



T.C.

ANKARA YILDIRIM BEYAZIT UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES

**THE NATURE AND MEASUREMENT OF FINANCIAL
CYCLES: EVIDENCE FROM TURKEY**

PHD THESIS

PAKİZE EDA KAYA

DEPARTMENT OF FINANCE AND BANKING

ANKARA 2023

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ANKARA 2023

ONAY SAYFASI

Pakize Eda KAYA tarafından hazırlanan “The Nature and Measurement of Financial Cycles: Evidence from Turkey” adlı tez çalışması aşağıdaki jüri tarafından oy birliği ile Ankara Yıldırım Beyazıt Üniversitesi Sosyal Bilimler Enstitüsü Finans ve Bankacılık Anabilim Dalı’nda Doktora tezi olarak kabul edilmiştir.

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DECLARATION

I declare that this thesis is my own work, that I have not had any unethical behavior infringing patent rights and copyright at any stages from the planning to writing of the thesis, that I have obtained all the information in this thesis within academic and ethical rules, and that I have cited all the information and comments used in this thesis. 11/07/2023

Pakize Eda KAYA





To Rüzgar

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ABSTRACT

The Nature and Measurement of Financial Cycles: Evidence from Turkey

The business cycles have been investigated deeply, and various methods have been developed in order to understand their nature and phases so far. Compared to business cycle literature, however, the financial cycle literature is not so extensive. After the Global Financial Crisis of 2007-2009, financial cycle concept has become popular related to its macro financial linkages. This dissertation aims to explore the main characteristics and nature of the financial cycles in Turkish economy for 2003Q1-2022Q2 with an extensive data set of financial variables including credit volume, credit to GDP, real BIST100 return index, real effective exchange rate, REIDIN Residential Property Price Index. The financial cycles are identified by using diverse approaches: classical approach of turning point analysis, a frequency domain trend based approach by using Hodrick Prescott Filter and an advanced model-based approach including an univariate unobserved components model. Moreover, the concordance and causality relationships between financial cycles and business cycles are also explored. Understanding “procyclicality” of the economy by identifying the phase (whether it is in a boom or bust) and also its interactions with financial cycles are crucial for the policy makers to apply macroprudential tools in order to limit the risk accumulation over the time. Developed within The Basel III framework, the “countercyclical capital buffer” is a macroprudential tool that draws upon the concept of “procyclicality”. The financial cycle literature has been extended in Turkey while searching alternative indicators for monitoring cyclicity besides the credit to GDP gap suggested by BIS. This dissertation contributes to literature by searching alternative indicators and by using various methods to identify financial cycles, and it aims to give the policy makers and economists a concept about the use of financial cycles at economic forecasts, financial stability and vulnerability analysis of Turkish economy.

Keywords: Business Cycles, Financial Cycles, Hodrick Prescott Filter, Turning Points Analysis, Macroprudential Tools.

ÖZET

Finansal Çevrimlerin Doğası ve Ölçümü: Türkiye Örneği

Günümüze kadar iş çevrimleri oldukça kapsamlı bir şekilde incelenmiş, iş çevrimlerinin niteliklerini ve bulundukları fazları anlamaya yönelik çeşitli yöntemler geliştirilmiştir. Ancak finansal çevrimlere ilişkin literatür iş çevrimleri literatürüne kıyasla nispeten sığ kalmıştır. Finansal çevrimler, 2007-2009 Küresel Finansal Krizi'nden sonra, makro finansal bağlantıları nedeniyle popüler bir çalışma alanı haline gelmiştir. Bu tezde, 2003Q1-2022Q2 dönemi için kredi hacmi, GSYH/ kredi oranı, reel BIST100 getiri endeksi, reel efektif döviz kuru ve REIDIN Konut Fiyat Endeksi gibi finansal değişkenleri içeren kapsamlı bir veri seti üzerinden Türkiye'deki finansal çevrimlerin temel özelliklerini ve doğasını ortaya koymak amaçlanmıştır. Finansal çevrimler, iş çevrimleri analizlerine benzer şekilde, klasik yaklaşım çerçevesinde çevrim noktası analizi, frekans bazlı ve trende dayalı bir yaklaşım olan Hodrick Prescott Filtresi analizi ve gelişmiş zaman serisi analizi kapsamında tek değişkenli gözlemlenemeyen bileşenler modelini içeren üç farklı yöntemle tespit edilmeye çalışılmıştır. Ayrıca, finansal çevrimler ile iş çevrimleri arasındaki uyum ve nedensellik ilişkileri de analizlere konu edilmiştir. Ekonominin içinde bulunduğu fazı (genişleme veya durgunluk fazı) belirlemek ve aynı zamanda finansal çevrimlerle etkileşimini de anlamak, zaman boyutunda risk birikiminin sınırlandırılmasına yönelik makro ihtiyatlı politika araçlarının geliştirilmesi ve uygulanması açısından politika yapımcılar için büyük öneme sahiptir. Özellikle Basel III uzlaşısı çerçevesinde geliştirilen "döngüsel sermaye tamponu", işleyişi finansal çevrimlerin fazına bağlı olarak belirlenen makro ihtiyatlı bir politika aracıdır. Türkiye'de finansal çevrimlere ilişkin literatür de döngüsel sermaye tamponunun işleyişinde finansal çevrimin tespitine yönelik finansal değişken arayışına bağlı olarak genişletilmiş, BIS tarafından önerilen kredi/GSYH açığına alternatif göstergeler analizlere konu edilmiştir. Bu tez, finansal çevrimleri alternatif göstergeler ve farklı yöntemlerle tespit ederek literatüre katkı sağlamakta ve finansal çevrimlerin ekonomik tahminlerde, finansal istikrar ve kırılganlık analizlerinde kullanımı konusunda politika yapımcılara ve ekonomistlere bir çerçeve sunmayı amaçlamaktadır.

Anahtar Kelimeler: Dönüm Noktaları Analizi, Finansal Çevrimler, Hodrick Prescott Filtresi, İş Çevrimleri, Makroihtiyatlı Politikalar.

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LIST OF ABBREVIATIONS

ADF: Augmented Dickey-Fuller
BBQ Algorithm: Bry and Boschan Quarterly Algorithm
BC: Business Cycle
BIS: Bank for International Settlements
BIST100: BIST100 Index
BSCCB: Bank-specific counter-cyclical capital buffer
CBRT: Central Bank of Turkey
CCB: Countercyclical Capital Buffer
CGDP: Credit to GDP
CI: Concordance Index
CPB: Capital conservation buffer
CPI: Consumer price producer index
EVDS: Electronic Data Delivery System
FC: Financial Cycle
GDP: Gross Domestic Product
GFC: Global Financial Crisis
HP Filter: Hodrick Prescott Filter
MLE: Maximum likelihood estimation
NBER: National Bureau of Economic Research
REER: Real effective exchange rate
REIDIN Index: REIDIN Residential Property Price Index
UCM: Unobserved Components Model
VIX: Chicago Board Options Exchange Volatility Index

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1. INTRODUCTION

The main focus of this dissertation is “financial cycles”. Compared to business cycle literature, the financial cycle literature is not so extensive. The business cycles have been investigated deeply, and various methods have been developed in order to understand their nature and phases so far.

However, the financial cycles came into question after the Global Financial Crisis (GFC) of 2007-2009. The studies about financial cycles have become popular as they see the financial cycles as a part of macro financial linkages. The pioneer studies claimed that that macroeconomics can not be separated from financial cycles as they play an important role in macroeconomics (Claessens et al., 2012; Drehmann et al., 2012; Borio, 2014). It is strongly suggested that it was like “Hamlet without the Prince” to think macroeconomics and financial cycle separately. In other words, the business fluctuations and their dynamics can not be handled without understanding the dynamics of financial cycles (Borio, 2014). Following this claim, this dissertation aims to detect financial cycles and understand their nature within a macro financial perspective.

Moreover, financial cycles has gained importance for the theories on the financial crises in search of why and how financial crises arise. They focused on the financial crises in search of this question: “May the financial crises arise related to business cycles, or may it arise autonomously?” They explored how the financial fluctuations contribute to origination of shocks. In search of the drivers of the financial crises, policy makers on macro finance paid attention to financial cycles.

The business cycle has an extensive literature for Turkish economy while financial cycle has a limited literature. To fill this gap, this dissertation aims to explore the main characteristics of the financial cycles in Turkish economy for 2003Q1-2022Q2. There is still no consensus on which financial indicator captures the financial cycle best. Thus, a set of financial variables including credit volume, credit to GDP, real BIST100 return index, real effective exchange rate, REIDIN Residential Property Price Index are complied as they can have the potential to capture the Turkish financial cycle.

The financial cycle literature borrows its methodologies from business cycle (output gap) literature. Consistent with existing literature, the financial cycles are identified by using diverse approaches. First, the traditional approach of turning point analysis is applied. This analysis entails the detection of peaks and troughs in the individual financial variables. After the turning points of financial cycles and their phases are detected, the characteristics of each phase are identified accordingly. Additionally, the concordance of the cycles are also examined in order to ascertain their distinctiveness from one another.

Second, in order to detect cycles, a frequency domain and trend based approach is applied by using frequency based filters, namely Hodrick Prescott Filter (HP Filter). After financial cycles and business cycles are identified by detrending, the causality relationship between the cycles are explored.

Third, an advanced univariate model-based approach is applied in order to detect business cycles and two credit-based financial cycles (credit and credit to GDP cycles) by using unobserved components time series models.

This dissertation aims to give the policy makers and economists a concept about the use of financial cycles at economic forecasts, financial stability and vulnerability analysis of Turkish economy. Especially in the prudential regulation framework, financial cycle literature may contribute the current macroprudential policies and inspire the development of new tools.

Given the time dimension of the macroprudential policies, the guiding principle is to utilize macroprudential tools to promote the accumulation of buffers in good times, which can be then used during bad times. Therefore, understanding “procyclicality” of the economy by identifying the phase (whether it is in a boom or bust) and also its interactions with financial cycles are crucial for the policy makers to apply macroprudential tools in order to limit the risk accumulation over the time.

Developed within The Basel III framework, the “countercyclical capital buffer” is a macroprudential tool that draws upon the concept of “procyclicality” from the financial cycle literature. It is utilized for determining the phase of the cycle for activating or releasing the additional buffer accordingly (Bank for International Settlements, 2014). While credit to GDP gap has been suggested by BIS as the primary indicator for monitoring cyclicality, this dissertation is in search of alternative indicators to monitor financial cycles in Turkey. It may

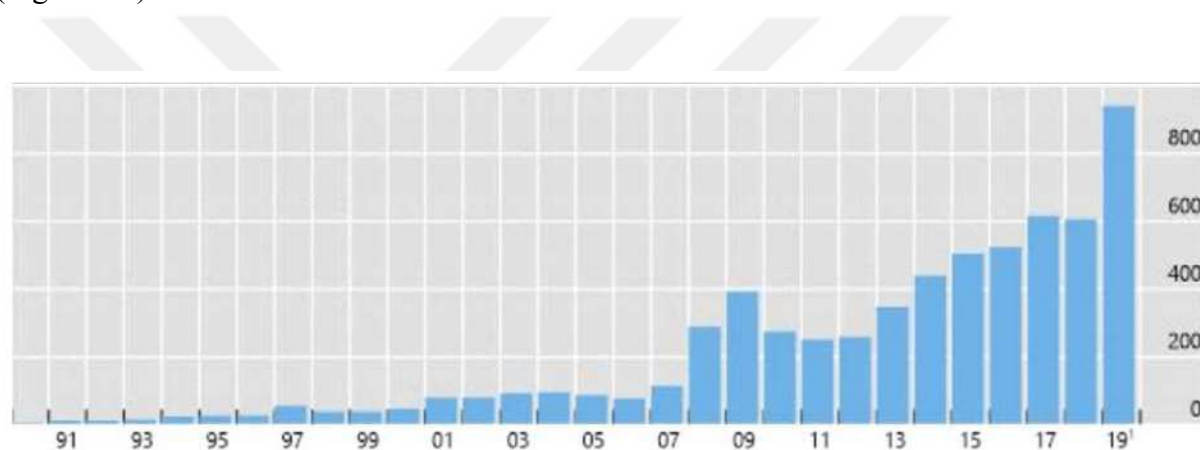
also have significant implications for the design and development of “countercyclical capital buffer” as a macroprudential tool within the macroprudential policy. Moreover, it may also have notable implications for the design and constraints of other policies (particularly monetary and fiscal policies) dealing with the increased leverage during the GFC and pandemic respectively.



2. THEORETICAL BACKGROUND

2.1. Definition of Financial Cycle

“Cycle” has been attributed to real economic fluctuations until Global Financial Crisis (GFC) by the economists. In macroeconomics, prior to the late 1990s, the sole “cycle” that was commonly discussed was “business cycle”. The primary focus of the literature was fluctuations in production that influenced employment and incomes, encompassing the ups and downs of the business cycles. However, there has been a surge in the recognition of the “financial cycle” concept of the since the GFC. The term “financial cycle” has gained popularity and its references in the press have witnessed a significant rise (Borio, 2019) (Figure 2.1).



*Data up to 30 June 2019, annualized
Source: Factiva

Figure 2.1. References to “financial cycle” term (from Borio, 2019)

Thus, there is a growing appreciation regarding the fact that it is not possible to analyze the macrofinancial cycle (or business cycle) without financial factors, and the “financial cycle” concept gained importance (Arenas, 2020). According to Borio (2014; 2019) inclusion of the financial cycle in macroeconomics is crucial as he likens the absence of it to “Hamlet without the Prince”. Recently, it is difficult to discuss the monetary or prudential policy without recognizing the fundamentals of financial concept, as it has become deeply ingrained within the intellectual framework.

Borio (2014) defines financial cycle as “*self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts.*” As per Borio’s perspective, these interactions have

the potential to magnify economic fluctuations, initiate imbalances and possibly result in severe financial turmoil and economic disruptions.

This definition is crucial because there remains a lack of consensus regarding the definition of financial cycles up until now. Thus, this dissertation draws on this definition and aims to reduce the uncertainty stemming from ambiguous definition of the financial cycle by measuring the financial cycle with several financial indicators.

This analytical definition is perceived to be closely linked to concept of the “procyclicality” of the financial system which focuses on financial and business fluctuations (Borio, 2014). In order to clarify this definition, “the five core features of financial cycles” are submitted in the study. These core features are primarily derived from the Drehmann et al.’s (2012) study analyzing six variables across seven countries (Australia, Germany, Japan, Norway, Sweden, the United Kingdom and the United States) using quarterly data spanning the period 1960-2011. According to Borio (2014), a systematic modelling of the financial cycle should contain these stylized facts:

- The financial cycles are often characterized in relation to credit and property prices, but not in relation to equity prices. Property prices and credit are sufficient indicators for analyzing the interplay between perceptions of value and risks and financing constraints. The most effective approach for capturing the essential characteristics of the connection between the financial cycle and the business cycle as well as financial crises seems to be the integration of credit and property prices.
- The financial cycle exhibits a lower frequency and higher amplitude compared to the business cycle. It is important to compare the frequency and amplitude of cycles.
- Most of the financial peaks are linked to systemic financial crises. In other words, the onset of financial crises which sometimes coincide with a peak in the cycle refers to “booms” in this context.
- The financial cycle helps in timely detection of risks associated with financial distress. Measuring the risk of financial crises in real time is indeed feasible. The most reliable leading indicators of financial crises are derived from simultaneous deviations (or gaps) of credit-to-GDP ratio and asset prices (property prices) from their historical data. Using a combination of two variables results in clearer signal than the models rely on a single variable.

- Its duration and amplitude are determined by policy regimes, which are defined as the financial regime, the monetary regime and the real economy regime.

Borio (2014) also emphasizes three main themes related to financial cycles: “Think medium term, think monetary, think global”. These themes help us to understand financial cycles in a broad perspective. According to Borio (2014), at first a medium term perspective is important for analyzing financial cycles due to difference of durations with business cycles. Secondly, when modelling the financial cycle, it is essential to acknowledge the fundamental monetary nature of the economy, thus monetary perspective is crucial. Thirdly, the financial cycles interact by either proceeding in sync or proceeding at varying speeds/phases across the globe, in other words global perspective should be taken into account.

The definition, core features and themes of financial cycles are handled in detailed from the perspective of Borio (2014) so far in order to clarify the financial cycle as a concept. However, some studies have shown that generalizing the validity of all five features mentioned by Borio’s (2014) study across all economies is not an entirely accurate approach. As the financial cycle literature has been extended, some of the core features and themes of Borio (2014) has also been challenged recently. Thus, this dissertation is in search of the validity of these five core features in Turkish experience.

Drehmann et al. (2012) argue that peaks in financial cycles, when filtered with lower frequencies, demonstrate a strong association with systemic banking crises. While the majority of the studies support the notion that financial cycles are longer in duration compared to business cycles (Borio, 2014; Aikman et al., 2015; Claessens et al., 2011(a); Galati et al., 2016; Schüller et al., 2015; Farrell & Kemp 2018); some studies challenged this concept. According Hiebert et al. (2014), their findings indicate that in Euro Area, the duration of credit cycle is approximately equivalent to that of the business cycle. However, the property and equity price cycles typically have shorter durations compared to business cycles. According to Gonzalez et al. (2015), their findings reveal that in several emerging markets, the length of financial cycles is similar to that of business cycles. Schüller et al. (2020) criticize the assumption of a similar durations of across countries and argue that this assumption has the potential to generate spurious cycles in common used proxies of the financial cycle, such as the Basel III credit to GDP gap.

As stated before, there remains a lack of agreement regarding the definition of financial cycles as well as lack of agreement regarding the set of the financial indicators to represent financial cycle. BIS claims that real credit growth, the credit-to-GDP ratio and real property price growth represent the smallest set of variables needed to see interaction between “financing constraints” and “perceptions of value and risks” that can cause serious macroeconomic dislocations and banking crises (Bank for International Settlements, 2014). That said, other variables, such as credit spreads, equity prices, risk premium and default rates, also may measure risk or risk perceptions and hence the up and downs of financial cycles.

Recently, the financial cycle has come to encompass the fluctuations in a broad range of financial indicators such as credit, asset prices, capital flows, or even exchange rate valuations. The comprehension of financial cycles is grounded the empirical evidence that credit and asset price fluctuations (upturns and downturns) are closely interconnected (Chen & Svirydzenka, 2021).

In addition to using a single indicator as a proxy for financial cycle, an aggregate index of multiple financial indicators has been also commonly used (Drehmann et al., 2012; Melolinna & Toth, 2016; Strohsal et al., 2019; Schüller et al., 2020). According to Schüller et al. (2020), there may be variations in the duration of the financial cycle across countries, thus the constructed financial cycle indices (using credit and asset prices) may outperform the ones with single indicators such as credit to GDP gap.

2.2. Financial Cycle Literature

There are two main (complementary) approaches (methods) in order to identify financial cycles in literature. The first one is “classic cycle” approach which identifies significant turning-points as peaks and troughs (Burns and Mitchell, 1946; Claessens et al. 2011(a,b), 2012). The second one is “growth cycle” approach which defines cycle relative to a trend (Drehmann et al., 2010; Drehmann et al., 2012; Borio, 2012).

The classic cycle approach generally employs an algorithm provided by **Bry and Boschan** (1971) for monthly time series first, however subsequently this algorithm was adapted to quarterly series by **Harding and Pagan** (2002). Hence, this method is also called “**BBQ** algorithm” because it is specifically re-designed for quarterly data analysis. This algorithm scans for maxima and minima within a specified period. It identifies pairs of

adjacent, locally absolute maxima (peak) and minima (trough) that satisfy specific censoring rules. For example, as a censoring rule, complete cycle must have a duration of at least five quarters, and of each phase (peak/trough) should last a minimum of two quarters (Claessens et al., 2011(a)).

The growth approach characterizes the financial cycle by frequency based filters. Hodrick Prescott (1997) Filter (HP Filter) is the most commonly used supplementary method due to its ease and quick implementation, making it a standard tool in financial cycle literature (Sakarya & Yayla, 2017).

Besides BBQ algorithm and frequency based filters (namely HP Filter and Band Pass Filter), more sophisticated methods have been utilized, e.g. univariate spectral analysis (Aikman et al., 2015; Gonzalez et al. 2015), multivariate spectral analysis (Schüler et al., 2020; Strohsal et al., 2019); unobserved component models (UCM) (Rünstler and Vlekke, 2016; Galati et al., 2016; Grinderslev et al., 2017; Farrell & Kemp, 2017; Melolinna & Tóth, 2016) and wavelet analysis (Verona, 2016; Yan & Huang, 2020).

As an advanced and model based method, “the unobserved components model” (UCM) developed by Harvey and Koopman (1997) is reviewed within the scope of this dissertation. It is an alternative measurement of financial cycles by means of a model. The UCM is categorized as a “structural model” in time series. The UCM decomposes the response series into components such as trend, seasonal, cycles, and the regression effects resulting from predictor series. It is a commonly employed method in the literature on output gap analysis.

Selected papers directly related to financial cycles are presented at Table 2.1. Financial cycles are determined by not only one method but also a combination of various methods at these papers. Main findings of the papers are also summarized at Table 2.1 .

Table 2.1 Selected literature review of financial cycles

Authors	Financial Cycles Variables	Business Cycle Variables	Countries	Method	Period	Main Results
Claessens et al. (2011a)	Credit Equity prices House prices		21 advanced countries	BBQ algorithm Concordance index	1960:1-2007:4	Financial cycles, particularly housing and equity cycles, exhibit longer durations and higher amplitudes. They demonstrate high level of synchronization within countries, especially with regards to credit and housing cycles. They reinforce and amplify each other, especially during simultaneous downturns in credit and housing markets.
Claessens et al. (2012)	Credit Equity prices House prices	Real GDP	44 countries (21 advanced OECD/ 23 emerging)	BBQ algorithm Multivariate regression models	1960:1-2010:4 (advanced c.) 1978:1-2010:4 (emerging c.)	The nature of the recessions in economy may differ depending on the concurrent financial cycle type and phase. When recessions coincide with financial disruptions (particularly house and equity price busts), they tend to be more prolonged and severe. On the other hand, when recoveries associated with rapid growth in credit and house prices, they tend to be often stronger.
Drehmann et al. (2012)	Credit to the private, non-financial sector Credit to GDP Equity prices Residential property prices An index of aggregate asset prices (residential/commercial property and equity prices)	Real GDP	Australia, Germany, Japan, Norway, Sweden, UK and USA	Band Pass Filter (Christiano and Fitzgerald) BBQ algorithm	1960-2011	Financial crises often align with the cycle peak points of the financial cycle. They are best captured by house prices and credit, not by equity. Their duration and amplitude have experienced a significant increase since the mid-1980s. It is considerably longer than the business cycle. The recessions become significantly deeper when they align with the contraction phase of the financial cycle.
Haavio (2012)	Real house prices Real stock prices Credit to GDP ratio Credit to deposits ratio Spread between long and short term interest rates	Real GDP	17 OECD countries	BBQ algorithm Concordance index	1980Q1-2010Q4	The peaks in real asset prices have a tendency to precede recessions. This relationship is stronger for real house prices compared to real stock prices. The relationship between financial and business cycles is stronger during recessions than during recoveries.
Borio et al. (2015)	Inflation Real interest rate Real total non-financial private sector credit growth Real residential property price growth	Real GDP	US	State Space Model Kalman Filter HP Filter	1980Q1-2012Q4	Financial factors specifically credit and property prices play a critical role in explaining cyclical fluctuations in output.

