	Data	Time duration	Major findings
Beveridge and Nelson (1981)	Beveridge and Nelson's procedure	U.S. economic data	--	Expansions and contractions were of roughly equivalent duration and the dating of cyclical episodes tended to lead the traditional NBER dating.
Harvey (1985)	Kalman filter	U.S. economic data	1909-1970	This paper provided some interesting insights into the dynamic structure of the series, particularly concerning cyclical behavior.
King *et al.* (1988)	Common deterministic trends model	Labor supply data	1955-1986	All endogenous variables had a common deterministic trend and fluctuations around the common linear trend were all of a transitory nature.
King and Rebelo (1993)	HP filter	U.S. real GNP	1945-1990	This paper illustrated the impact of HP filtering on the character of cyclical components.
Hodrick and Prescott (1997)	HP filter	Postwar U.S. real GNP	1951.Q2-1984.Q4	The economy's growth state cohered greatly well with NBER dating and this method can be used as an alternative objective method for evaluating BC dates.
Baxter and King (1999)	BK filter	--	--	This paper developed a set of approximate band-pass filters and illustrated their application for measuring the BC component of macroeconomic activities.
Ravn and Uhlig (2002)	Adjusted HP filter	Postwar U.S. GDP data	--	This paper suggested that the HP filter parameter should be adjusted when changing the frequency of observations.
Christiano and Fitzgerald (2003)	CF filter	U.S. economic data	Around 1960	There had been a significant shift in the money–inflation relationship before and after 1960.

Table 4. Continued

Source	Approach	Data	Time duration	Major findings
Yogo (2008)	Multiresolution wavelet analysis method	U.S. real GDP	1947.Q1 - 2003.Q1	The business-cycle component of the wavelet-filtered series closely resembled the series filtered by the approximate bandpass filter.
Hamilton (2018)	Hamilton filter	U.S. economic data	1950.Q1-2016.Q4	This filter can isolate a stationary component from any I(4) series, and it is a better alternative HP filter.

Table 5. 10 popular articles on MS modes

Source	Approach	Data	Time duration	Major findings
Goldfeld and Quandt (1973)	Markov model	--	--	This paper introduced a model that allowed for numerous switches and successfully used it in an economic example.
Hamilton (1989)	Markov regime-switching model	Postwar U.S. real GNP data	1951.Q2-1984.Q4	The economy's growth state cohered greatly well with NBER dating and this method might be used as an alternative objective method for evaluating BC dates.
Filardo (1994)	MS TVTP model	U.S. economic data	January 1948-August 1992	There was a high correlation between the evolution of the phases inferred from this method and traditional reference cycles for monthly output data.
Goodwin (1993)	Hamilton MS model	Eight developed market economic data	1957.Q2-1990.Q1	This model was only a marginal improvement over a linear one. Turning points in BC of the eight countries were closely correlated with that from traditional methods.
Kim (1994)	Dynamic linear model with MS	U.S. real GDP growth	1952.Q2-1984.Q4	The filtering, smoothing and maximum likelihood estimation procedures employed in this paper perform an excellent job.
Kim and Nelson (1999)	Bayesian MS approach	U.S. real GDP growth	1953.Q2-1997.Q1	There were two main sources of stabilization in U.S. real GDP growth: a narrowing gap between growth rates during expansions and recessions and a decline in the variance of shocks.
Artis *et al.* (2004)	MS-VAR model	9 European countries' Economic data	May 1965-June 1997	This paper found a common unobserved component that can contribute to European BC dynamics and dated the European BC.
Cologni and Manera (2009)	MS autoregressive models	Real GDP growth in Canada and France	1970-2004	Models with exogenous oil variables performed better than the corresponding univariate specifications.

Table 5. Continued

Source	Approach	Data	Time duration	Major findings
Guerin and Marcellino (2013)	MS mixed data sampling model	U.S. economic data	1959.Q1-2009.Q4	This method was a very useful specification that can accurately predict changes in regimes.
Eo and Kim (2016)	Improved MS Models	U.S. real GDP growth	1947.Q4-2011.Q3	This model greatly outperformed the Hamilton model in detecting recessions and in making inferences about the mean growth rates.