Table 2.1 (Continued) Selected literature review of financial cycles

Authors	Financial Cycles Variables	Business Cycle Variables	Countries	Method	Period	Main Results
Schüler et al. (2015)	Credit Equity prices Residential property prices Benchmark government bond yields	Real GDP Unemployment rate Consumer price inflation	13 European Union countries	Multivariate Spectral Analysis	1970Q3-2013Q4	Financial cycles tend to be long, especially in upswing phases, and exhibit a significant variations across countries. On average, the narrow financial cycle has a duration of 15.6 years, with Japan experienced the longest cycle (23.0 years), while Germany experienced the shortest (7.4 years). The alignment of financial and business cycles is observed approximately two-thirds of the time.
Gonzalez et al. (2015)	Credit to GDP gap	Real GDP	28 countries	HP Filter Bayesian Structural Time Series Univariate Spectrum Analysis	1996-2013	In sample, the majority of countries financial cycles have a duration of ranging from 13 to 20 years, on the other hand, as for a smaller group the duration of financial and business cycles are similar (3 to 7 years).
Rünstler & Vlekke (2016)	Credit House prices	Real GDP	US and the 5 largest European economies	Multivariate UCM	1973Q1-2014Q4	Their findings reveal the existence of large and prolonged cycles in credit and house prices, which exhibit high correlation with a medium-term component in GDP cycles (except in Germany).
Melolinna & Toth (2016)	Financial conditions indeces	GDP, unemployment rate, inflation, long term unemployment rate	United Kingdom	Semi-structural UCM Kalman Filter HP Filter	1995-2014	Inclusion of financial cycle variables is crucial in estimating output gaps in the UK. The model that incorporates financial conditions index provides more optimistic perspective on potential output after the financial crisis compared to the model without the index.
Galati et al. (2017)	Credit Credit to GDP House prices		US and the 5 largest European economies	Univariate and Multivariate UCM	1970–2014	They discovered that financial cycles can be modelled by using house prices, total credit, the credit-to-GDP ratio. They exhibit similar medium-term cyclical patterns, which have longer durations and higher amplitudes compared to business cycles; and that their duration and amplitude vary over time and across countries.
Grinderslev et al. (2017)	Real house prices Real Credit	Real GDP	Denmark	UCM	1971Q1-2016Q3	They observe significant comovements in house prices, credit and GDP at both business and medium term frequencies (11-30 years). They find that financial cycles are closely linked to the real economy, and the historical peaks in the financial cycle has been served as predictors of financial crises.

Table 2.1 (Continued) Selected literature review of financial cycles

Authors	Financial Cycles Variables	Business Cycle Variables	Countries	Method	Period	Main Results
Farrell & Kemp (2017)	Credit Equity prices (JSE returns) House prices	Real GDP	South Africa	BBQ algorithm Concordance index Band Pass Filter Univariate and Multivariate UCM	1966-2016	The financial cycle in South Africa exhibits a longer duration and a larger amplitude compared to business cycle. During periods of stressed financial conditions, they coincide with the peaks in the financial cycle. The credit and house prices prove to be significant indicators in capturing the financial cycle, while the equity prices do not.
Shen et al. (2018)	Credit to GDP ratio House prices Equity prices	Chinese Business Index	China	BBQ algorithm Concordance index Granger Causality Test	1995:Q4-2016:Q1	The frequency of financial cycles are less than those of business cycles. When durations are compared, the expansion phase is notably longer than contraction. Financial cycles precede business cycles but reverse is not true.
Strohsal et al. (2019)	A composite index (including national credit and house price index)		USA and UK	Multivariate spectral analysis Granger causality analysis	1970Q1-1984Q4 and 1985Q1-2013Q4	A noteworthy Granger causality exist from the financial cycle of US to that of UK financial cycle, while the reverse is not observed . This relationship is strong particularly for financial cycles spanning durations ranging of 8 to 30 years.
Porada Rochon, M. (2020)	Credit to GDP gap	GDP	Poland	HP filter, Baxter and King filter, Christiano Fitzgerald filter, Beveridge Nelson decomposition	1992:1-2018:4	Financial cycles in Poland have an average duration of 14.1 quarters, which is slightly longer than the business cycle (12.6 quarters). The financial cycles have a significant impact on Poland's business cycle, influencing long-term growth.
Yan and Huang (2020)			USA	Wavelet Power Spectrum VAR Model	1970:1- 2018:4	There is a strong positive correlation between the business cycle and the financial cycle, particularly at medium-term (8 to 30 years). The business cycle leads financial cycle. The financial cycle plays a crucial role in shaping the real interest rate and becomes a key driver of the business cycle.
Schüler et al. (2020)	Composite financial cycle (including credit, house prices, equity prices, corporate bond prices)	Composite business cycle (GDP, consumption, investment, hours worked)	G-7 countries	Multivariate spectral analysis	1970Q1:2018Q4	There may be variations in the duration of the financial cycle across countries. The constructed financial cycle indices (using credit and asset prices) may outperform the ones with single indicators such as credit to GDP gap.

2.2.1. Classic Cycles Methods

The financial cycle literature borrows its “classic method” from business cycle literature. This method is built upon the pioneering research of Burns and Mitchell (1946), establishing the fundamental principles for analyzing business cycles in US.

Burns and Mitchell (1946) provided a definition for business cycles stating to following:

“A **cycle** consists of expansions occurring at about the same time in many **economic activities**, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; where this sequence of changes is recurrent but not periodic.”

The “economic activity” refers to business while “cycle” refers to fluctuations. Thus, as for “financial cycle”, we refer the financial fluctuations. Both cycles are identified by the same methods as the financial cycle literature borrows the methods from the business cycle, however, different variables are employed.

The traditional turning point analysis is based on a dating algorithm firstly introduced by Bry and Boschan (1971) and subsequently adapted to quarterly series by Harding and Pagan (2002). The method is also called “**BBQ** algorithm” because it is specifically re-designed for quarterly data analysis. It is used to detect the peaks and troughs in the fluctuations of a logarithmic level series. (Claessens et al., 2011b).

To implement this algorithm, the maximum and minimum values are searched over a specified period. Then, the algorithm finds out pairs of adjacent, locally absolute maximum and minimum points based on pre-specified censoring rules. Harding and Pagan (2002) determined some censoring rules for quarterly frequency based analysis, and they can be summarized as follows (Binici et al., 2016):

- A complete cycle consists of two distinct phases: the *contraction/recession phase* , which spans from peak to trough, and the *expansion phase* which extends from trough to the subsequent peak.¹

¹ There are two turn phases: contraction (downturn) phase and expansion (upturn) phase.

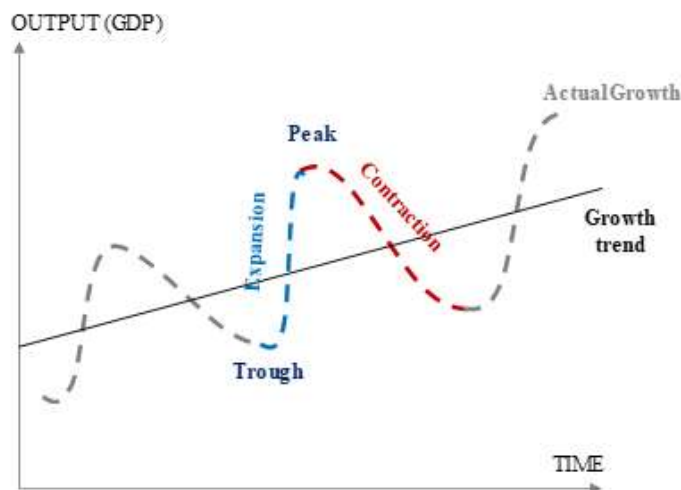
- A complete cycle is determined for a minimum *duration* of five quarters (contraction plus expansion duration). This cycle length of minimum five quarters is called as “Minimum Cycle parameter”.
- Each *phase* of the cycle is required the last for a minimum duration of two quarters. When dating the phases (expansions /contractions), it is common to apply a two quarter minimum, aligning with the rules employed by NBER. This is also called as the “Minimum Phase parameter”.
- A *peak* of the series (f_t) is detected at time t when,

$$\{(f_t - f_{t-2}) > 0, (f_t - f_{t-1}) > 0\} \text{ and } \{(f_{t+2} - f_t) < 0, (f_{t+1} - f_t) < 0\}$$

- A *trough* of the series (f_t) is detected at time t when,

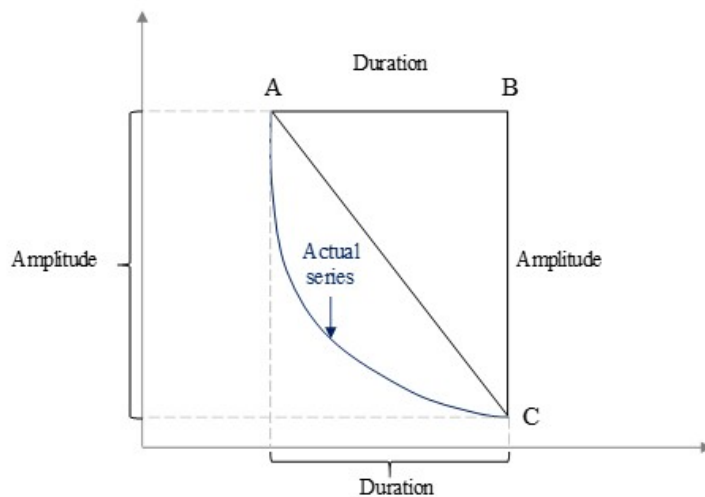
$$\{(f_t - f_{t-2}) < 0, (f_t - f_{t-1}) < 0\} \text{ and } \{(f_{t+2} - f_t) > 0, (f_{t+1} - f_t) > 0\}$$

The peak and trough of the cycles besides the contraction and expansion phases are illustrated in Figure 2.2. The point where expansion phase turns into contraction phase refers to “peak” (A) while the point where the contraction phase turns into expansion phase refers to “trough” (C) of the cycle. Thus, this method is also called “turning point” analysis, because identifying the transition points of the phases is the primary focus. It is expected that the financial crises coincide with peak points because of risk accumulation at this period.



Source: Eviews Blog

Figure 2.2 Illustration of a cycle



Source: Eviews Blog

*(A) is the peak and (C) is the trough of the cycle. (AB) is the duration, (BC) is the amplitude and (AC) is the slope of the cycle.

Figure 2.3 Illustration of the contraction phase

The main characteristics of the phases are the duration, amplitude and slope of the cycle. The aim of this analysis is to search the duration, amplitude and slope of the phases after determining peaks and troughs. According to Claessens et al. (2011a), these characteristics of the phases are defined as follows, and they are also illustrated in Figure 2.3.

- **Duration:** The duration (AB length) of a contraction phase is measured as the number of quarters between a peak (A) and the subsequent trough (C). Similarly, the duration of an expansion phase is the number of quarters required for the indicator to recover and surpass its previous peak. It is seen as the time span for recoveries.
- **Amplitude:** The amplitude (BC) of the contraction is determined by measuring the decline in the financial indicator from the peak (A) to trough (C). The amplitude of the expansion is determined by one-year change in each financial indicator from the trough (C) to peak (A). Thus, it quantifies the magnitude of the decrease/increase in the respective indicator during the downturn/expansion phase.
- **Slope:** The slope of the contraction phase is determined by dividing its amplitude (BC) to the duration (AB) of the cycle. It quantifies the rate at which the variable declines during the contraction phase, providing insights into the steepness of the contraction. The slope of expansion is the amplitude from the trough to the quarter at which the indicator has surpassed its previous peak, divided by its duration.

These features are searched as they provide detailed information about the nature and dynamics of the respective cycles.

The classical cycle analysis utilizes the “**concordance index**” developed by Harding and Pagan (2002) in order to examine the extent of synchronization across different financial cycles. It provides a quantitative measure to assess synchronicity of the cycles.

According to Harding and Pagan (2002, 2016), as for two cycles (x and y), the concordance index (CI_{xy}) over period $t=1, T$, is measured by following formula:

$$CI_{xy} = \frac{1}{T} \sum_{t=1}^T [C_t^x \cdot C_t^y + (1 - C_t^x) \cdot (1 - C_t^y)]$$

Where

$C_t^x = \{0, \text{if } x \text{ is in downturn phase at time } t; 1, \text{if } x \text{ is in expansion phase at time } t\}$

$C_t^y = \{0, \text{if } y \text{ is in downturn phase at time } t; 1, \text{if } y \text{ is in expansion phase at time } t\}$

The BBQ algorithm also utilizes a binary random variable, denoted as $S(t)$, to represent phases with the of “1” indicating expansions and “0” indicating contractions. Thus, the expansion and contraction phases of all cycles are determined with the states of “1” and “0” respectively for each quarter by BBQ. Then the concordance index is computed by these states (Claessens et al., 2011a,b).

Determined by analyzing peaks and troughs, a variable at time t can be in either expansion phase (1) or contraction phase (0) but not both. CI measures the proportion of two sequences that share the same phase as taking values 1 or 0 at the time. If CI index is equal to 1, two variables are considered as perfectly procyclical, because X and Y are always at the same phase (either expansion or contraction). If CI equals to 0, two variables are perfectly countercyclical, because when X is on its expansion phase and Y is always on the other phase. When CI gets a higher, it implies higher synchronization between the phases of cycles (Chang, 2016). On the other hand, the value of 0.5 indicates no systematic relationship between the dynamics of the two variables, thus they are considered independent (Claessens et al., 2011a,b).

The higher synchronization suggests a higher degree of similarity at the dynamics of the related cycles. The concordance index is applied in order compare dynamics and see interaction between cycles, particularly between financial cycles and business cycles.

In the turning point analysis, after the peaks and troughs are determined by the BBQ algorithm, the main characteristics of the phases (duration, amplitude and slope) for both financial cycles and business cycles are researched and the findings are compared to gain insights to dynamics of the cycles. Then the concordance index is computed to see the interconnectedness between them. The early researches that measured classical cycles discovered several key findings by this analysis. The financial cycles, when compared to business cycles, they tend to be more prolonged; and the CI shows that the phases of cycles can exhibit a high degree of synchronization. Moreover, the economic recessions that occur after financial disruptions (like credit crises and asset price busts) are generally tend to be more prolonged and more costly (Borio, 2014, Claessens et al., 2011(a,b); Drehmann et al., 2012).

In their study, Claessens et al. (2011a) employ classic cycle method to examine financial cycles in 21 advanced countries from 1960 to 2007. As using credit, house, equity prices as a proxy of financial cycle, they find that financial cycles have long durations and substantial impacts on the economies particularly in housing and equity markets. The financial cycles (especially credit and housing markets) are highly synchronized across selected economies which points out the interconnectedness of the cycles. The financial cycles have impacts on each other, especially the effects are intensified and magnified when credit and housing markets experience simultaneously downturns.

Claessens et al. (2012) extend their earlier study, mentioned previously, by broadening the country sample to include 44 countries (21 advanced OECD countries and 23 emerging market countries). Furthermore, they extend the period of the analysis from 2007 to 2010, allowing for a more extensive investigation. In their research, besides the classic cycle method, they applied multivariate regression models to examine the recessions/ recoveries of the economy by paying attention connections between business cycles and financial cycles. Their research claims that the nature of the recessions in economy may differ depending on the concurrent financial cycle type and phase. For instance, they find that when recessions are coincide with financial disruptions (particularly house and equity price busts), they tend to be more prolonged and severe than other recessions. On the other hand, when

recoveries associated with rapid growth in credit and house prices, they are tend to be often stronger than the ones following asset price busts. Thus, the fluctuations of house prices have both impacts on severity of recessions and strength of recoveries. Therefore, it is crucial to adopt a comprehensive perspective on different type of financial cycle fluctuations, considering that some downturns (or upturns) in financial markets coincide with financial crises while the others do not (Claessens et al., 2012).

According to Cagliarini and Price (2017), turning point analysis method offers the advantage of using the classical cycle series, instead of using growth rates of the cycles. In this method, log levels of the series are utilized in BBQ algorithm. On the other hand, the method has certain drawbacks. It is critiqued as it is based upon a statistical measure without any underlying economic theory. Additionally, the results of the BBQ algorithm may change with different pre-specified censoring parameters (like minimum cycle/phase parameter), making it sensitive to such choices (Cagliarini and Price, 2017).

Despite its drawbacks, the turning point analysis with BBQ algorithm is still one of the most widely used techniques in financial cycle researches. However generally they are applied with other alternative ones together to support and compare the results.

2.2.2. Trend Based Methods

As pioneers in their research, Cooley and Prescott (1995) applied variable moments of the parametric (detrend) models to identify the business cycles. This method is based on parametric models and offers valuable insights to business cycles. Similarly, the trend based approach to financial cycles (also known as growth cycle approach) defines cycle relative to a trend (Drehmann et al. 2010; Drehmann et al. 2012; Borio, 2012). Financial cycles are determined by frequency based filters.

The time series data can be decomposed into a trend component and a residual component referred as cycle. The trend is subtracted from the data to identify the cycles. Among several kinds of filtering methods, Hodrick Prescott (1997) Filter (HP Filter) is the most common used supplementary tool. It is favored for its ease of implementation and quick application, making it a standard tool for such purposes (Sakarya and Yayla, 2017).

Initially, the HP filters were primarily applied to detrend GDP growth to decompose it into components. Later on, the HP Filter is also utilized by employing financial variables in order to identify financial cycles in addition to business cycles (Drehmann et al., 2010).

The trend component (g_t) is subtracted from the series (y_t) to obtain the cyclical component (c_t), resulting the equation as $y_t = g_t + c_t$ in HP filtering method. At this point, Hodrick and Prescott (1997) suggest obtaining the trend by solving the following optimization problem:

$$\min_{\{g_t\}_{t=1}^T} \sum_{t=1}^T (y_t - g_t)^2 + \lambda \sum_{t=1}^T (g_{t+1} - 2g_t + g_{t-1})^2$$

In this formula, cyclical component (c_t) is the difference between the series (y_t) and trend (g_t), given by $c_t = y_t - g_t$. It is also commonly referred as the “gap” of the related series compared to its trend. The model introduces λ (lambda) as the smoothing parameter. The lost function consists of two terms: The first term penalizes the variance of the cyclical component, and the second puts a penalty on the lack of smoothness in the trend. The trade-off between the smoothness of the trend and its closeness to the original series are the crucial aspects (Drehmann et al., 2010).

There are two well-known solutions for this problem: First, if λ is zero, the optimal solution is $y_t = g_t$. On the other hand, the trend converges to a linear time trend with $g_t = \beta * t$ when λ approaches infinity ($\lambda \rightarrow \infty$) (Drehmann et al., 2010).

The value λ determines the level of smoothness in the trend. Thus, the selection of λ is important as it affects the smoothness of the trend. Hodrick and Prescott (1997) recommend setting $\lambda = 1,600$ for quarterly series in their study. This value has become the standard for analyzing business cycles using quarterly data. In terms of this analysis, a business cycle is assumed to have a frequency of around 7.5 years (Hodrick and Prescott, 1997).

Drehmann et al. (2010) conducted an analysis on the the performance of the credit to GDP gap² using different values for λ and they suggest that the higher value of lambda, especially 400,000, captures the crises better. Drehmann et.al (2010), Drehmann et.al (2012)

² It is the difference of the credit to GDP ratio from its trend values.

and Borio (2012) assumed that credit cycles are four times as long as business cycles, reflecting the long-term trends in private borrowing, and thus, they suggested the use of 400,000 as lambda. λ is set as following this procedure:

$\lambda = 1,600 = 1^4 * 1600$, with the assumption of credit cycles and business cycles have the same length,

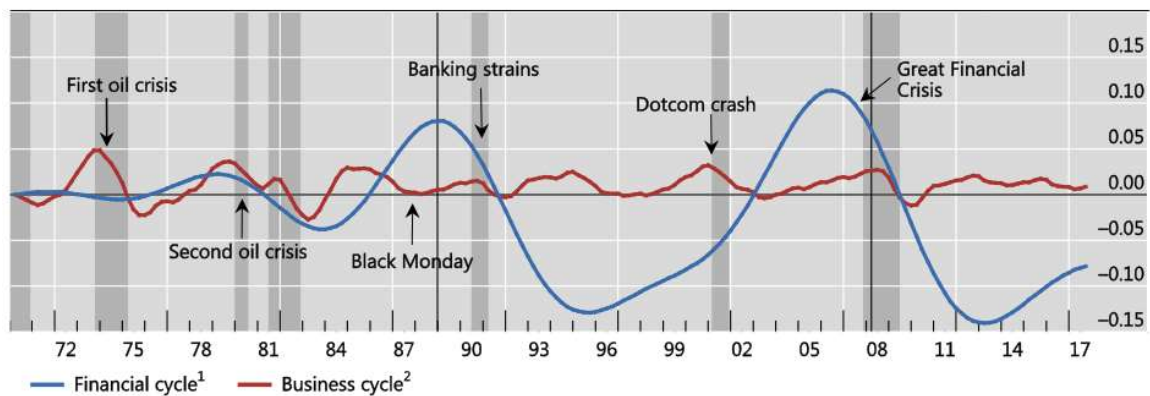
$\lambda = 25,000 \approx 2^4 * 1600$, with the assumption that credit cycles are two times as long as business cycles,

$\lambda = 125,000 \approx 3^4 * 1600$, with the assumption that credit cycles are three times as long as business cycles,

$\lambda = 400,000 \approx 4^4 * 1600$, with the assumption that credit cycles are four times as long as business cycles.

Thus, as previously mentioned in detail, $\lambda = 400,000$ is suggested based upon the assumed length of credit cycles compared to business cycles by Drehmann et al. (2010), Drehmann et al. (2012) and Borio (2012).

Drehmann et al. (2012) identifies financial cycles and business cycles in US by using trend based method. Their study examines the business cycles and financial cycles by applying frequency-based (band pass) filter in US. The financial cycles are measured by employing fluctuations in real credit, the credit to GDP ratio and real house prices over a period ranging from 32 to 120 quarters. The business cycle, on the other hand, is measured by handling fluctuations in real GDP over a period from 5 to 32 quarters (Drehmann et al. 2012). Their findings indicate that since the early 1980s, the domestic financial cycle has experienced an increase in amplitude and has become significantly longer than the business cycle. Additionally, it is observed that the financial cycle peaks often precede in recessions and coincide with periods of banking distress. In the provided visual representation Figure 2.4, the shaded areas represent recessions, while the solid black lines indicate the beginning of a banking crisis, as defined and included to graph by Laeven and Valencia (2018).



¹ Financial cycle is measured by frequency-based (bandpass) filters capturing medium-term cycles in real credit, the credit-to-GDP ratio and real house prices,

² Business cycle is measured by a frequency-based (bandpass) filter by detrending real GDP.

Source: Drehmann et al. (2012), Laeven and Valencia (2018).

Figure 2.4 The financial and business cycles in US (From Drehmann et al. 2012)

After the GFC, the Basel III framework introduced the concept of “countercyclical capital buffer” as a macroprudential tool to be implemented at national banking systems. Accurate measurement of financial cycles is critical for the effective implementation of the tool in legislated countries. In order to facilitate the activation and release of the countercyclical capital buffer, the BIS utilizes credit to GDP ratio as a reference indicator. They recommend that additional capital should be raised when a country’s credit to GDP exceeds its long run trend by a predetermined threshold (Drehmann et al., 2010). As the appropriate method for measuring long-run trend, BIS suggests a one-sided, or “real-time”, HP filter analysis including smoothing parameter as 400,000 (Giese et al., 2014).

The trend based method is seen as simple and easy to implement and that is the main advantage of this method. However, it has a tendency to detect relatively short-lived episodes and the effectiveness of the identification procedure heavily relies on the selection of lambda. Additionally, the another disadvantage of this method is presence of the end-of-sample bias³, which can be significant and adversely affect statistical inference (Borgy et al., 2014). This property may limit the real-time policy use. Unreliable real-time properties of filters may result in substantial ex post revisions of financial cycle measures. Thus, it brings uncertainty in the real-time calibration of macroprudential policies (Schüler et al., 2020).

³ End-of- sample bias, also known as “end-point problem”, refers to phenomenon in which the estimates get closer to the end of the sample as new data is included into the model, leading significant revisions in the estimates.

2.2.3. Unobserved Component Models Method

The detrending of cycles can be done through various methods, and one of the simplest way is to detrend by a filter, namely a HP Filter or band-pass filter. As an advanced method, the UCM introduced by Harvey and Koopman (1997) is considered a model-based technique. It is categorized as a “structural model” in the field of time series analysis. The UCM is formulated directly in terms of unobservable components including trend, cyclical, seasonal, and irregular components. These components represent the crucial features of the time series to understand their underlying dynamics.

UCM has been utilized for the identification of financial cycles in US and Euro Area (Galati et al, 2016 and Rünstler and Vlekke, 2016), Denmark (Grinderslev et al., 2017), South Africa (Farrell & Kemp, 2017) and United Kingdom (Melolinna & Tóth, 2016) so far.

Importantly, the UCM is seen as advantageous because there is no need to define a priori length of the cycles while it is defined in BBQ algorithm. In the UCM, the length of the cycles is determined by the estimating model parameters (Grinderslev et al., 2017).

The UCM can be modelled as either univariate or multivariate models. The univariate models encompass both structural component and time varying regressions. On the other hand, the multivariate models consist of common trends, common cycles, common seasons and seemingly unrelated time series equations that incorporate exogenous variables and interventions (Mendelssohn, 2011). The multivariate enable a comprehensive analysis of the relationships and dynamics among multiple variables and components.

Following Clark (1987), Harvey and Jaeger (1993) the univariate UCM can be specified as follows (Durbin&Koopman, 2012):

$$y_t = \underbrace{\mu_t}_{\text{trend}} + \underbrace{\gamma_t}_{\text{seasonal}} + \underbrace{c_t}_{\text{cycle}} + \sum_{j=1}^k \underbrace{\beta_j x_{jt}}_{\text{explanatory}} + \underbrace{\varepsilon_t}_{\text{irregular}}$$

$$\underbrace{\mu_{t+1}}_{\text{level}} = \mu_t + v_t + \eta_{t+1} \quad \eta_{t+1} \sim N(0, \sigma_\eta^2)$$

$$\underbrace{v_{t+1}}_{\text{trend}} = v_t + \zeta_{t+1} \quad \zeta_{t+1} \sim N(0, \sigma_\zeta^2)$$

The **trend component** is a dynamic extension of a regression model that incorporates an intercept and a linear time-trend. The **level component** is a generalization of the intercept term, allowing it to vary dynamically over time. Similarly, the trend component is a generalization of the time-trend enabling the slope to dynamically vary across time. These components (level and trend) can be considered in different modeling scenarios by including or excluding the component. However, if the trend is included, it is necessary to include level component. Additionally, this component can be deterministic or stochastic (depending on the variance on the error term may or may not confined to zero). The model provides flexibility to capture the inherit characteristics of the series (Harvey and Jaeger, 1993).

Trends are generally defined as the inherit tendency of the series to increase, decrease or remain constant over a period of time period, independent of other influencing variable. UCM can model trend in two ways: Firstly, it can be modelled as random walk model assumes the slope remains roughly constant throughout time period of the series. Secondly, it can be modelled as locally linear trend model allowing an upward or downward slope, meaning a gradual increase or decrease over time (Harvey and Jaeger, 1993).

The **seasonal component** can be expressed as follows (Durbin&Koopman, 2012):

$$\gamma_t = - \sum_{j=1}^{s-1} \gamma_{t+1-j} + \omega_t \quad \omega_t \sim N(0, \sigma_\omega^2)$$

The periodicity or number of seasons is donated as “s”. One defining characteristic is that (without the error term), the seasonal components sum to zero across one complete cycle. However with the inclusion of an error term, seasonal effects are allowed to vary over time providing for potential fluctuations or changes in seasonal patterns.

The variants of this model depend on two factors: the periodicity (s) and the treatment of seasonal effects (deterministic or stochastic). Periodicity refers to length of the seasonal

pattern (quarterly, daily, weekly variations, etc.). A seasonal pattern exists when there is a consistent and recurring variation in data that can be attributed to seasonal factors.

The **cycle component** is designed to capture long term cyclical effects that extend beyond the seasonal component. The cycle can be expressed by follows (Durbin&Koopman, 2012):

$$\begin{aligned} c_{t+1} &= c_t \cos \lambda_c + c_t^* \sin \lambda_c + \tilde{\omega}_t & \tilde{\omega}_t &\sim N(0, \sigma_{\tilde{\omega}}^2) \\ c_{t+1}^* &= -c_t \sin \lambda_c + c_t^* \cos \lambda_c + \tilde{\omega}_t^* & \tilde{\omega}_t^* &\sim N(0, \sigma_{\tilde{\omega}}^2) \end{aligned}$$

The parameter λ_c , which represents the frequency of the cycle is an additional parameter that needs to be estimated by maximum likelihood estimation (MLE).

The **irregular component** is assumed to be a white noise error term. Its variance is a parameter to be estimated by MLE. The variance is assumed to be normally distributed, constant across all values of the independent variable X, and with no autocorrelation between errors.

The **explanatory variables** can be added to model by including additional terms (Durbin&Koopman, 2012):,

$$\sum_{j=1}^k \beta_j x_{jt}$$

or for intervention effects by including:

$$\begin{aligned} \delta w_t \quad \text{where} \quad w_t &= 0, & t < \tau, \\ &= 1, & t \geq \tau \end{aligned}$$

These additional parameters could be estimated by MLE or by incorporating them as components within state space formulation.

Compared to non-parametric filters (like HP Filter), the multivariate structural time series models are considered more suitable for giving additional insights into the dynamic

characteristics of financial cycles and their interaction with business cycles. Non-parametric filters, which rely on pre-specified frequency bands, may run the risk of neglecting certain aspects of cyclical dynamics, conversely, may generate spurious cycles (Murray, 2003).

The structural time series models are also preferred because of the “end-point problem”, which univariate filters used for trend-cycle decomposition include. Melolinna & Tóth (2016) argue that this issue makes decomposition approaches relying on univariate filters inappropriate for real time policy analysis. They present a case study focusing on the analysis of UK output gap, highlighting that the pre-crisis Hodrick-Prescott (HP) output gap trend-cycle decomposition changed substantially as new data became available.

Rünstler and Vlekke (2016) set up a multivariate UCM that incorporates the correlation between the cycles. They employed their model to estimate trend and cyclical components in real GDP, real credit volumes and real house prices for the U.S. and the five largest European economies, using data from 1973Q1 to 2014Q4. Their findings reveal the presence of large and prolonged cycles in credit and house prices, which exhibit high correlation with a medium-term component in GDP cycles (with the exception of Germany). The variation in cycle duration and magnitude across countries seems to be linked to the characteristics of their national housing markets. Moreover, the predicted real-time estimates for credit and house price cycles is approximately similar to that of GDP cycles.

Following Rünstler and Vlekke (2016), the multivariate UCM is applied by Grinderslev et al. (2017) for Danish economy. Grinderslev et al. (2017) employed data from 1971Q1 to 2016Q3 for real GDP, real house price, and real credit. In their multivariate model, GDP is considered to be influenced by a time-varying trend and a cyclical component. The cyclical components of GDP are allowed to depend on past cyclical components of the other variables (real house price and real credit) and vice versa. The model is formulated in state-space form, and estimated using Kalman filter. Rünstler and Vlekke (2016) use classical maximum likelihood estimation, while Grinderslev et al. (2017) use Bayesian techniques.

In their study, Grinderslev et al. (2017) observe significant comovements in house prices, credit and GDP at both business and medium term frequencies (11-30 years). They find that financial cycles are closely linked to the real economy, and the historical peaks in the financial cycle have been served as predictors of financial crises (Grinderslev et al., 2017).

Galati et al (2016) applied both univariate and multivariate UCM models by using credit to GDP ratio, real credit and real house prices in order to extract financial cycles for the US and the five largest euro area (EA) countries from 1970 to 2014. Firstly, they extracted cycles from each individual time series using an univariate UCM. Secondly, they examined whether the cycles identified by a multivariate UCM exhibited common characteristics. In order to see whether ‘similar’ cycles exist in US and the EA countries, standard likelihood ratio tests are also employed. They discovered that financial cycles can be modelled by using house prices, total credit, the credit-to-GDP ratio. These financial cycles exhibit similar medium-term cyclical patterns, which have longer durations and greater amplitudes compared to business cycles. Furthermore, they observed that the length and amplitude of these medium-term cycles vary over time and differ across countries (Galati et al., 2016)

In their study, Farrell & Kemp (2017) extract the financial cycles of South Africa by using credit, house prices and equity prices. They applied three different methodologies: traditional turning-point analysis, band-based filters and univariate/multivariate UCMs. They find that financial cycle in South Africa exhibits a longer duration and a larger amplitude compared to business cycle. They observe the coincidence of the periods where financial conditions are stressed and the existing peaks in the financial cycle. Notably, the credit and house prices prove to be significant indicators in capturing the financial cycle, while the inclusion of equity prices in the measurements seem to be less certain (Farrell & Kemp, 2017).

2.3. Use of Financial Cycles in Policy

During GFC, systemic risks were accumulated and then led to economic distress, the increase of financial leverage, failure of institutions, collapse of several financial systems and loss of financial stability in general. In the pursuit of understanding the drivers of the financial crises, financial cycles has gained importance especially for the policy makers on macro finance.

International regulation and risk management policies were also reviewed to consider role of financial cycles within macro financial linkages. A structural microprudential policy measure known as “countercyclical capital buffer” (CCB) has been implemented within Basel-III regulations.

BIS (2010) declares the primary objective of the CCB regime is as to utilize a capital buffer to achieve the broader macroprudential goal of safeguarding the banking sector against periods of excessive aggregate credit expansion, which have often been associated with the accumulation of systemic risk. The main goal is to address the systemic risk accumulation over time and to ensure that the banking sector, as a whole, possesses adequate capital on hand to sustain credit flows in the economy without solvency during the periods in which financial system experiences stress following the excess credit growth. BIS (2010) also claims that the CCB regime may also contribute to lean against the build-up of the cycle in the first place, because when credit stock has reached to excessive levels compared to historical benchmarks, raising additional capital will increase the cost of credit, and therefore dampening its own demand. Thus, CCB serves an additional buffer to complement the existing minimum capital requirements, providing a hedge against cyclical risks.

According to Basel III standards, banks are required to maintain a minimum common equity tier 1 capital of 4.5% and an additional proportion of risk-weighted assets as CCB. However, implementation of the CCB is left to the discretion of local authorities, as outlined in the guidance by the Basel Committee on Banking Supervision. Local authorities would also need to exercise judgement in determining whether to increase or decrease the buffer over time, within the range of zero to 2.5% of risk weighted assets. Depending on the assessment of system-wide risks, authorities may choose to increase or decrease the CCB, The common reference guide for this assessment is the aggregate private sector credit to GDP gap, as outlined in the guidelines (Bank for International Settlements, 2010).

While advising use of the credit to GDP gap as reference variable for setting the CCB, BIS also suggests considering additional indicators such as asset prices, macroeconomic conditions, balance sheet indicators and funding rate spreads, along with the supervisory judgement. Accordingly, the country authorities have explored alternative indicators to monitor cyclicity. For instance, in addition to the credit to GDP gap indicator recommended by the Basel Committee, the Hong Kong Monetary Authority sets the CCB rate by also considering the housing price/rent gap indicator. This indicator compares the housing prices to rent ratio with the long-term trend and used in monitoring cyclicity (Yetkin, Z. E; Önal, İ., 2019).

As for Turkey, the capital conservation buffer (CPB) and Bank-specific counter-cyclical capital buffer (BSCCB) ratios are implemented by the Regulation on Capital

Conservation and Countercyclical Capital Buffers⁴ in order to prevent own funds becoming inadequate due to the losses caused by deterioration in economic and financial indicators. CPB ratio is determined as 2.5% to be full implemented by 2019, after a transition period starting from 2016.

In the context of CPB, BRSA takes the BIS supposed “credit to GDP gap” as the primary reference of policy designing. 3% and 15% thresholds of credit/GDP gap are taken as the main reference in determining the cyclical buffer. In this context, it is announced that as supporting indicators; basically, developments observed in GDP, BIST-100 and banking sector return on equity have been also followed.⁵ Moreover, BSCCB ratio is designed based on country specific geographic distribution of the banks’ own credit portfolio, within the principles and procedures determined by the BRSA Board.

From the macroprudential perspective, identifying credit cycles is crucial for determining countercyclical capital buffer. Because, the degree of credit growth overshooting the present thresholds is considered to raise an additional capital buffer up to a maximum of 2.5% of risk-weighted assets. On the other hand, if the credit growth is modest or within acceptable levels, the CCB is set at zero. Hence, holding additional buffer depends on the expansion and the contraction phase of financial cycle. The CCB imposes a cost on bank capital, making it critical for regulatory authorities to effectively estimate the financial cycle and enhance this with additional relevant quantitative and qualitative data/indicators. (Sakarya and Yayla, 2017).

As a macroprudential tool, CCB draws attention to financial cycle literature and it has also contributed the financial cycle literature as its fundamentals are based on the financial cycles theory. The financial cycles get attention of macro financial policy makers to develop macroprudential tools within the prudential policy. Thus, the financial cycles has been included to economic forecasts, financial stability and vulnerability analysis of policy makers and economics.

The literature on the financial cycle emphasizes the significant role of financial factors in explaining fluctuations in business cycles, highlighting the strong interconnections between different phases of the financial and business cycles (Borio et al. 2015; Claessens

⁴ It is published in the Official Gazette dated November 5, 2013, No:28812.

⁵ For details, see Board Decision No: 6602 dated 18.12.2015.

et al. 2011 a,b; Drehmann et al. 2012; Rünstler & Vlekke, 2016; Melolinna & Tóth, 2016; Grinderslev et al. 2017). Borio (2013) emphasizes three key points about financial cycle and its linkages to macroeconomy: Firstly, financial cycle should be considered to be at the core in our understanding of the macroeconomy. Secondly, the financial cycle has important implications for the designing and determining the constraints of macroprudential policy. Lastly, it also has significant implications for the design and limitations of other policies, particularly monetary and fiscal policies (Borio, 2013).

Borio (2013) also mentions about how the prudential policy should address financial cycle. The prudential policy should adapt a systemic or macroprudential approach handling the “procyclicality” of the financial system. This refers to the “time dimension” of macroprudential policy and involves managing to evaluate how system wide or systemic risk evolves over time. The general principle is building up buffers during financial booms so as to draw them down during busts. This policy has two objectives: increasing the system's resilience during busts and curbing excessive expansion during booms (Borio, 2013).

Following the GFC, the pandemic hit the world and the extraordinary policy measures were implemented to mitigate economic impact of the pandemic led to the financial leverage, reaching levels comparable to those observed during GFC (Chen & Svirydzenka, 2021).

The increase in the financial leverage after pandemic should be handled by financial cycle literature implications. Indeed, while the extraordinary policies implemented during pandemic may have support the economic growth in the short run, it also carries potential risks for the medium term outlook of the economy. These risks arise from the potential side effects created by prolonged period of policy support, which could raise downside risks to the real economy.

The cyclical properties of the financial indicators and identification of financial excesses have yet to find a consensus. The policy challenge about the tradeoff between “supporting still fragile growth” and “staving off financial crises down the road” should be handled by targeted macro prudential measures that address financial excesses accordingly. In other words, the policy challenge of balancing between supporting fragile economic growth and preventing future financial crises should be effectively addressed through targeted macroprudential tools. (Chen & Svirydzenka, 2021). At this point, developing macroprudential measures like CCB is a crucial on the focus of this policy challenge.

To attain long-term and sustainable economic growth, it is important for policymakers to diligently monitor financial cycles and adjust their fiscal and monetary policy accordingly. By doing so, policymakers and financial practitioners can develop and implement a sound financial policy that mitigate potential risks causing financial national and global crises. (Porada Rochon, 2020)



3. THE FINANCIAL CYCLES OF TURKEY

3.1. Literature Review

Main literature regarding the Turkish economy handle “financial cycle” in search of identifying key indicators to macroprudential policy decisions, particularly regarding the “Countercyclical Capital Buffer” framework to introduce regulatory rule according to estimated cycle. The financial cycle is mainly investigated in accordance with “growth cycle” approach by using HP filter (Yayla, Sakarya and Savran, 2014; Sakarya and Yayla, 2017; Altuntaş, 2015). However, there is a limited literature based on “classic cycle” approach which detects stress periods by using BBQ algorithm, and generally BBQ algorithm and Hodrick Prescott (HP) Filter are employed together (Binici et al. 2016; Akar, 2016; Gökalp, 2018; Karagöl & Doğan, 2021; Balaban, 2022). On the other hand, Güney et al (2018) employs the UCM only for forecasting loan growth of Turkey.

The selective literature is summarized at Table 3.1

Table 3.1 Selected literature review of cycles- Turkey

Paper / Thesis	Financial Cycles Variables	Business Cycle Variables	Method	Period
Yayla et al. (2014)	Credit to GDP Credit volume		HP Filter Band Bass Filter	
Altuntaş (2015)	Credit to GDP BIST100 Index CDS spreads- 5 year Return on asset (before tax) Return on asset Return on equity		HP Filter	1988Q1-2015Q1
Binici et al. (2016)	Real credit Credit to GDP Real BIST100 Index (deflated by CPI) Real effective exchange rate	Real GDP	HP Filter BBQ algorithm Concordance index	1987Q1-2015Q4
Akar (2016)	BIST100 Credit (deposit banks- private sector)	Real GDP Household consumption	HP Filter BBQ algorithm Concordance index Dynamic conditional correlation method	1998Q1-2014Q4
Sakarya et al. (2017)	Credit to GDP Real BIST100 Index (deflated by CPI) Return on equity (quarterly annualized) Composite Performance Index Financial Stress Index	GDP growth	HP Filter (for credit to GDP and BIST100) BBQ algorithm (only for GDP Growth)	
Gökalp (2018)	BIST100 Credit (commercial banks - households)	GDP Household consumption	HP Filter BBQ algorithm Concordance index Dynamic conditional correlation method	2002Q1-2017Q1

Table 3.1 (Continued) Selected literature review of cycles- Turkey

Paper / Thesis	Financial Cycles Variables	Business Cycle Variables	Method	Period
Güney et al (2018)	Loan growth rate Commercial loan growth rate Consumer loan growth rate		Unobserved Components Model	2007:1-2018:3
Değneli (2018)	Real credit volume index (deflated by CPI) Real Asset Price Index (deflated by CPI) St. Louis FED Financial Stress Index Housing Price Index (REIDIN) Real effective exchange rate index	Industrial production index Consumption index Government expenditures index Export and import indexes Investment index Consumer price producer index Real interest	HP filter Cross-correlation analysis Vector autoregressive model (VAR) approach Impulse Response Function Granger Causality Test Variance Decomposition	2003:1 – 2015:12
Karagöl et. al. (2021)	Real credit volume Credit to GDP Interbank interest ratio Real BIST100 Return Index Real effective exchange rate	Real GDP	BBQ algorithm HP Filter Hacker and Hatemi-J symmetric causality test	1998Q1 - 2019Q4
Balaban (2022)	Real effective exchange rate Real credit (deflated by cost of living index) Credit to GDP BIST100 (dollars) Foreign portfolio investments	Industrial production index	BBQ algorithm HP Filter Concordance index Baxter and King filter DCC-GARCH Granger Causality Test	1987Q1- 2021Q3

Binici et al. (2016) conducted a study to explore characteristics of financial cycles by using various financial variables from different markets (including credit, stock, and exchange rate markets). They analyzed the cycles over the period 1987-2015 by applying both BBQ algorithm and HP Filter. The research findings contain important insights for understanding the cycles in Turkey. They found that credit cycles have a longer the average duration compared to business cycles. Both business and financial cycles tend to have longer expansion phases following relatively shorter contraction periods. When the average amplitudes are compared, they are higher at financial cycles than the ones of business cycles. Stock market index and real effective exchange rate cycles experience more frequent stress periods compared to other cycles, but these stress periods tend to be relatively shorter in duration. The concordance index results indicate a high level degree of synchronization between business and credit cycles (Binici et al., 2016).