Table 6. The 10 popular articles on DF models

Source	Approach	Data	Time duration	Major findings
Sargent and Sims (1977)	DF model	U.S. economic data	1950-1970	Most of the changes in some important economic variables can be explained by two dynamic factors.
Stock and Watson (1989)	DF model	U.S. economic data	1960-1988	The DF model proposed in this paper is numerically similar to the current consensus index of the U.S. Department of Commerce.
Diebold and Rudebusch (1996)	Multivariate DF-MS model	U.S. economic data	1952.Q1-1993.Q1	This paper developed a new model for analyzing the co-movement and different phases of BCs.
Kim and Nelson (1998)	Improved DF-MS method	U.S. economic data	January 1960-January 1995	This study developed approximation-free inference in DF-MS model and tested whether the estimated results of regime switches show evidence of BC duration dependence.
Forni and Lippi (2001)	Generalized DF model	--	--	This model can be used for the empirical study of macroeconomic and financial data sets characterized by various observations both cross-section and over time.
Owyang *et al.* (2009)	DF model	U.S. economic data	1999.Q2-2006.Q2	The closeness of state economies to the national business cycle was related not only to differences in industry mix but also to non-industry variables
Kabundi and Loots (2007)	DF model	Southern African economic data	1980-2002	The results showed that South Africa cannot isolate itself from its neighbors and that regional policy coordination was of the utmost importance.
Crucini *et al.* (2011)	DF model	G-7 countries' economic data	1960-2005	Productivity was the main source of BC, with other drivers isolated to particular nations or sub-periods.

Table 6. Continued

Source	Approach	Data	Time duration	Major findings
Camacho *et al*. (2018)	MS-DF model	U.S. monthly economic data	1967.Q4-2017.Q4	The performance improvements relied on the factor loadings, the dynamics of the common factor, the idiosyncratic variances and the differences between the means in BC states.
Berger and Wortmann (2022)	DF model	106 countries' economic data	1960-2014	Output, consumption and investment played much larger roles in the national BC than before.

Table 7. 10 popular articles on VAR-based modes

Source	Approach	Data	Time duration	Major findings
Sims (1980)	VAR model	U.S and German economic data	1949-1975 for the U.S.;1958-1976 for Germany	The identification claimed for existing large-scale BC models was incredible and an alternative strategy called unconstrained VAR was proposed for empirical macroeconomics.
Blanchard and Quah (1989)	SVAR model	U.S. economic data	1950.Q2-1987.Q4	There were two types of disturbances- supply disturbances and demand disturbances- that generated unemployment and output dynamics.
Dees *et al.* (2007)	global VAR model	26 countries' economic data	1979-2003	This model was shown to be quite effective in capturing the common factor interdependencies and international co-movements of BCs.
Canova *et al.* (2007)	Multi-country Bayesian panel VAR model	G-7 countries' economic data	1979.Q1-2002.Q4	There was a significant world cycle in G-7 cycles and country-specific indicators had a smaller role.
Buckle *et al.* (2007)	a four-block SVAR model	U.S. economic data	1983.Q1-2004.Q2	International trade price and climate shocks were more significant sources of BC fluctuations than international or home financial shocks.
Forinirni *et al.* (2017)	Dynamic SVAR identification	U.S. economic data	1960.Q1-2010.Q4	Long-run and noise shocks explain a large fraction of the fluctuations of GDP, investment and consumption at BC horizons.

Table 7. Continued

Source	Approach	Data	Time duration	Major findings
Cologni and Manera (2008)	Structural Cointegrated VAR Model	7 countries' economic data	1980.Q1-2003.Q4	The oil price shock was followed by an increase in inflation rate and by a decline in output growth.
Ramajo *et al.* (2017)	Multiregional Spatial VAR Model	Spanish regions' economic data	1964-2003	There was significant spatial dependence across Spanish regions and some regions played a key role in the transmission of regional BCs.
Forni *et al.* (2014)	Structural factor-augmented VAR model	U.S. economic data	1960.Q1-2010.Q4	News shocks played a smaller role in accounting for BC than found in the existing literature.
Korobilis and Pettenuzzo (2019)	Simulation-free estimation algorithm for VAR	U.S. economic data	1959.Q1-2015.Q4	This algorithm featured several desirable properties and worked extremely well with Bayesian VARs.

Table 8. 10 popular articles on DSGE modes

Source	Approach	Data	Time duration	Major findings
Kydland and Prescott (1982)	Competitive equilibrium growth model	U.S. economic data	1950.Q1-1979.Q4	The proposed model was quite fitted to the data in light of the model's simplicity.
Long and Plosser (1983)	RBC model	U.S. economic data	--	The proposed model could explain some major features of BCs, like persistence and co-movement.
Backus *et al.* (1992)	Two-country RBC model	12 developed countries' economic data	1960.Q1-1990.Q2	Different from the output, the consumption was more highly correlated across countries, and the investment and the trade balance were much more volatile than they were shown in the data.
Smets and Wouters (2003)	DSGE model with sticky prices and wages	Euro economic data	1971.Q1–1999.Q4.	It was a useful tool to capture the stochastics and the dynamics in the Euro data.
Christiano *et al.* (2005)	DSGE model with staggered wage and price contracts	U.S. economic data	--	It accounted well for estimating the dynamic response of the U.S. economy to a monetary policy shock.
Smets and Wouters (2007)	Bayesian DSGE approach	U.S. economic data	1966.Q1-2004.Q4	The proposed model had a fit comparable to that of Bayesian VAR models and investment adjustment costs were the most important fractions in reducing the prediction errors of the approach.