Akar (2016) explored the relationship between the financial and business cycles in Turkey by using various financial variables data from 1998Q1 to 2014Q4. He applied Hodrick-Prescott (HP) filter to identify cycles. The concordance index, cross-correlation and Dynamic Conditional Correlation (DCC) models are applied for revealing synchronization of cycles. The findings of Akar (2016) reveal a high degree of synchronization between financial and business cycles, experiencing a break during the GFC. The study also highlights that the credit cycle plays the leading role on the business cycle, while the BIST 100 cycle leads the business cycle.

Karagöl & Doğan (2021) explored the interaction between financial cycles and business cycles from 1998Q1 to 2019Q4. They find that the number of financial cycles experienced is higher compared to number of business cycles. The financial cycle is more sloped and rapid compared to business cycles. The study further highlights the significant synchronization between the financial and business cycles, particularly during contraction phases. Additionally the study notes the existence of both a symmetric and asymmetric causality relationship running from financial cycles to business cycles in Turkey.

Balaban (2022) examines the interaction between financial and business cycles in Turkey from 1987:1 to 2021:3. Main finding is that financial cycles in Turkey precede and cause the business cycles. According to the results of Granger causality analysis, while all variables used to represent financial cycles (loans, stock prices, real effective exchange rates and foreign portfolio investments) are Granger-cause business cycles (proxied by the

industrial production index), business cycles only Granger-cause credit-GDP ratio. The findings of DCC-GARCH analysis reveal the ability of financial and business cycles to co-move increases in times of crisis. Thus, Balaban (2022) claims that neglecting the fluctuations in financial cycles has the potential to cause serious real economic costs in the future.

Güney et al. (2018) utilizes an univariate UCM to forecast the credit growth in various segments including annual total, commercial and consumer credits, from 2007:1 to 2018:3. The average cycle length is found approximately 35 months (2.91 years). It is also found that UC models exhibit lower forecast errors compared to benchmark univariate time series model in all loan categories, and detect cyclical movements of loan growth. Hence, the evidence regarding the cyclical movements of loan growth obtained from the UC model may provide implications for policymakers to take timely measures (Güney et al., 2018).

In this dissertation, the univariate UCMs will be employed to identify cyclical movements of credit cycles and credit to GDP cycles, contributing the existence literature on financial cycles in Turkey. Additionally, in order to examine the cyclical movements of real economy and compare the lengths and frequencies with those of financial cycles, an univariate UCM model is also applied to estimate output gap.

3.2.Data

To determine the financial cycles in Turkish economy and explore the main characteristics and nature of them, various financial variables spanning a period of 20 years are analyzed. The quarterly data is used to detect financial cycles and identify expansion/contraction phases for the period from 2003Q1 to 2022Q6.

The selected variables as a proxy of financial cycles, in accordance with the literature, are as follows:

- Real credit volume (deflated by CPI)
- Credit to GDP
- Real BIST100 return index (deflated by CPI)
- Real effective exchange rate
- REIDIN Residential Property Price Index (adjusted for inflation, TR7, June 2007=100)

The data source for **credit volume** is BIS. For credit series, the definition used aligns with the requirements of Basel Committee, aiming to capture the most extensive and accurate measure that reflects accumulation of risk (Sakarya and Yayla, 2017). Thus, the credit volume is determined as “the credit to private non-financial sector from all sectors at market value”. According to BIS metadata document (BIS, 2022), the “private non-financial sector” includes non-financial corporations (both private-owned and public-owned), households and non-profit institutions serving households as defined in the System of National Accounts 2008. Here, “credit” also includes debt securities (valuated by market value) besides credits (valuated by nominal value).⁶ The series used in analysis have a quarterly frequency and capture the outstanding amount of credit at the end of the reference quarter.

The **credit to GDP** series are also derived from BIS database. It is calculated by dividing the credit (credit to private non-financial sector from all sectors at market value) by annualized GDP, resulting in GDP ratio. BIS has been publishing time series on the “credit to GDP gap” for a number of countries as it has been identified as a reliable early warning indicator of impending financial crises. The credit to GDP gap is defined and calculated as the difference between the credit to GDP ratio and its long-run trend, which is extracted by detrending the ratio with Hodrick Prescott Filter (BIS 2010). BIS publishes its own calculations on the credit to GDP trend and the credit to GDP gap series. In this dissertation the credit to GDP series are employed as a proxy of financial cycle; and in order to extract cycles, credit to GDP trend and gaps are measured by terms of the trend based analysis, by the same way of BIS. The results of trend analysis will be compared the those of BIS to provide consistency.

BIST100 Return Index (trade closed) is derived from Reuters to analyze and identify cycles in equity markets, in line with the existing literature.

In order to see the fluctuations on housing markets, **REIDIN Residential Property Price Index (adjusted for inflation, TR7, June 2007=100)** is employed as it a reliable benchmark for housing prices of Turkey. The data source of the Index is REIDIN Data Analytics and its own database. The public data can not be used due to data limitations. Until

⁶ Some of the studies utilize the credit volume to private non-financial sector in their analysis. However, BIS credit volume definition and data (including debt securities) is used in this dissertation. The choice of credit definition and data can impact the results of the analysis.

CBRT publishes public data, the availability of real estate prices data has primarily relied on private firms (like REIDIN). However, it is important to note that private firms may tailor the data to their own requirements and public interest may not be taken account. Besides, the data does not cover all the cities of Turkey, so the data is not extensive as CBRT's index. CBRT has been publishing the Residential Property Price Index since May 2010. Thus, this past data gap has been limited empirical researches on real estate prices so far. As the Index of CBRT goes back to 2010, this dissertation extends the analysis by REIDIN Housing Price Index data. REIDIN's index series (deflated, so that in real terms) are calculated monthly for sales covering 7 major cities (Adana, Ankara, Antalya, Bursa, Istanbul, Izmir and Kocaeli). The composite index is constructed by taking a weighted average of the city indices based on the methodology of REIDIN.

The **real effective exchange rate (REER)** data is derived from EVDS of CBRT. Nominal Effective Exchange Rate (NEER) is defined by CBRT as a “weighted average value of TL with relative to a basket of currencies”. This basket is formed by considering the countries which have significant shares in Turkey's foreign trade.⁷ It is announced as a monthly index by CBRT with a base year of 2003. REER is selected as it has a potential to affect real economy through the trade and consumption, because an increase in REER results in exports becoming more expensive and imports becoming cheaper.

The consumer price producer index (CPI), derived from EVDS of CBRT, is used to ensure nominal series (credit volume and nominal BIST100 Return indices) in real terms. They are all deflated by dividing CPI.

In order to determine business cycles and detect recessions in economy, **real GDP** is selected as the main proxy. In addition to GDP, industrial production index (Değneli, 2018; Balaban, 2022); household consumption (Akar, 2016; Gökalp, 2018) and unemployment rates (Melolinna & Toth 2016) have been employed as proxies of business cycles so far. In this dissertation, real GDP is preferred as it is the most widely used and commonly accepted indicator. The nominal GDP series are derived from EVDS of CBRT and divided by CPI to convert them into real terms.

⁷ CBRT, www.tcmb.gov.tr. The determination of the weights of NEER relies on bilateral trade flows. REER modifies NEER for the effects of relative prices.

As a proxy of global risk, Chicago Board Options Exchange Volatility Index (VIX)⁸ is used in order to analyze global financial cycle and compare with national financial cycles of Turkey. The data for VIX is derived from FRED web site.

Time series of the variables are given at Figure 3.1.

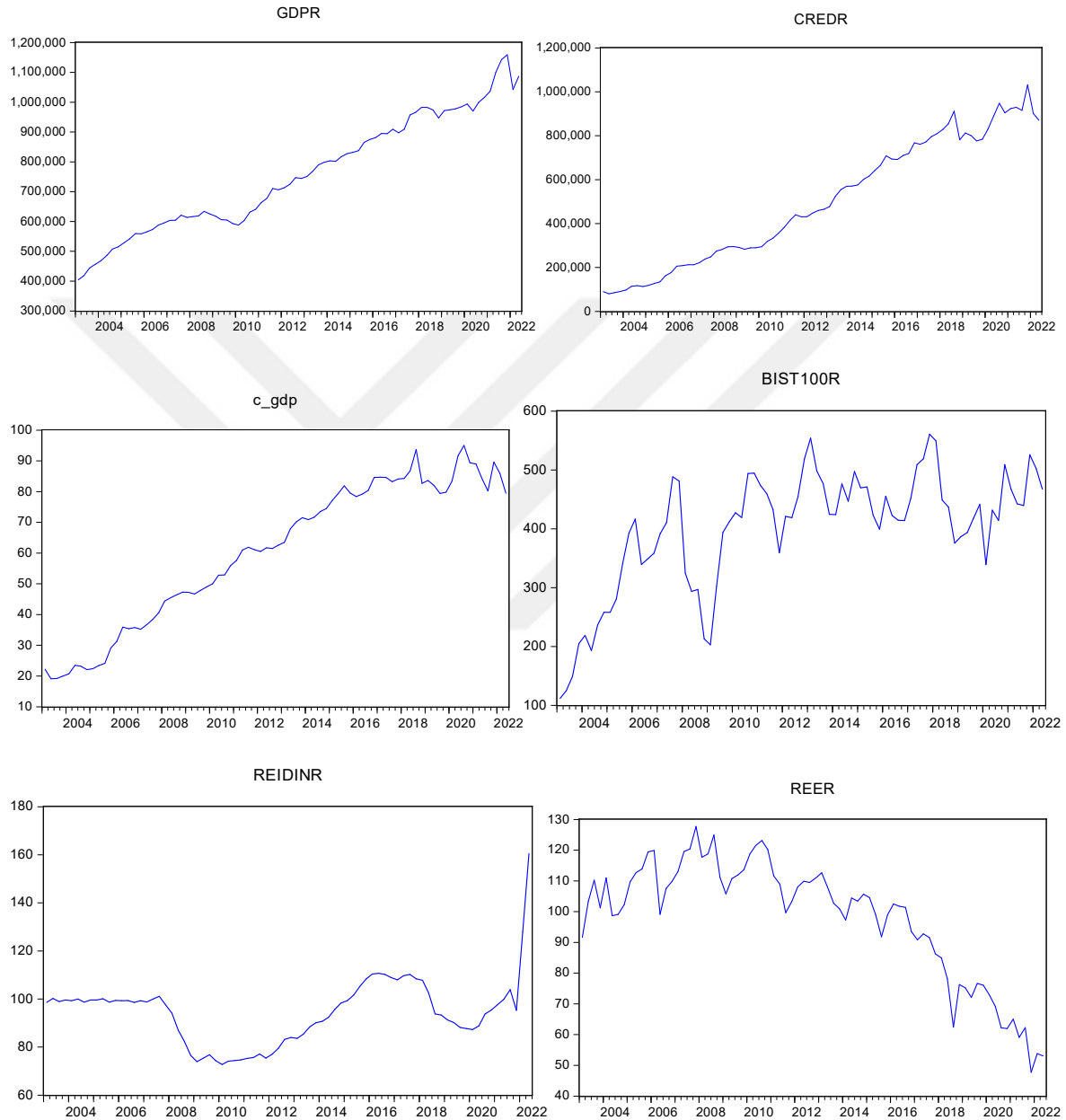


Figure 3.1 Time series of the variables⁹

⁸ VIX is a measure of market expectation for near term volatility based on stock index option prices.

⁹ In order to facilitate an effective comparison with real credit as well as credit to GDP series, annualized real GDP is plotted on the graph.

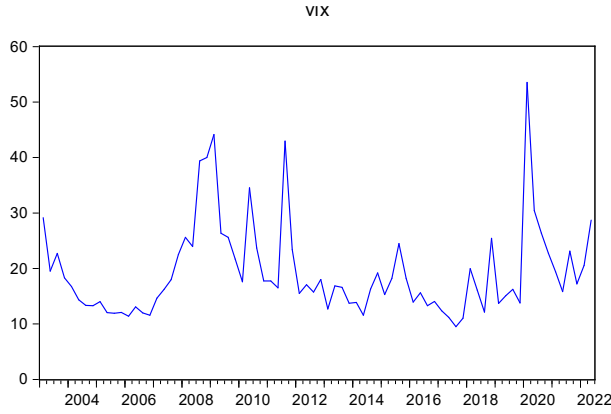


Figure 3.1 (continued) Time series of the variables

The financial cycles are determined for each of five variable and analyzed individually, instead of employing a composite index developed to see market impacts all together (Karagöl & Doğan, 2021).

The variables are seasonally adjusted via Census X12 method when necessary and converted by logs (except credit to GDP ratio).¹⁰ All the variables and their classification are presented at Table 3.2.

Table 3.2 Data classification

Data	Transformed Data	Variables	Cycles	Abv.
BIST100R	LBIST100	Real BIST100 Return Index	Financial Cycle 1	F1
CREDR	LCREDR	Real Credit Volume	Financial Cycle 2	F2
C_GDP	C_GDP	Credit to GDP	Financial Cycle 3	F3
REIDINR	LREIDINR	REIDIN Residential Property Price Index	Financial Cycle 4	F4
REER	LREER	Real Effective Exchange Rate	Financial Cycle 5	F5
GDPR	LGDP	Real GDP	Business Cycle	BC
VIX	LVIX	Chicago Board Options Exchange Volatility Index	Global Cycle	GC

Descriptive statistics are presented at Table 3.3.

¹⁰ Credit to GDP data is neither seasonally adjusted nor logarithmic transformed as it is expressed as percentage points. Real credit and VIX series are not subjected to seasonally adjustment.

Table 3.3 Descriptive statistics

	LBIST100	LCREDR	LGDP	LREER	LREIDINR	LVIX	C GDP
Mean	5.944343	12.904	12.18334	4.562085	4.538299	2.892965	60.42564
Median	6.04722	13.04396	12.17456	4.640417	4.582227	2.821373	62.25
Maximum	6.324331	13.84682	12.85017	4.840172	5.058401	3.980429	95
Minimum	4.69303	11.29385	11.64022	3.875619	4.296038	2.252344	19.1
Std. Dev.	0.328949	0.733031	0.283552	0.228408	0.140601	0.362817	23.35116
Skewness	-1.782026	-0.653286	0.167946	1.254135	0.282707	0.862564	-0.37419
Kurtosis	6.008341	2.272008	2.268894	3.702132	4.161046	3.420412	1.791716
Observations	78	78	78	78	78	78	78

3.3. Methodology

3.3.1. Classical Cycles Analysis

The financial cycles and business cycles are identified by the same way of Binici et al. (2016). First, turning points of all series and their phases are detected via BBQ algorithm individually. Then the main characteristics of each phase (contraction/expansion) are examined accordingly. The financial cycle phases are compared in terms of their duration, amplitude, slope. Similar procedure is conducted for GDP and VIX to extract business cycle and global cycle turning points and phases, and their characteristics are also compared to those of financial cycles. In order to see the degree of synchronization between the financial cycles and business cycle, concordance indices are computed. Secondly, the stress periods are also determined by detrending the series by HP Filter.

The preconditions of the BBQ analysis are similar to those Harding and Pagan (2002): a minimum cycle parameter of five quarters and a minimum phase parameter of two quarters are applied to BBQ algorithm. The maximum and minimum values are searched according to this censoring rules.

The turning points (peaks and troughs) and the number of cycles identified by BBQ algorithm are presented at Table 3.4. The phases of turning points are also given at Figure 3.2 in which the shaded areas show the contraction phases while the others show the expansion phases.

Table 3.4 Turning points of cycles

LBIST100		C GDP		LCREDR		LREER		LREIDINR		LVIX		LGDPR	
Peaks	Troughs	Peaks	Troughs	Peaks	Troughs	Peaks	Troughs	Peaks	Troughs	Peaks	Troughs	Peaks	Troughs
2006Q1	2006Q3	2004Q2	2004Q4	2008Q4	2009Q2	2003Q3	2004Q3	2005Q1	2006Q3	2009Q1	2006Q1	2006Q4	2007Q2
2007Q4	2009Q1	2006Q2	2007Q1	2015Q3	2016Q1	2005Q4	2006Q2	2007Q3	2009Q1	2015Q3	2014Q2	2008Q1	2009Q1
2010Q4	2011Q4	2008Q4	2009Q2	2018Q3	2019Q3	2007Q4	2009Q1	2009Q3	2010Q3	2020Q1	2017Q3	2011Q3	2012Q1
2013Q1	2014Q1	2011Q3	2012Q1	2021Q4		2010Q3	2011Q3	2016Q2	2017Q1		2021Q2	2018Q2	2020Q2
2014Q4	2015Q4	2015Q3	2016Q1			2013Q1	2014Q1	2017Q3	2020Q1				
2017Q4	2018Q4	2017Q1	2017Q3			2014Q4	2015Q3						
2019Q3	2020Q1	2018Q3	2019Q3			2016Q3	2018Q3						
2020Q4	2021Q3	2020Q3	2021Q3			2019Q3	2021Q4						
7		7		3		7		4		3		3	

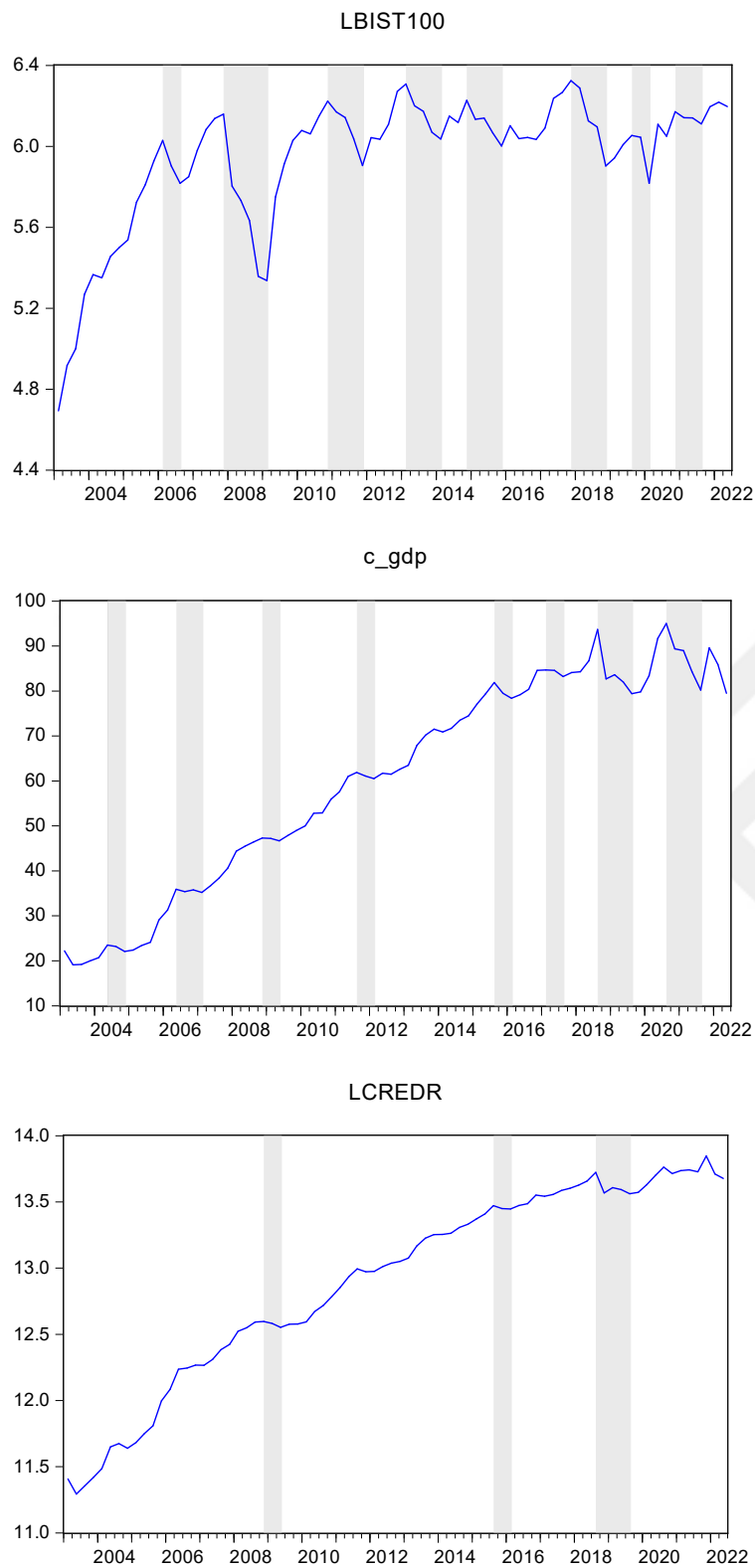


Figure 3.2 Turning point analysis cycle phases¹¹

¹¹ Shaded areas are contraction phases, while the others are expansion phases.

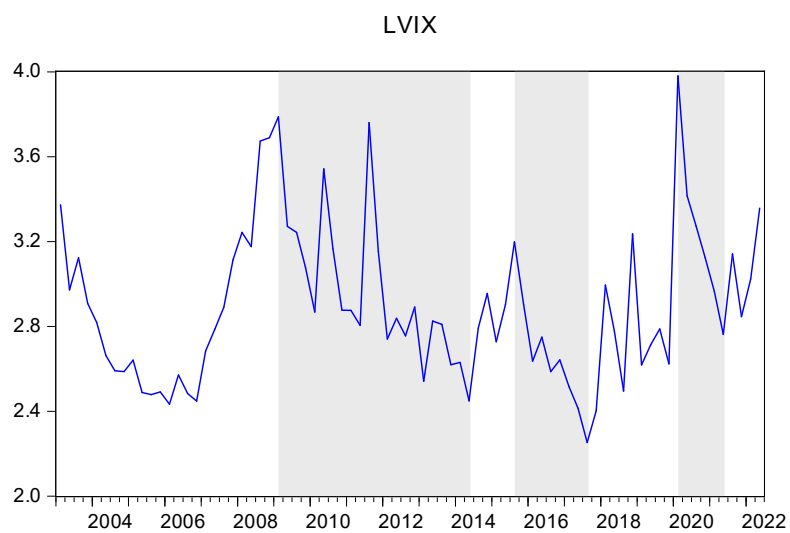
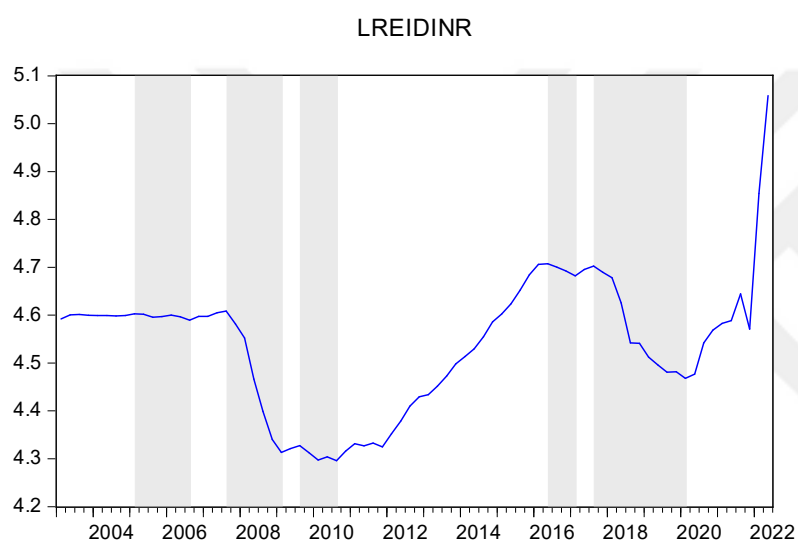
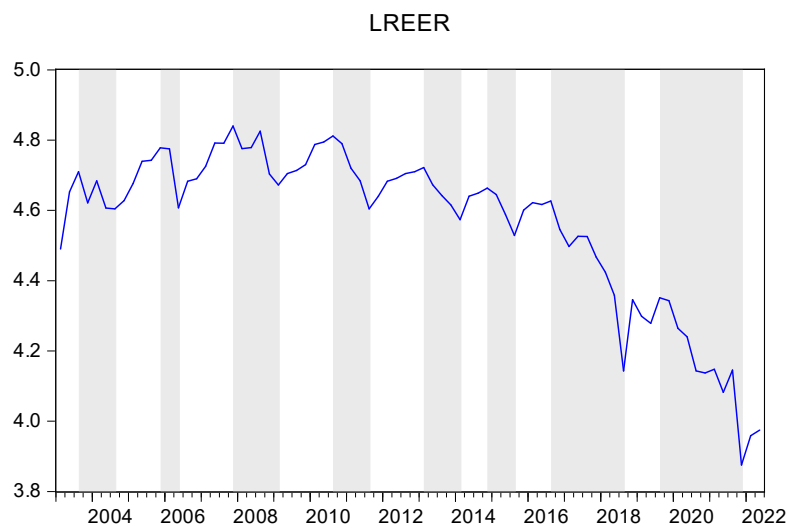


Figure 3.2 (continued) Turning point analysis cycle phases

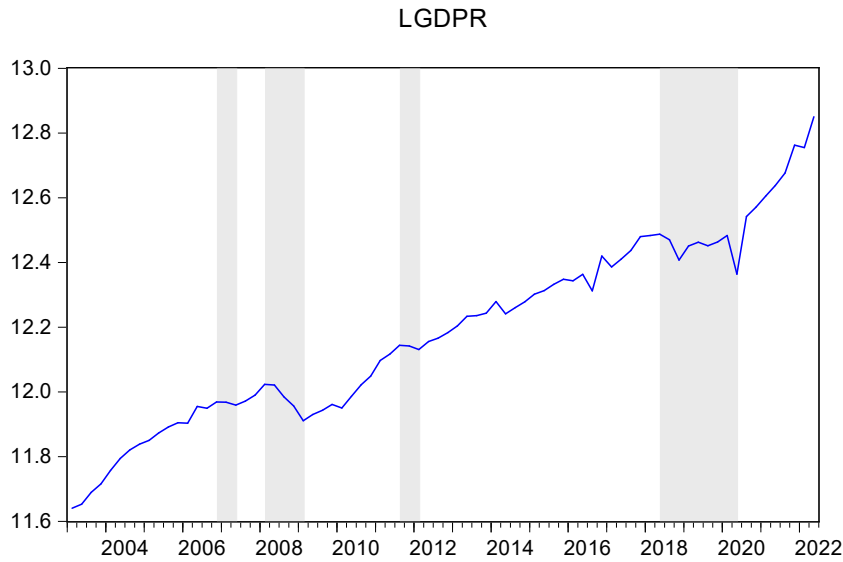


Figure 3.2 (continued) Turning point analysis cycle phases

According to analysis results, a total of three business cycles exists for 2003Q1 - 2022Q2. They represent the 2008 Global Crisis and 2018-2019 Foreign Currency Crisis. 2009Q1 is a trough for GDP, REIDIN, REER and BIST100 cycles while it is a peak for VIX cycle, which is linked to large volatility resulting from increased uncertainty. Throughout this period, external demand weakened, global liquidity shrank, and portfolio outflows was realized at emerging markets. These factors collectively had a negative impact on firms resulting in deteriorating the financial conditions and limiting growth opportunities (Frank and Hesse, 2009; Coulibaly et al., 2013; Dimitriou et al., 2013). According to Çolak et al. (2020), as an emerging economy, Turkey has a similar experience in terms of economic activity, specially concerning real sector firms.

The results obtained from the BBQ algorithm are presented at Table 3.5. The numbers of cycles and the main features (duration, amplitude, cumulative loss and slope) of cyclical phases are given at the table. The peaks and troughs of each series are also given at Appendix 1.

Table 3.5 BBQ algorithm results

	LBIST100	C_GDP	LCREDR	LREER	LREIDINR	LVIX	LGDP
Number of Cycles	7	7	3	7	4	3	3
Duration: (number of quarters)							
expansion	4.86	6.86	14.67	4.86	7.75	9.00	12.67
contraction	3.50	2.63	2.67	4.88	5.80	11.33	4.00
Amplitudes (%):							
expansion	0.38	13.56	0.49	0.15	0.12	1.28	0.22
contraction	-0.32	-4.78	-0.08	-0.24	-0.12	-1.17	-0.06
Cumulation (%)							
expansion							
contraction	-0.81	-12.20	-0.22	-0.66	-0.54	-9.02	-0.15
Slope (%)							
expansion	0.08	1.98	0.03	0.03	0.01	0.14	0.02
contraction	-0.09	-1.82	-0.03	-0.05	-0.02	-0.10	-0.02

According to findings, the numbers of a complete cycle are lower at business cycles (LGDP) and global cycles (VIX) than those of financial cycles, except for credit cycle (LCREDR). The numbers of credit cycle and GDP cycle are equal, and they experienced three complete cycles at the analysis period. The number of cycles indicates frequency of the cycles. It is found financial cycles of Turkey have a higher frequency than the business cycles. On the other hand, the credit cycle and business cycles have similar frequencies. Among financial cycles, LBIST100, C_GDP, LREER cycles have the highest frequency. Thus, Borio's (2014) one of main stylized features which indicates the lower frequency of financial cycles than those of business cycles is not applicable for Turkish economy.

The duration of expansions is higher than the duration of contractions for both business cycle and financial cycles (except for LREER cycle). On the other hand, duration of expansions seem to be lower than those of contractions for global cycles (VIX). The expansion phase of VIX cycle indicates the increasing volatility due to increased uncertainty, while the contraction phase meaning decreasing volatility. Thus, it is found that the global cycle generally experience more prolonged contraction phases (where volatility decreases) than expansion phases (where volatility decreases).

As for business cycle (LGDDP), the duration of the expansion phase is 12,6 quarters, while the duration of the contraction phase is 4 quarters. Binici et al. (2016) also points out this asymmetry between the duration of both phases, and reveals that Turkish economy has

experienced much longer expansion periods after short time contraction periods in the last 30 years.

The average duration of credit cycles (14.7 quarters) are higher than those of business cycles (12.7 quarters) for expansion phase, while duration of business cycles (4 quarters) takes longer than credit cycles (2,7 quarters) for contraction phase. This finding challenges the general view that financial cycles take longer than business cycles (Borio, 2014; Aikman et al., 2015; Claessens et al., 2011; Galati et al., 2016; Schuler et al., 2015; Farrell & Kemp 2017) and supports the opposite views (Hiebert et al., 2014; Gonzalez et al. 2015; Schöler et al. 2020). It is found that financial cycles generally experience a lower duration in Turkey. However, there are some exceptions and it can be different depending on the current phase. The sole financial cycle which has a longer duration is credit cycle as for expansion phase. On the other hand, LREER and LREIDIN cycles experience higher durations than those of LGDP at contraction phase.

LBIST100 and LREER cycles seems to be occurred more frequent but take shorter than other FCs at expansion phase. This is largely due to the high sensitivity of the relevant markets to changes in capital flows (Binici et al., 2016).

The average amplitudes of all financial cycles are higher than those of the business cycles in contraction phase. As for expansion phase, credit, credit to GDP and BIST100 cycles have higher amplitude than those of business cycles. Among financial cycles, credit to GDP has the highest amplitude for both phases.

The financial cycles (except LREIDINR) exhibit a more sloped pattern than business cycles for both expansion and contraction phases. While the frequency of financial cycles higher than those of business cycles, they exhibit a more sloped and rapid cycle than business cycles (Karagöl & Doğan, 2021).

The cumulative loss is considered as another widely used indicator for recessions, combining the duration and amplitude to proxy cost of a recession (Claessens et al., 2012). The cumulative loss is of real GDP (%0.15) is lower than the financial cycles. That is the evidence of the recessions of financial cycles are more costly. Claessens et al. (2011) emphasized that the significant cumulative loss in financial cycles can lead high production loss.

After the turning points of financial cycles, business cycle and global cycle are determined by BBQ algorithm, the co-movements of expansion and contraction phases are measured by the concordance index (CI). The BBQ algorithm also utilizes a binary random variable, denoted as $S(t)$, to represent phases with “1” indicating expansions and “0” indicating contractions. CI is computed by using these binary determined states.

The CI is computed by the way of Harding and Pagan (2002):

$$CI_{xy} = \frac{1}{T} \sum_{t=1}^T [C_t^x \cdot C_t^y + (1 - C_t^x) \cdot (1 - C_t^y)]$$

Where

$C_t^x = \{0, \text{if } x \text{ is in downturn phase at time } t; 1, \text{if } x \text{ is in expansion phase at time } t\}$

$C_t^y = \{0, \text{if } y \text{ is in downturn phase at time } t; 1, \text{if } y \text{ is in expansion phase at time } t\}$

CI determines to what extent the phases of the two cycles coincide with each other and it is on a scale between 0 and 1. It equals to 1 if two cycles are perfectly procyclical. On the other hand, it equals to 0 if the two cycles are countercyclical. The value of 0.5 indicates no systematic relationship between the dynamics of the two cycles as they are independent to each other (Claessens et al., 2011).

The concordance index between business cycle and each financial cycle is given Table 3.6. According to findings, credit cycle (CREDR) has the highest concordance with business cycle as CI takes the value of 0.79. This evidence is compatible with the literature. Binici et al. (2016) calculates CI between real credit cycle and business cycle as 0.85, and claims that real credit cycle have the most simultaneous movement in the growth and contraction periods of the business cycles in Turkey for the period of 1987Q1-2015Q4. Gökalp (2018) also calculates CI between credit cycle and GDP cycle as 0.80 for the period of 2002:Q1 to 2017:Q1. Balaban (2022) finds a high concordance between the credit cycle and industrial production index cycle with a CI value of 0.73.

CI between business cycle and credit gap cycle (CGDP)/ housing cycle (REIDINR) are calculated as 0.73 and 0.71 respectively. CI between the business cycle and equity cycle

(BIST100) is calculated as 0.67. However, CI between business cycle and REER cycle is found 0.5, which indicates no systematic relationship between two cycles.

Table 3.6 Concordance index (Level)

	GDPR	VIX
BIST100	0.67	0.32
CGDP	0.73	0.44
CREDR	0.79	0.35
REER	0.50	0.46
REIDINR	0.71	0.31
VIX	0.27	-

*CI is calculated with the binary states of BBQ algorithm results.

The CI between business cycle and global cycle (VIX) is also computed. CI is found as 0.27 indicating a weak countercyclical relationship between the business and the global cycle. That's because it is found that the global cycles generally exhibit longer periods of contraction in volatility rather than expansions in volatility. The CI between global cycle and each financial cycle is also computed, and their CIs are all found lower than 0.5 indicating a weak countercyclical relationship.

Since there may be a lagged relationship between financial and business cycles, considering only simultaneous synchronization may result in underestimating the fit. (Binici et al. 2016). Therefore, the synchronization between the lagged values of financial cycles and business cycles (level) is calculated. CI between the business cycles and lagged phases of financial cycles/ global cycle are given at Table 3.7.

Table 3.7 Concordance index (Lagged values)

	GDPR								
Quarters	4	3	2	1	0	-1	-2	-3	-4
BIST100	0.57	0.55	0.53	0.58	0.67	0.71	0.71	0.68	0.61
CGDP	0.64	0.67	0.67	0.70	0.73	0.70	0.67	0.64	0.62
CREDR	0.70	0.76	0.79	0.82	0.79	0.78	0.79	0.79	0.76
REER	0.51	0.48	0.46	0.47	0.50	0.52	0.51	0.52	0.55
REIDINR	0.58	0.61	0.62	0.65	0.71	0.73	0.75	0.75	0.69
VIX	0.50	0.44	0.38	0.32	0.27	0.23	0.22	0.21	0.26

* The lagged concordance indices are computed by using the lagged financial states, lagged VIX states besides the level states of GDPR. Negative lags indicate previous quarters.

CI between business and credit cycle is very high (greater than 0.70) for all lagged quarters of credit cycles. CI between business cycle and equity cycle (BIST100) gets higher at BIST100 (-1), BIST100 (-2) and BIST (-3) quarters, which means BIST100 turning points tend to act as pioneers to business cycle turning points. This finding is compatible with the findings of Binici et al. (2016) and Balaban (2022). Similarly, housing cycle (REIDINR) gets higher values REIDINR (-1), REIDINR (-2) and REIDINR (-3) quarters, thus REIDINR cycle tend to act as pioneers to business cycle. However, CI between business cycle and lagged REER cycles still gets very low values, which means no systematic relationship in the dynamics of these cycles. CI between business cycle and global cycle (VIX) gets lower at VIX (-1), VIX (-2) and VIX (-3) quarters, meaning that global volatility cycle tend to act as pioneers to business cycle turning points in a countercyclical pattern.

3.3.2. Trend Based Method

The financial cycle is determined by frequency based filters at trend based methods. The time series data is decomposed its trend and cycle components by this method. The trend is subtracted from the data and the cycles are also identified so (Hodrick&Prescott, 1997). Among various kinds of benchmark methods, HP Filter is commonly preferred due to its inclusion in Basel III legislation and widespread popularity in the literature. Hodrick and Prescott (1997) suggest obtaining the trend by solving the following optimization problem:

$$\min_{\{g_t\}_{t=1}^T} \sum_{t=1}^T (y_t - g_t)^2 + \lambda \sum_{t=1}^T (g_{t+1} - 2g_t + g_{t-1})^2$$

The cyclical component (c_t) is the difference between the series (y_t) and trend (g_t), given by $c_t = y_t - g_t$. The model introduces λ (lambda) as the smoothing parameter (Hodrick&Prescott, 1997).

As it was clarified before, the smoothing parameter (λ) is important for HP filtering. Hodrick and Prescott (1997) recommend setting $\lambda=1,600$ for quarterly series in their study for quarterly series. Following Hodrick and Prescott (1997), the long-run financial trends are calculated by HP filter with a smoothing parameter of 1,600. Moreover, 400,000 is also used as (λ), suggested by BIS (Drehmann et al., 2010). A comparison is made between the cycles which are detrended with using various smoothing parameters. Thus, all financial cycle

series and global cycle are detrended by $\lambda = 1,600$ (C1) and $\lambda = 400,000$ (C2) respectively. For each financial variable, two cycles with different λ parameters are computed.

In their study, Başkaya et al. (2011) explored the business cycles of Turkey by applying HP Filter on GDP data from 1987:1 to 2007:3. They examined different smoothing parameters and suggested that optimal smoothing parameter for the Turkish economy is 98. (Başkaya et al., 2011).

Because of the sensitivity of cycles to smooth parameter, the business cycle analysis is made by using $\lambda = 1600$ (C1), $\lambda = 400,000$ (C2) and $\lambda = 98$ (C3) respectively. As for only GDP, three cycles with different λ parameters are computed.

It can be seen that, regardless of λ , the positive gap between the real GDP (LGDPR) and potential GDP (trend) gets its maximum levels before 2008 Global Crisis and 2018-2019 Foreign Currency Crisis. After the crises, the positive out gap turns negative (Figure 3.3).

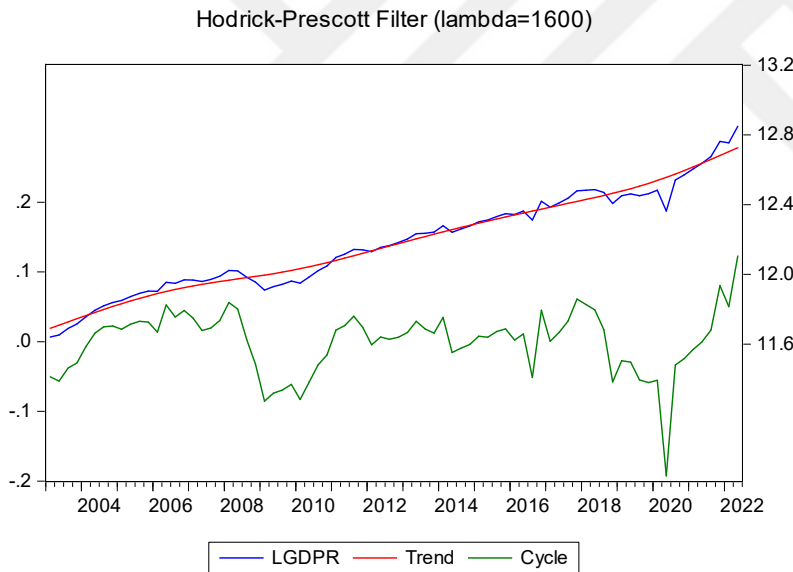
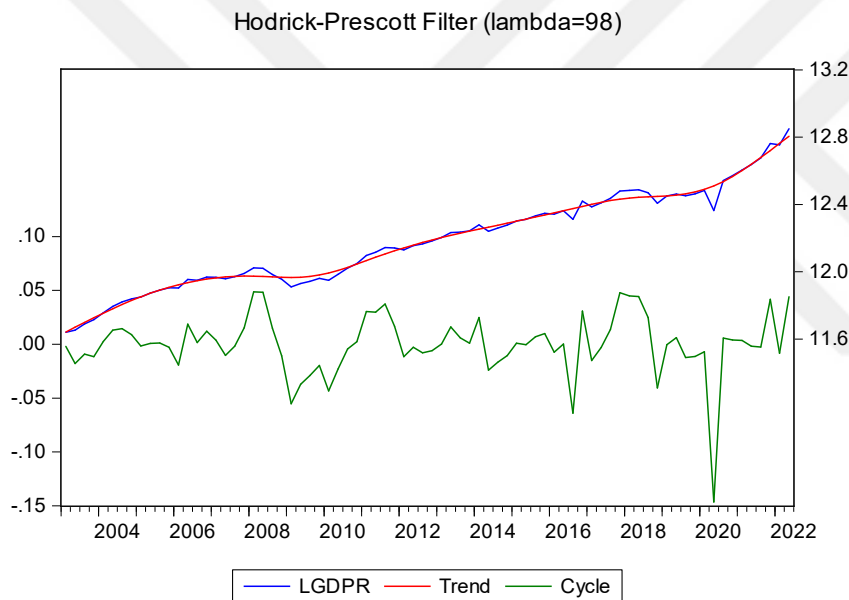
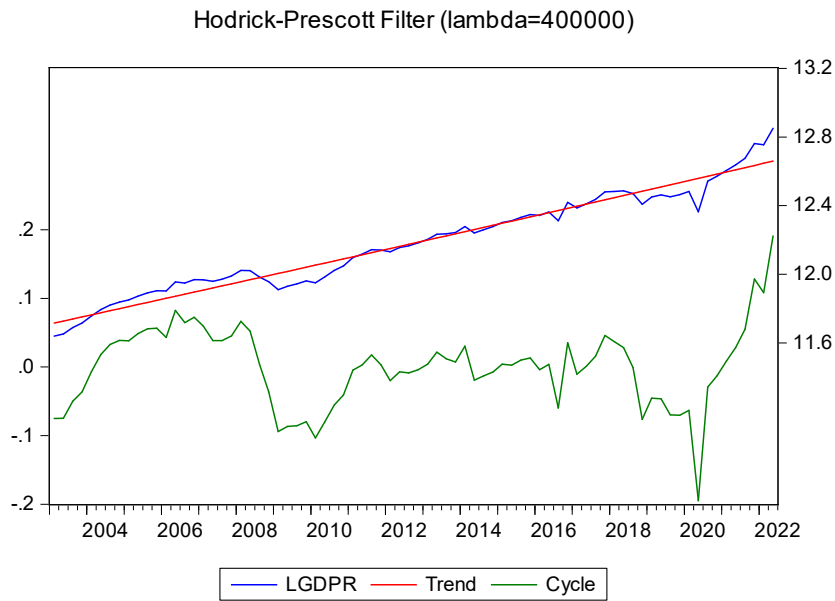