Table 8. Continued

Source	Approach	Data	Time duration	Major findings
Christensen and Dib (2008)	New Keynesian model with a financial accelerator	U.S. economic data	1979.Q3-2004.Q3	The financial accelerator amplified and propagated the effects of demand shocks on investment, while it dampened those of supply shocks.
Justiniano *et al.* (2010)	The new neoclassical synthesis model	U.S. economic data	1954.Q3-2004Q4	Investment shocks were the main drivers of movements in hours, output and investment over the cycle.
Christiano *et al.* (2014)	Standard monetary DSGE model	U.S. economic data	1985.Q1-2010.Q2	Fluctuations in risk were the most important shock causing BC.
Bloom *et al.* (2018)	A DSGE model with time-varying uncertainty	U.S. economic data	1972.Q1-2010.Q4	Recessions were best modeled as being driven by shocks with a negative first moment and a positive second moment.

Figure 1. Schematic diagram of BC

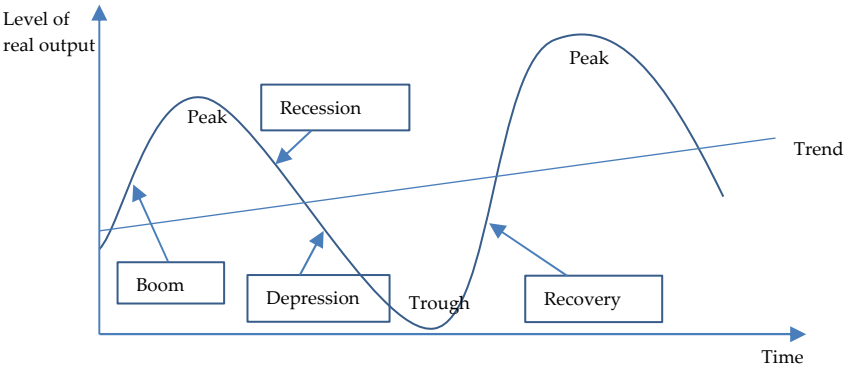

Figure 2. The comprehensive literature review process

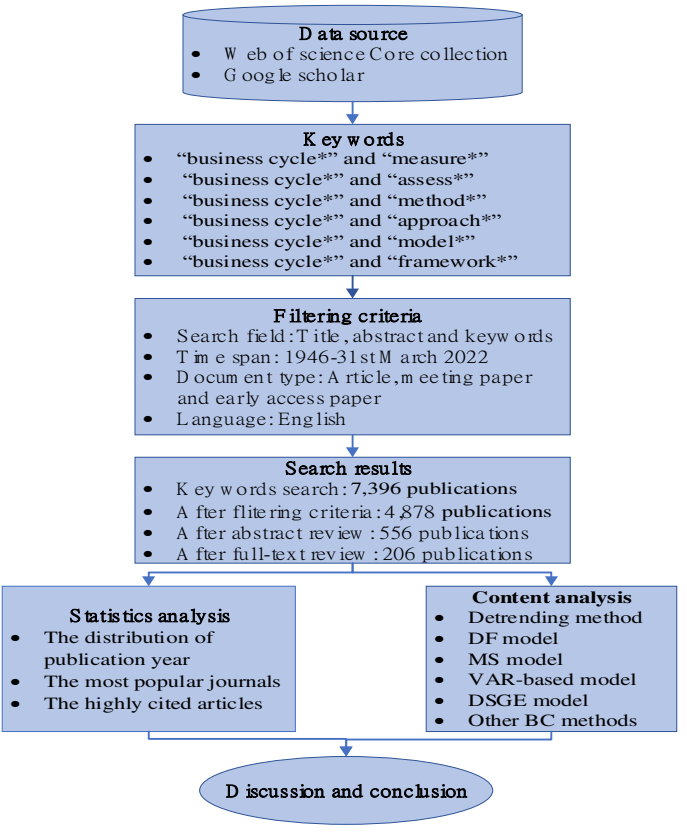

Figure 3. Distribution of papers by publication year