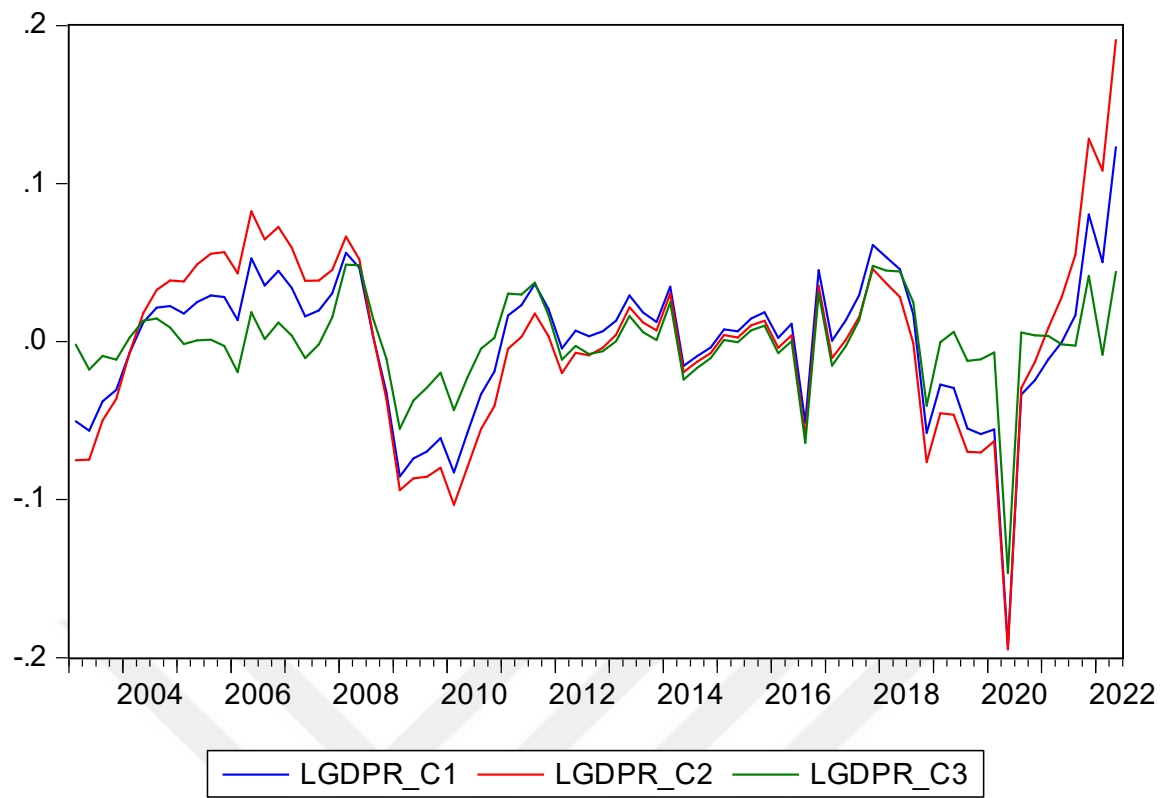
Figure 3.3 HP Filter real GDP trends and cycles



C1: cycle with $\lambda = 1,600$; C2: cycle with $\lambda = 400,000$, C3: cycle with $\lambda = 98$

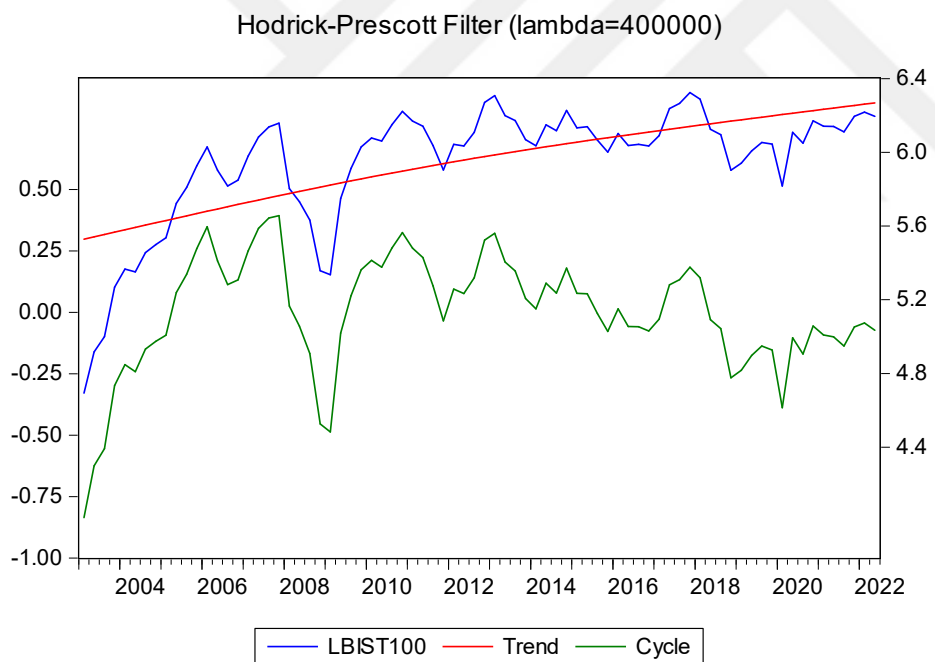
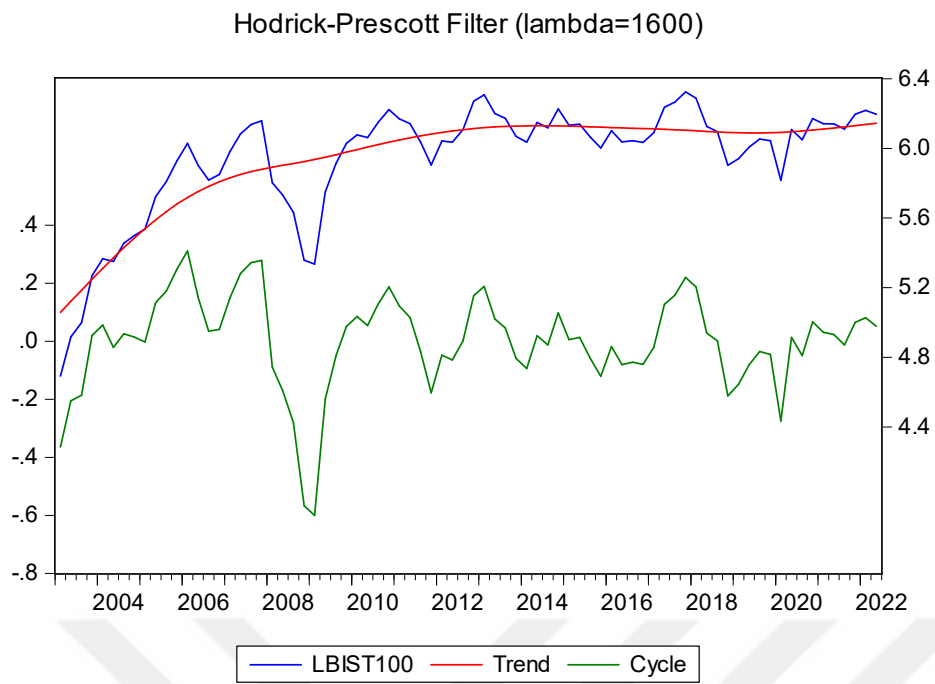
Figure 3.3 (continued) HP Filter real GDP trends and cycles

As it can be seen at Figure 3.4, the choice of λ affects the magnitude of the output gap. As the value of the smoothing parameter increases, the output gap decreases. However, in all cycle series, the negative output gap gets its maximum value at 2020Q2.



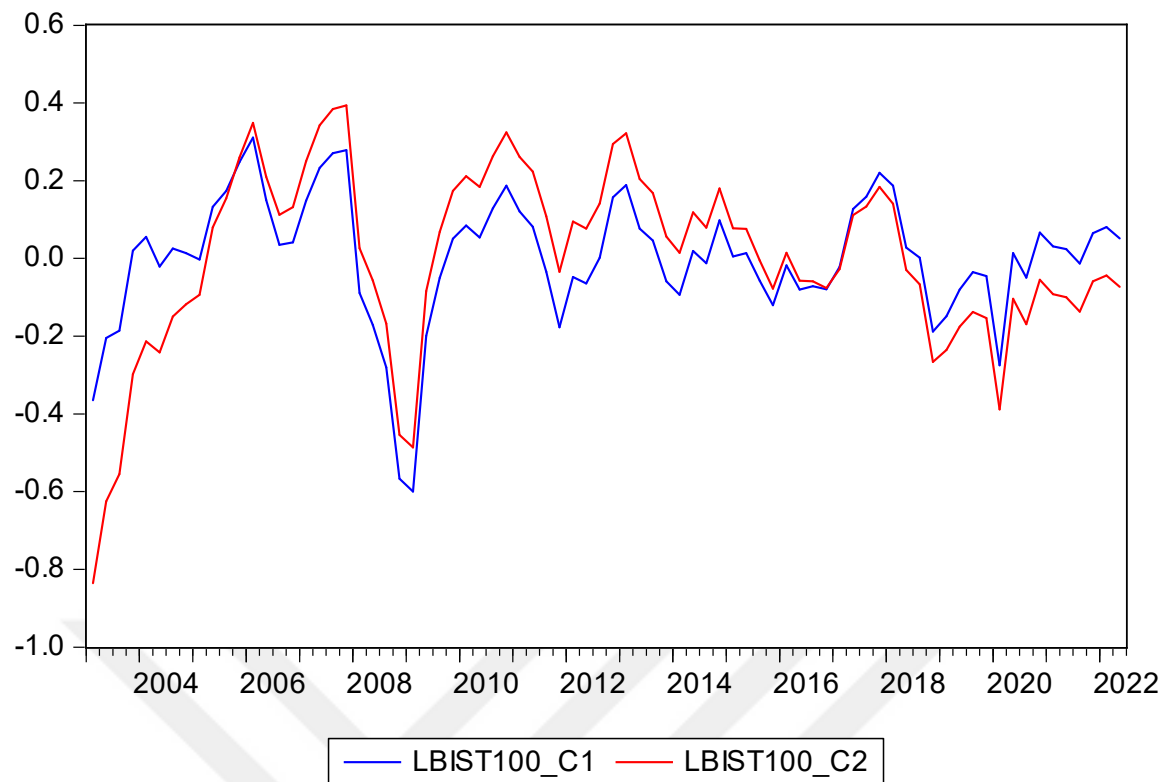
*C1: cycle with $\lambda = 1,600$; C2: cycle with $\lambda = 400,000$, C3: cycle with $\lambda = 98$

Figure 3.4 HP Filter real GDP cycles



*C1: cycle with $\lambda=1,600$; C2: cycle with $\lambda=400,000$

Figure 3.5 HP Filter BIST100 Return Index trends and cycles



*C1: cycle with $\lambda=1,600$; C2: cycle with $\lambda=400,000$

Figure 3.6 HP Filter BIST100 Return Index cycles

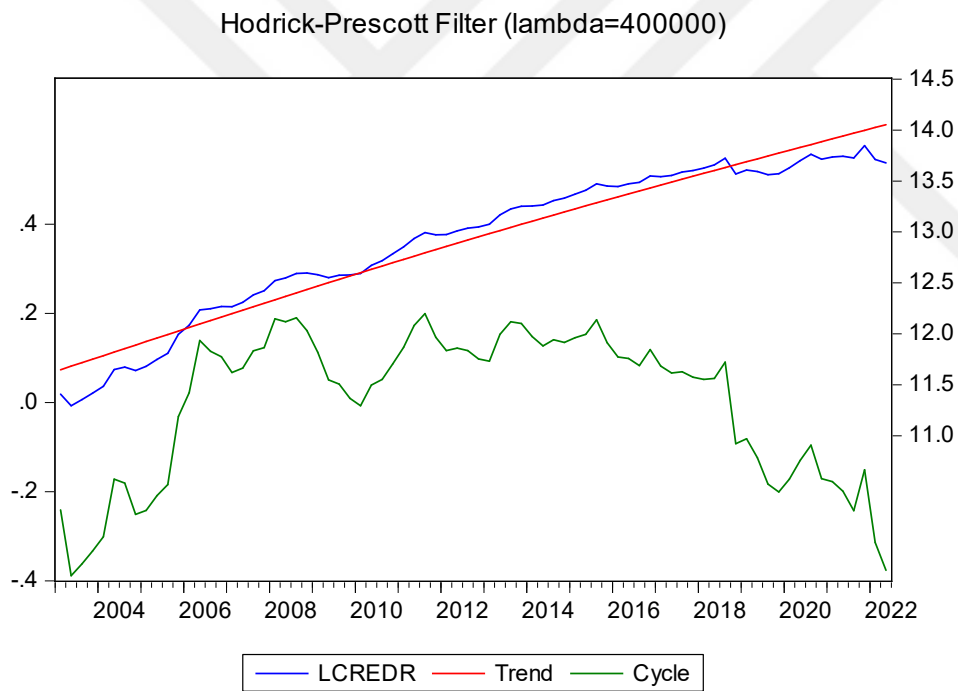
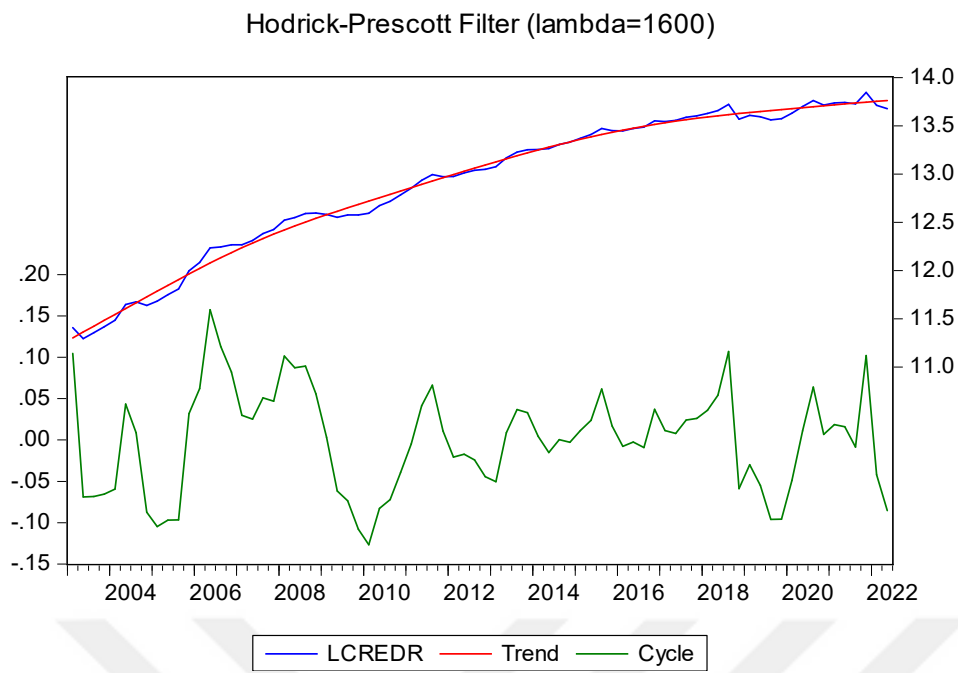
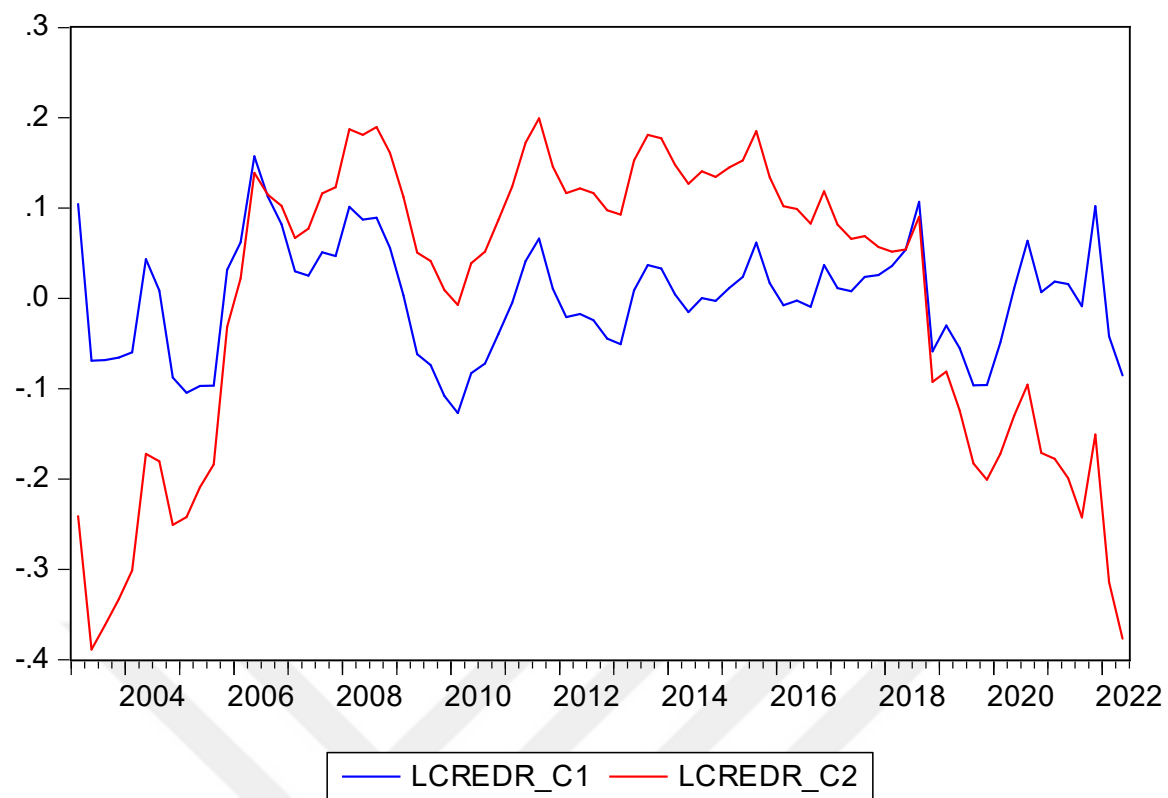
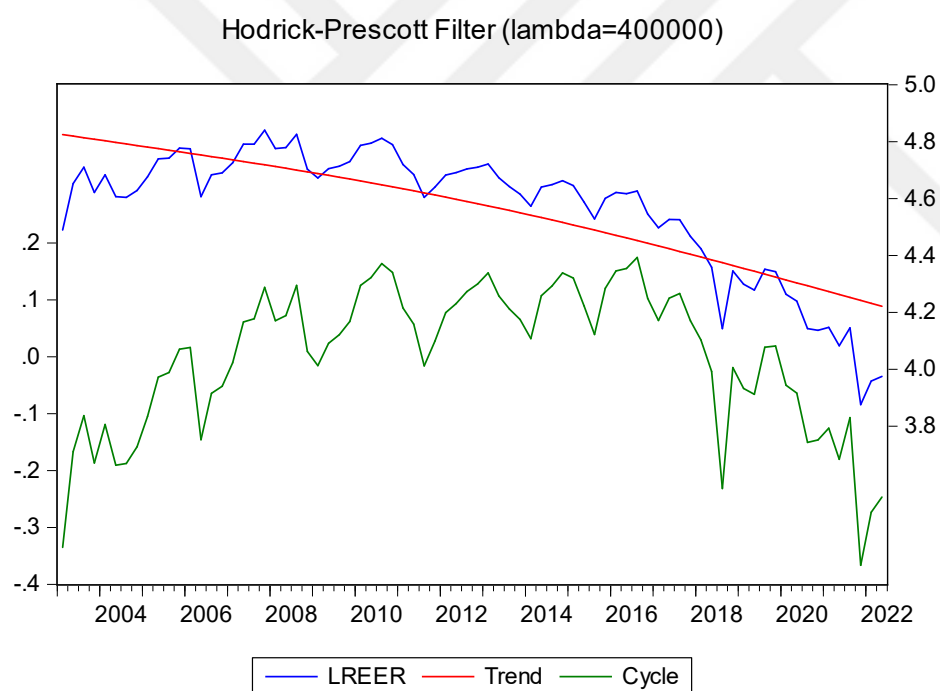
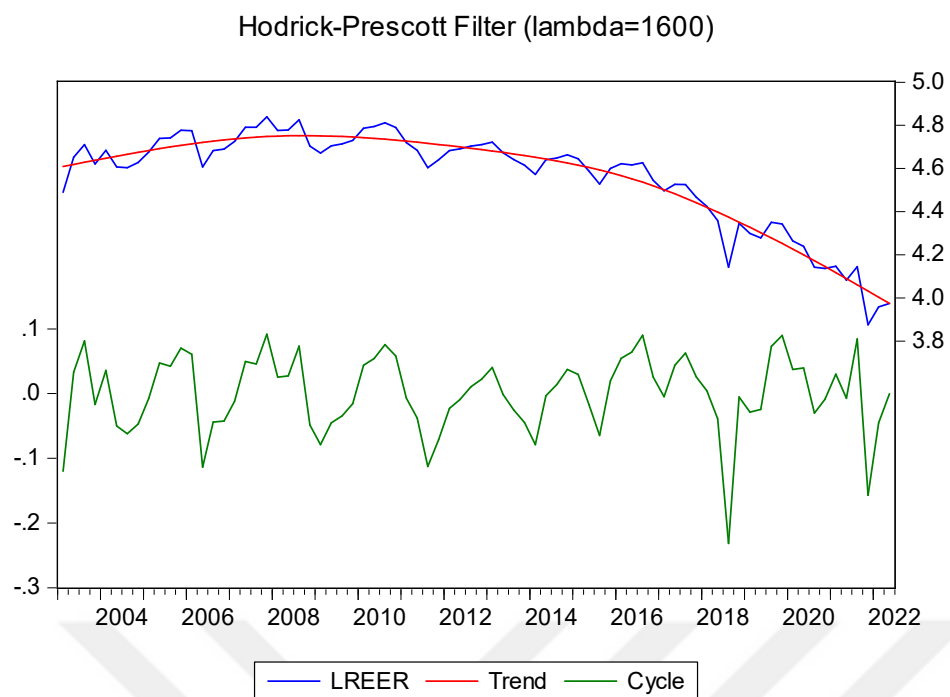


Figure 3.7 HP Filter real credit trends and cycles



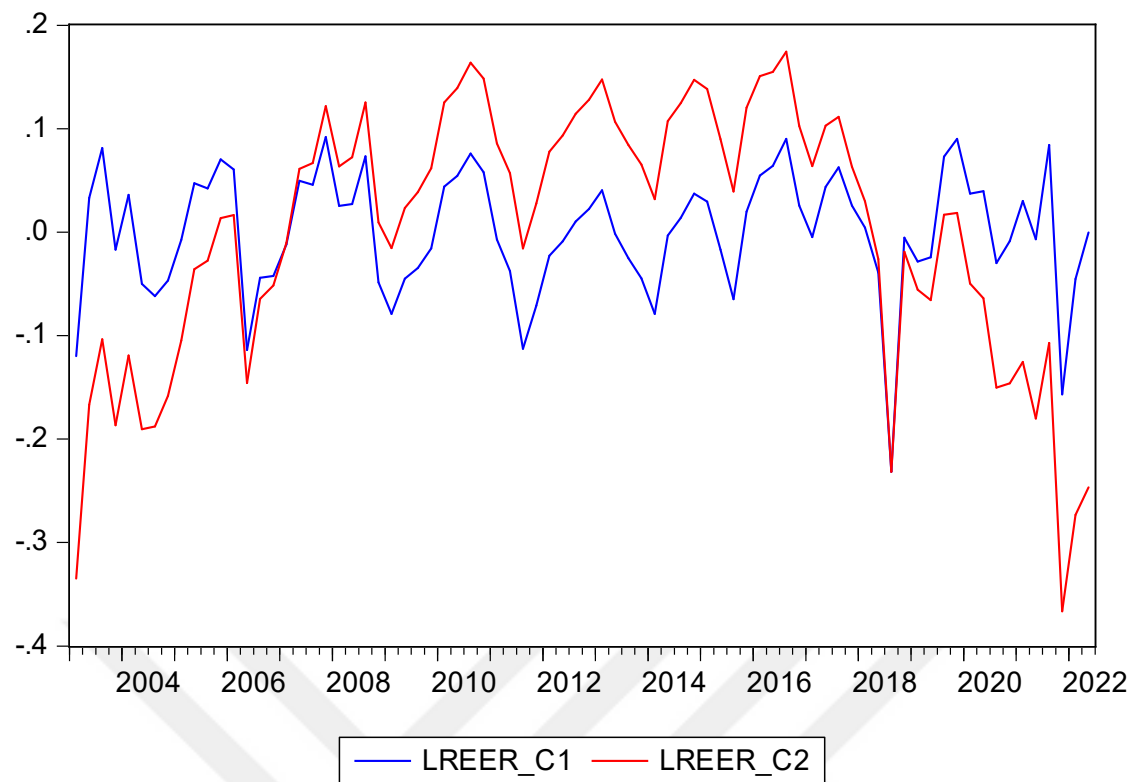
*C1: cycle with $\lambda = 1,600$; C2: cycle with $\lambda = 400,000$

Figure 3.8 HP Filter real credit cycles



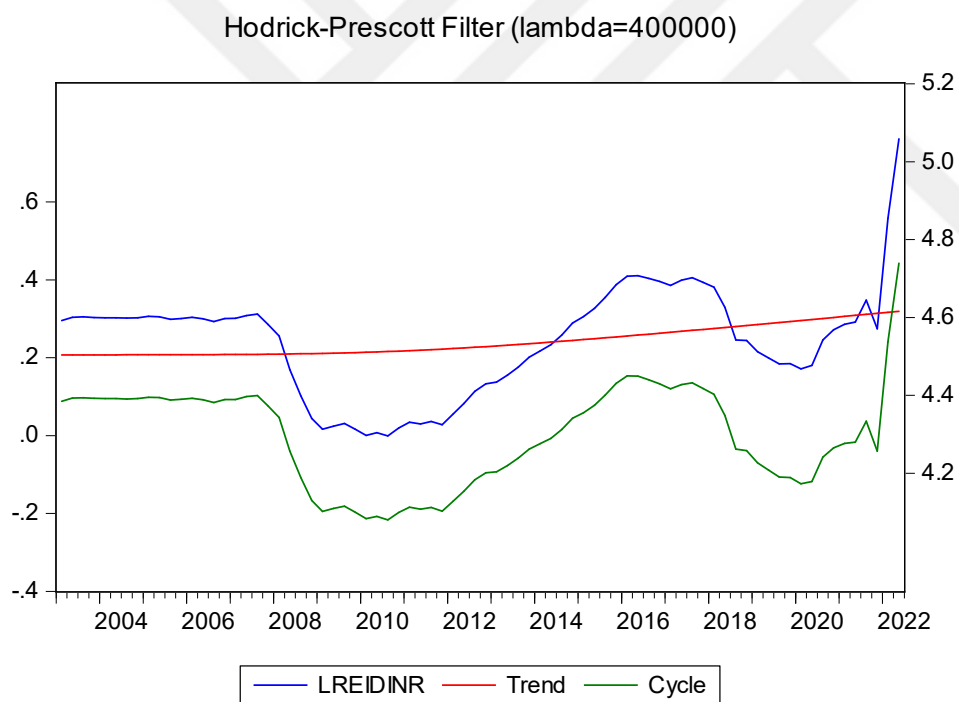
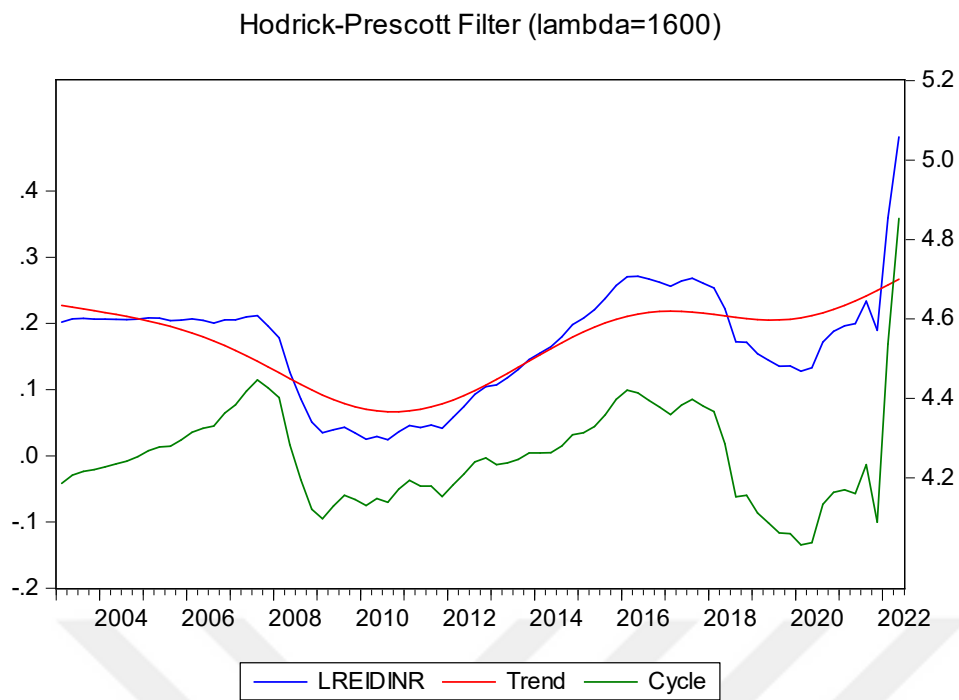
*C1: cycle with $\lambda = 1,600$; C2: cycle with $\lambda = 400,000$

Figure 3.9 HP Filter real effective rate trends and cycles



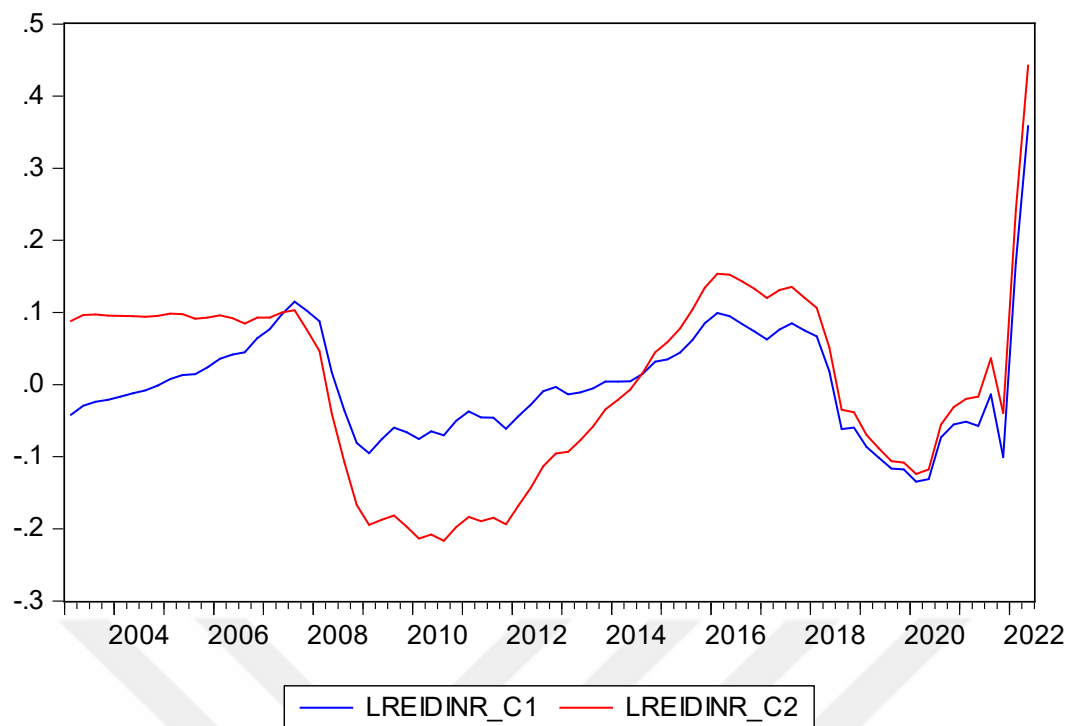
*C1: cycle with $\lambda = 1,600$; C2: cycle with $\lambda = 400,000$

Figure 3.10 HP Filter real effective rate cycles



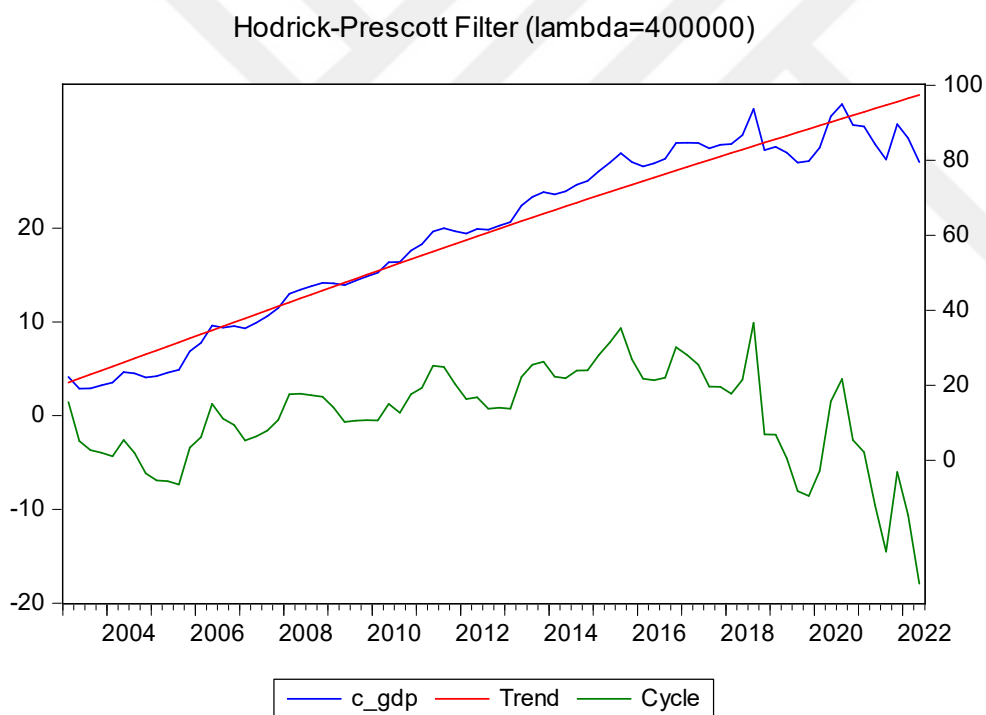
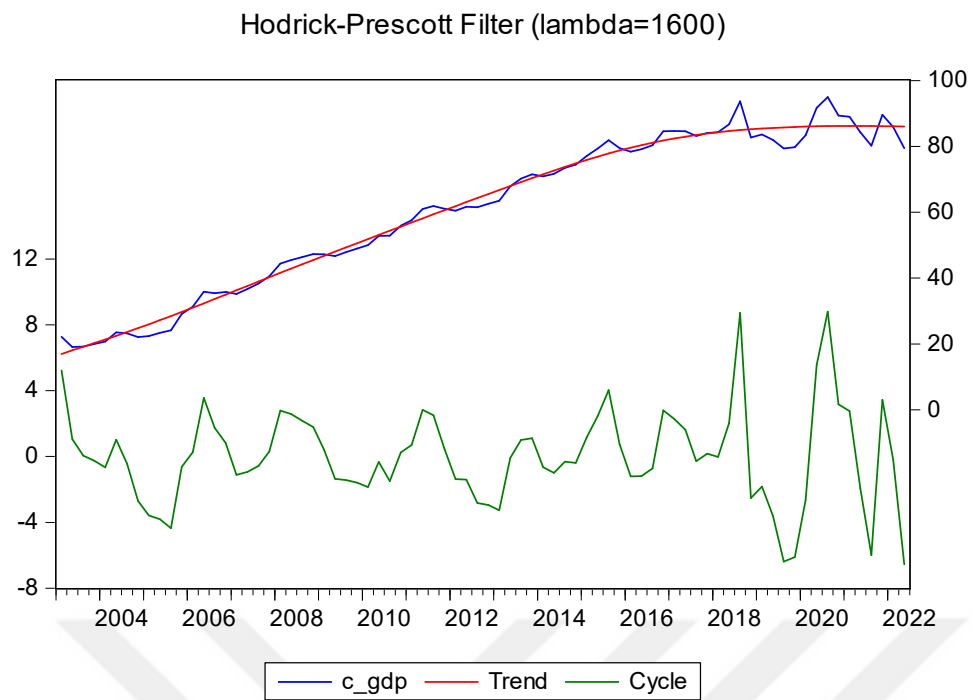
*C1: cycle with $\lambda=1,600$; C2: cycle with $\lambda=400,000$

Figure 3.11 HP Filter REIDIN trends and cycles



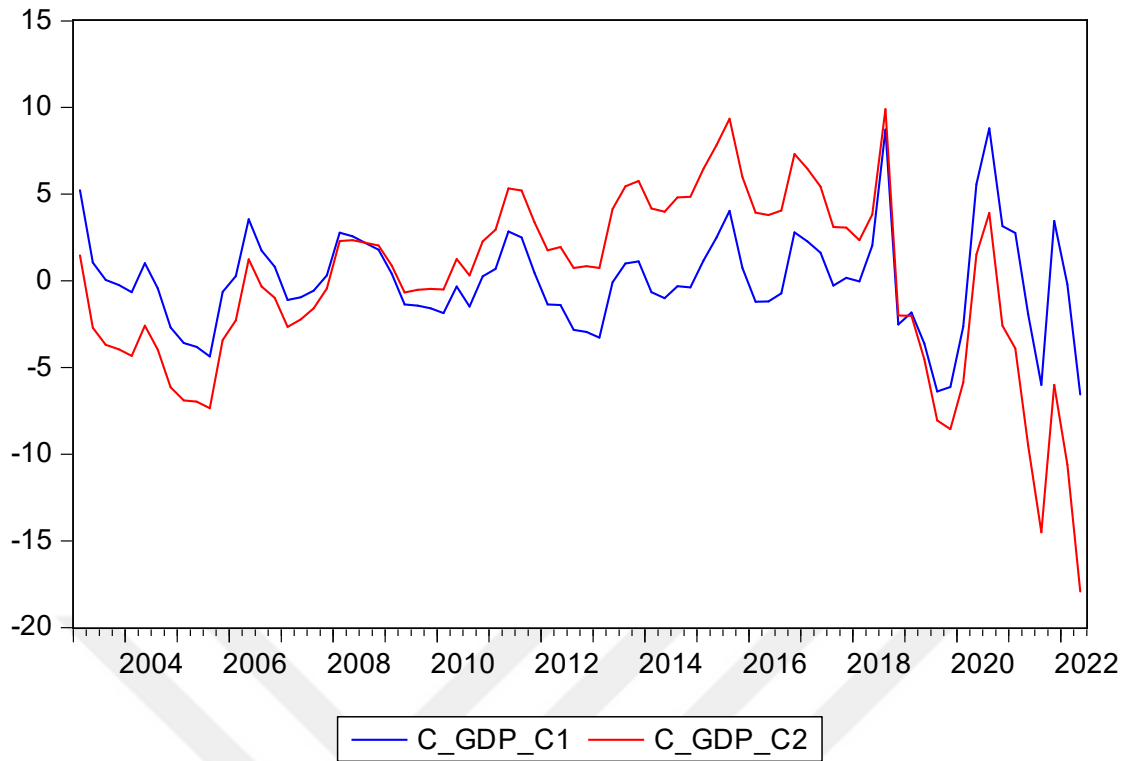
*C1: cycle with $\lambda = 1,600$; C2: cycle with $\lambda = 400,000$

Figure 3.12 HP Filter REIDIN cycles



*C1: cycle with $\lambda=1,600$; C2: cycle with $\lambda=400,000$

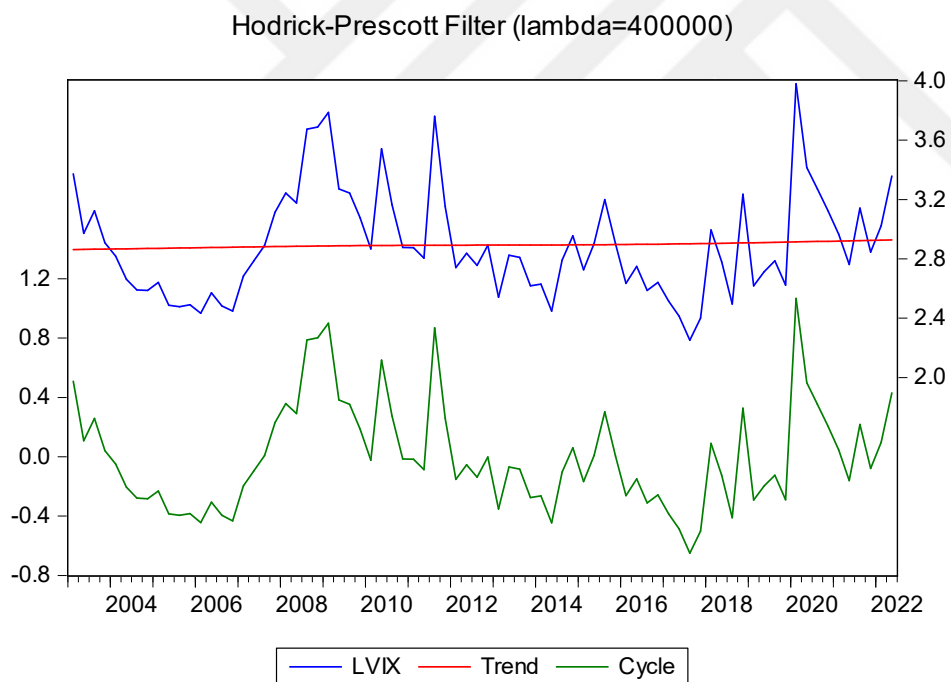
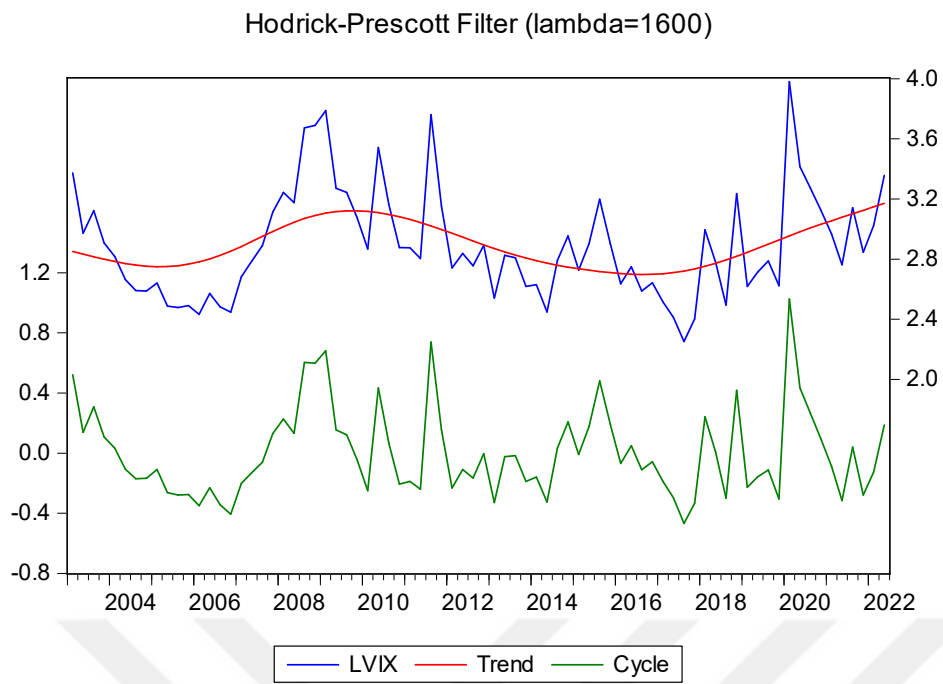
Figure 3.13 Credit to GDP trends and cycles



*C1: cycle with $\lambda = 1,600$; C2: cycle with $\lambda = 400,000$

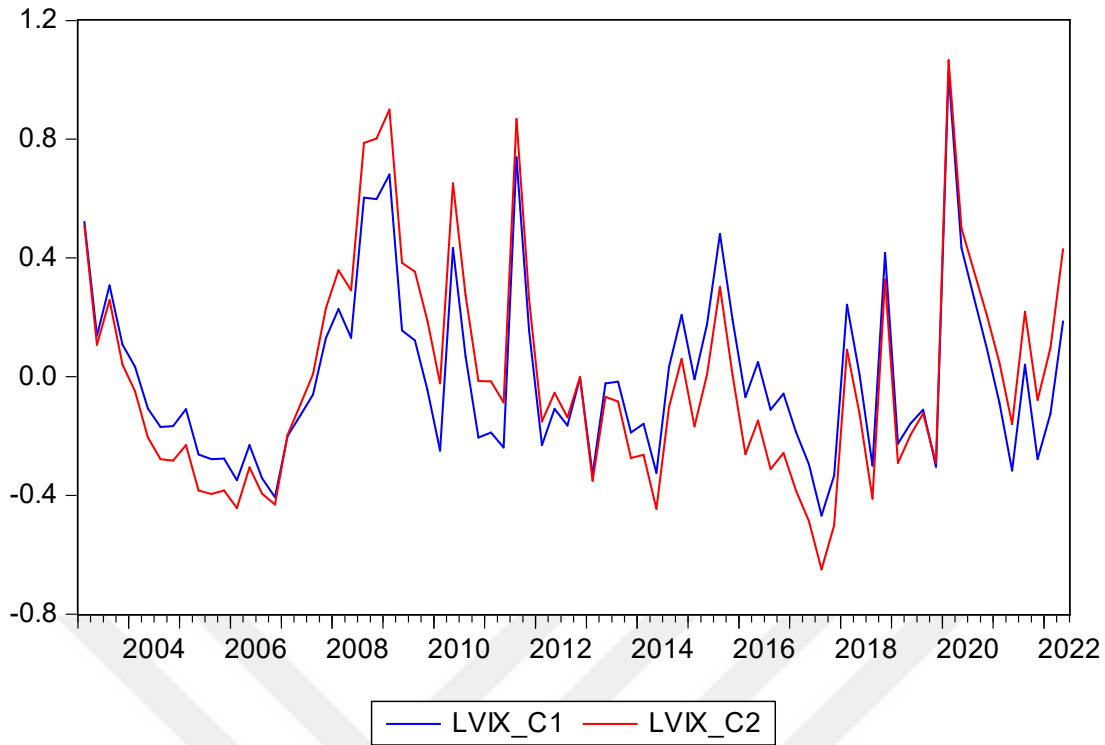
Figure 3.14 Credit to GDP cycles

The credit to GDP cycles are also identified by the way of BIS (2010), as they are detrended by employing a λ of 400,000. CGDP_C2 (the cycle with a lambda of 400,000) is similar to BIS calculations, while the time period of our analysis is shorter. The BIS credit to GDP series (actual, trend and cycle) is given at Appendix 2.



*C1: cycle with $\lambda=1,600$; C2: cycle with $\lambda=400,000$

Figure 3.15 VIX trends and cycles



*C1: cycle with $\lambda = 1,600$; C2: cycle with $\lambda = 400,000$

Figure 3.16 VIX cycles

In order to see the relationship between business and financial cycles identified by Hodrick Prescott Filter, causality tests are applied to the cycles extracted by using the standard smoothing parameter (cycle with $\lambda = 1,600$). Before conducting causality tests, unit root testing is made to examine the stationarity of the variables. As a stationarity test, Augmented Dickey Fuller (ADF) is employed and the relationship between series are tested via Granger causality test developed by Granger (1969).

For causality tests, it is essential that the variables being stationary at the same levels. Thus, the cycles decomposed by HP filter subjected to unit root tests. The stationarity of series (level and first difference) are tested in with constant and with constant-trend models. Then lag length is determined for variables using appropriate criteria by applying VAR model.

The ADF test results are given at Table 3.8. According to results, all the cycle series are stationary at levels except for LREIDIN_C1 in constant model. Similarly, the series are stationary at levels except for LREIDIN_C1 and LGDPR_C1 in constant and trend models.

Thus, the first difference of all series are applied to ADF tests as well and all series are found stationary for both with constant and constant & trend models.

Table 3.8 Augmented Dickey Filter test results (Cycles with $\lambda= 1,600$)

	Level				1st Difference			
	Intercept		Intercept& Trend		Intercept		Intercept& Trend	
Variables	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
LBIST100_C1	-4.1380*	0.0015	-4.1309*	0.0087	-7.8973*	0.0000	-7.8475*	0.0000
LCREDR_C1	-4.1150*	0.0016	-4.0934*	0.0097	-9.4905*	0.0000	-9.4308*	0.0000
LGDPR_C1	-3.3577**	0.0156	-3.31570	0.0714	-11.9452*	0.0001	-11.8770*	0.0001
LREER_C1	-6.8712*	0.0000	-6.8232*	0.0000	-6.8989*	0.0000	-6.8565*	0.0000
LREIDIN_C1	-1.4982	0.5292	-1.2755	0.8864	-5.1544*	0.0000	-5.2744*	0.0002
C_GDP_C1	-5.9556*	0.0000	-5.9219*	0.0000	-7.1090*	0.0000	-7.0619*	0.0000
LVIX_C1	-5.9350*	0.0000	-5.8960*	0.0000	-8.9334*	0.0000	-8.8864*	0.0000

*According to Schwarz Information Criteria (SIC),** represent stationary at 1% and 5% significance levels respectively.

In order to determine lag length criteria for Granger Causality tests, VAR model is computed and it is determined as 6 lags according to AIC and FPE criterias (Table 3.9).¹²

Table 3.9 VAR lag length (Cycles with $\lambda= 1,600$)

Endogenous variables: D(LGDPR_C1) D(LBIST100_C1) D(C_GDP_C1)
D(LCREDR_C1) D(LREER_C1) D(LREIDINR_C1) D(LVIX_C1)
Exogenous variables: C

Lag	LogL	LR	FPE	AIC	SC	HQ
0	416.8019	NA	2.29e-14	-11.54371	-11.32063*	-11.455
1	494.5849	138.0375	1.02e-14	-12.3545	-10.56986	-11.64481*
2	540.9463	73.13351	1.15e-14	-12.28018	-8.933962	-10.94949
3	602.8374	85.42711*	8.83e-15	-12.64331	-7.735523	-10.69164
4	657.4016	64.55482	9.28e-15	-12.80005	-6.330693	-10.22739
5	719.6157	61.33783	9.25e-15	-13.17227	-5.141353	-9.97863
6	797.1071	61.12000	7.75e-15*	-13.97485*	-4.382361	-10.16022

*indicates lag order selected by the criterion

¹² FPE refers to final prediction error criteria while AIC refers to Akaike information criteria.

According to the results of Granger causality analysis of the first differences of cycles with $\lambda=1,600$, financial cycles and global cycle do not represent Granger-cause business cycles. Similarly, business cycles do not Granger-cause of financial cycles or global cycle. The results are given at Appendix 3.

Thus, causality tests are applied to the cycles identified by using the BIS proposed parameter (cycles with $\lambda= 400,000$). The ADF results are given at Table 3.10. According to results, LBIST_C2, LVIX_C2 and LREER_C2 are stationary at levels in with constant models, while LBIST_C2 and LVIX_C2 are stationary in with constant & trend models. Thus, the first difference of all series are applied to ADF tests as well and all series are found stationary for both with constant and constant & trend models.

Table 3.10 Augmented Dickey Filter test results (Cycles with $\lambda= 400,000$)

Variables	Level				1st Difference			
	Intercept		Intercept& Trend		Intercept		Intercept& Trend	
	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
LBIST100_C2	-3.9968*	0.0024	-3.8676**	0.0182	-7.5281*	0.0000	-7.5904*	0.0000
LCREDR_C2	-0.8971	0.7842	-0.7980	0.9609	-8.3333*	0.0000	-9.2863*	0.0000
LGDPR_C2	-2.1567	0.2237	-2.1009	0.5369	-11.0135*	0.0001	-10.9878*	0.0000
LREER_C2	-2.9544**	0.0439	-2.9092	0.1655	-11.2892*	0.0001	-11.5658*	0.0001
LREIDIN_C2	-0.7486	0.8274	-0.5466	0.9791	-4.4638*	0.0005	-4.7933*	0.0011
C_GDP_C2	-1.3746	0.5905	-1.2847	0.8843	-8.5218*	0.0000	-8.6658*	0.0000
LVIX_C2	-4.4953*	0.0005	-4.4575*	0.0033	-12.2921*	0.0001	-12.2388*	0.0001

*According to Schwarz Information Criteria (SIC), */** represent stationary at 1% and 5% significance levels respectively.

In order to determine lag length criteria for Granger Causality tests, VAR model is computed with the first differences of all series and it is determined as one lag according to FPE and HQ criteria (Table 3.11).¹³

¹³ FPE refers to final prediction error criteria while HQ refers to Hannan-Quinn information criteria.

Table 3.11 VAR lag length (Cycles with $\lambda=400,000$)

Endogenous variables: D(LGDPR_C2) D(LBIST100_C2) D(C_GDP_C2)
D(LCREDR_C2) D(LREER_C2) D(LREIDINR_C2) D(LVIX_C2)
Exogenous variables: C

Lag	LogL	LR	FPE	AIC	SC	HQ
0	394.4267	NA	4.30e-14	-10.91343	-10.69035*	-10.82471
1	476.0629	144.8756	1.72e-14*	-11.83276	-10.04811	-11.12306*
2	517.4246	65.24666	2.22e-14	-11.6176	-8.271378	-10.28691
3	578.9976	84.98803*	1.73e-14	-11.97176	-7.063978	-10.02009
4	619.6713	48.12105	2.69e-14	-11.73722	-5.267868	-9.164564
5	679.2853	58.77435	2.88e-14	-12.03621	-4.005286	-8.842563
6	752.2873	57.57906	2.74e-14	-12.71232*	-3.119831	-8.897691

*indicates lag order selected by the criterion

According to the results of Granger causality analysis of the first differences of cycles with $\lambda=400,000$, financial cycles (LBIST100_C2, LCREDR_C2, LREIDINR_C2) and global cycle (LVIX_C2) Granger-cause business cycles (LGDPR_C2) (Table 3.12). On the other hand, the first differences of C_GDP_C2 and LREER_C2 cycles are found not to be the Granger- cause of business cycles (LGDPR_C2). It is also found that business cycles do not Granger-cause of financial cycles or global cycle (Appendix 4).

Table 3.12 Granger Causality test results (Cycles with $\lambda=400,000$)

Null hypotheses	p-value
C_GDP_C2 is not the Granger cause of LGDP_C2	0.3206
LBIST100_C2 is not the Granger cause of LGDP_C2	0.0432
LCREDR_C2 is not the Granger cause of LGDP_C2	0.0268
LREER_C2 is not the Granger cause of LGDP_C2	0.4700
LREIDINR_C2 is not the Granger cause of LGDP_C2	0.0000
LVIX_C2 is not the Granger cause of LGDP_C2	0.0068

3.3.3. Unobserved Component Model Analysis

The UCM is applied for the detection of financial cycles in US and Euro Area (Galati et al. 2016; Rünstler and Vlekke 2016), Denmark (Grinderslev et al., 2017), South Africa (Farrell & Kemp, 2018) and United Kingdom (Melolinna & Tóth, 2016).

As for Turkey, the UC model has been commonly used in the estimation of the interest rate, inflation, and particularly the output gap. Akdogan et al. (2013) applied the UC model within the decomposition-based model structure in estimating the short-term inflation rate. It was found that the UC model forecasts performed better than baseline random walk model for 1 quarter and 4 quarters horizon. Kayacan Yalçın (2018) examined GDP, unemployment and inflation in terms of its components using UCM methods and statistical theories on which they are based. On the other hand, Güney et al. (2018) utilizes UCM to forecast the credit growth for selected credit segments (commercial, consumer, total)

In this study, univariate model-based approach is applied in order to detect business and financial cycles (credit and credit-to GDP gap) by using UCM. The univariate UCM can be specified by the way of Clark (1987), Harvey and Jaeger (1993). The univariate UCM can be specified as follows (Durbin&Koopman, 2012):

$$y_t = \underbrace{\mu_t}_{\text{trend}} + \underbrace{\gamma_t}_{\text{seasonal}} + \underbrace{c_t}_{\text{cycle}} + \sum_{j=1}^k \underbrace{\beta_j x_{jt}}_{\text{explanatory}} + \underbrace{\varepsilon_t}_{\text{irregular}}$$

All variables are seasonally adjusted via Census X12 method when necessary and converted by logs (except credit to GDP ratio). Thus, the seasonal component is excluded in our models. The additional terms for intervention effects (explanatory regression terms) are included into the models.¹⁴

The **trend component** is a dynamic extension of a regression model that incorporates an intercept and a linear time-trend. The level component is a generalization of the intercept term, allowing it to vary dynamically over time. Similarly, the trend component is a

¹⁴ Intervention variables are selected automatically or manually by the STAMP Programme for each model individually.

generalization of the time-trend enabling the slope to dynamically vary across time ((Durbin&Koopman, 2012).

$$\underbrace{\mu_{t+1}}_{\text{level}} = \mu_t + v_t + \eta_{t+1} \quad \eta_{t+1} \sim N(0, \sigma_\eta^2)$$

$$\underbrace{v_{t+1}}_{\text{trend}} = v_t + \zeta_{t+1} \quad \zeta_{t+1} \sim N(0, \sigma_\zeta^2)$$

The **cycle component** is included to capture long term cyclical effects. It can be expressed as follows (Durbin&Koopman, 2012):

$$c_{t+1} = c_t \cos \lambda_c + c_t^* \sin \lambda_c + \tilde{\omega}_t \quad \tilde{\omega}_t \sim N(0, \sigma_\omega^2)$$

$$c_{t+1}^* = -c_t \sin \lambda_c + c_t^* \cos \lambda_c + \tilde{\omega}_t^* \quad \tilde{\omega}_t^* \sim N(0, \sigma_\omega^2)$$

The parameter λ_c (the frequency of the cycle) is estimated by MLE (maximum likelihood estimation).

The **irregular component** is assumed to be a white noise error term. Its variance is also estimated by MLE.

The **explanatory variables** are added to model by including additional terms (Durbin&Koopman, 2012):

$$\sum_{j=1}^k \beta_j x_{jt}$$

or for intervention effects by including:

$$\delta w_t \quad \text{where} \quad w_t = 0, \quad t < \tau, \\ = 1, \quad t \geq \tau$$

These additional parameters are also estimated by MLE. Re-estimating the local level model with the interventions (explanatory regression terms) creates a model that “level” changes solely as a result of interventions.

Inclusion of the autoregressive regression terms besides the explanatory regression terms allows designing a more powerful model with unobserved autoregressive and explanatory regression effects (Fomby, 2008). Thus, by the inclusion of autoregressive effects, model can be specified as following:

$$y_t = \mu_t + \gamma_t + \psi_t + r_t + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^m \beta_j x_{jt} + \varepsilon_t$$

An UCM is computed for each variable by STAMP Programme. STAMP is a statistical/econometric software system used for structural time series analysis. It use state space methods and Kalman filtering to perform estimation and signal extraction.

In state space models, there are some basic conditions to be provided: The residuals exhibit normal distribution. The variance of the residuals remains constant across all values of the independent variable X, which is also referred as ‘Homoscedasticity’. There should no autocorrelation between errors (Kayacan Yalçın, 2018).

In model-based analysis relies, diagnostic statistics play a crucial role in assessing the accuracy and reliability of the model. The diagnostic statistics employed and provided by the STAMP in our models are as follows:

- **Normality (N):** Normality of the residuals is checked by Jarque and Bera (1980) test statistic. It is the sum of the squares for the sample standardized third and fourth moments. It is also known as the Bowman–Shenton test in statistics (Bowman and Shenton, 1975). It is widely used in econometrics to test normality (Kim, 2016). JB test statistic is given in all models and compared to χ^2 distribution table with 2 degrees of freedom. This comparison helps determine whether the JB statistic falls within the critical region, indicating normality.
- **H (h):** The assessment of heteroscedasticity is made by H (h) test, which serves as measure of heteroscedasticity and it refers to Goldfeld and Quandt (1965) test statistics. It is then compared to $F_{h,h}$ table, considering with (h,h) degrees of freedom in order to evaluate

$$H(h) = (\sum_{t=h}^n e_t^2) / (\sum_{t=1}^{h+1} e_t^2)$$

- **Q (q, q-p):** The autocorrelation is checked by Box-Ljung (1978) statistic, which is calculated based on the first q autocorrelations. The Box-Ljung test statistics are compared to χ^2 distribution table considering (p,q) degrees of freedom.

$$c_j = (1/nm_2)(\sum_{t=j+1}^n (e_t - m_1)(e_{t-j} - m_1))$$

$$Q(p) = n(n+2)(\sum_{j=1}^p c_j^2 / n - j)$$

Business cycle and financial cycles are extracted by univariate UCM. Following the output gap literature, the univariate (LGDP) UCM model is computed by Kalman Filter to capture business cycle.

In the business cycle and output gap literature, estimations are made by expressing a stochastic trend component of GDP with a stationary cyclical component following the AR(2) process (Clark, 1987; Kayacan Yalçın, 2018; Kayacan Yalçın, Üçdogruk Birecikli, 2017). Following the literature, the business cycle model is defined as follows:

Model 1: LGDP = Trend + Irregular + Cycle 1 + AR(2) + Interventions

The model relies on the decomposition of the LGDPR into long-term trends (encompassing level and trend) and cycles represented by cycle 1 and AR(2). The irregular component, in this context, is expected to follow a normal distribution with mean zero and variance $\sigma^2_{\varepsilon,i}$, and serially independent, meaning that there is no correlation between successive values of irregular components. The unknown statistic parameters are estimated by the method of maximum likelihood. In order to perform numerical maximization, Kalman filter is utilized to compute the loglikelihood function. Two interventions are included to model 1: 2016Q3 and 2020Q2.¹⁵

The plots of Model 1 are given at Figure 3.17. It is seen that real GDP (LGDPR) and the potential GDP (level+interventions) moving together. The positive gap between the real GDP and potential GDP gets its maximum levels before 2008 Global Crisis and 2018-2019 Foreign Currency Crisis. It is possible to explain the output gap surpluses with the economic crises experienced in these periods (Kayacan Yalçın, 2018). With the effect of the crises, the potential output exceeds the real output, resulting in negative output gap in 2009 and 2019.

¹⁵ STAMP automatically detects possible points of intervention in series, and local level of model re-estimated accordingly. Thus, the interventions affect the “level”.

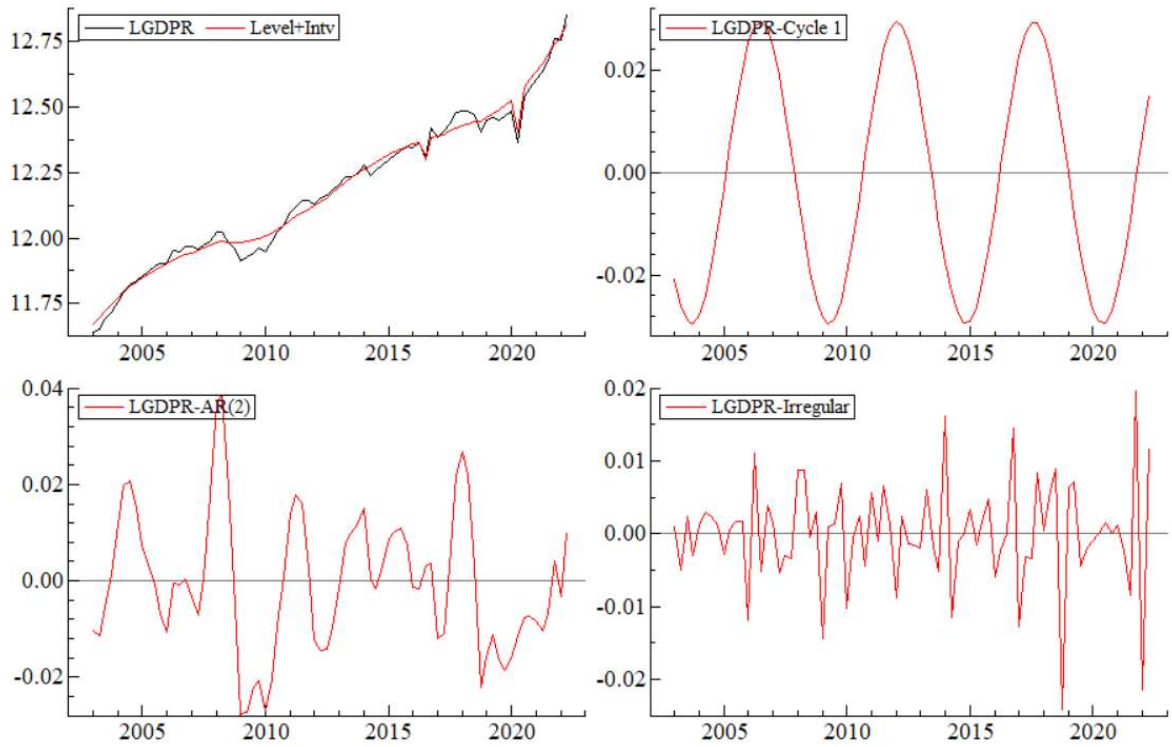


Figure 3.17 LGDPR- UCM spots (Model 1)

The residuals for diagnostic checking and model results are given at Table 3.13. P indicates the number of parameters. Normality (N), heterodoxicity (H(24)), Box-Ljung statistic (Q(15,7)) are the diagnostic statistics. The q ratio is the signal-to-noise ratio term which shows relative variance of the parameters.

Table 3.13 LGDPR UCM results (Model 1)**Summary statistics**

p	8.0000	
N	2.3036	[5.991]*
H(24)	1.9736	[1.980]*
DW	1.9803	
r(1)	-0.029561	
q	15.000	
r(q)	-0.10668	
Q(15,7)	11.047	[15.507]*

Variances of disturbances

	Value	(q-ratio)
Level	4.3670	(0.06135)
Slope	1.8885	(0.02653)
Cycle	4.50577e-009	(6.330e-006)
AR(2)	0.0007	(1.000)
Irregular	0.0001	(0.1731)

Cycle parameters:

Variance	0.00058
Period	22.25790
Period in years	5.56447
Frequency	0.28229
Damping factor	1.00000
Order	1.00000
AR(1) coefficient	1.15799
AR(2) coefficient	-0.33524

State vector analysis

	Value	Prob
Level	12.81376	[0.00000]*
Slope	0.03754	[0.00012]*
Cycle 1 amplitude	0.02958	[.NaN]

Regression effects

	Coefficient	RMSE	t-value	Prob
Outlier 2016(3)	-0.07611	0.01670	-4.55887	[0.00002]
Outlier 2020(2)	-0.14650	0.01670	-8.77456	[0.00000]

Goodness of Fit

Log-Likelihood	271.386 (-2 LogL = -542.772).
Prediction error variance	0.000574037
std.error (pev)	0.023959
Rd^2	0.6

*Implies significance at the %5 level. RMSE refers to the residual mean square error.

The model 1 meets the diagnostic conditions (normality, heteroscedasticity and autocorrelation) at the significance level at 0.05. The variation of the irregular component in the model is very close to zero, and that indicates the model variation can be explained with trend component (level+slope) and cycle component. The q ratio of the components indicate

that the model contain trend (level and slope), cycle and AR(2) process. The estimated business cycle period (including AR(2)) is found 22.2 quarters (5.6 years). It is similar to Kayacan Yalçın's (2018) finding as she estimates cycle period for GDP and unemployment as approximately 6 years for the period of 1998:Q1-2016:Q2.

The model 1 forecasting spots for the next 8 quarters horizon is also given at Figure 3.18. As the potential output (level+ inventions) estimated by UCM and the real GDP move together and catch similar breaking points, the forecasts of the model can be used in forward-looking estimations and economic decision-making processes.

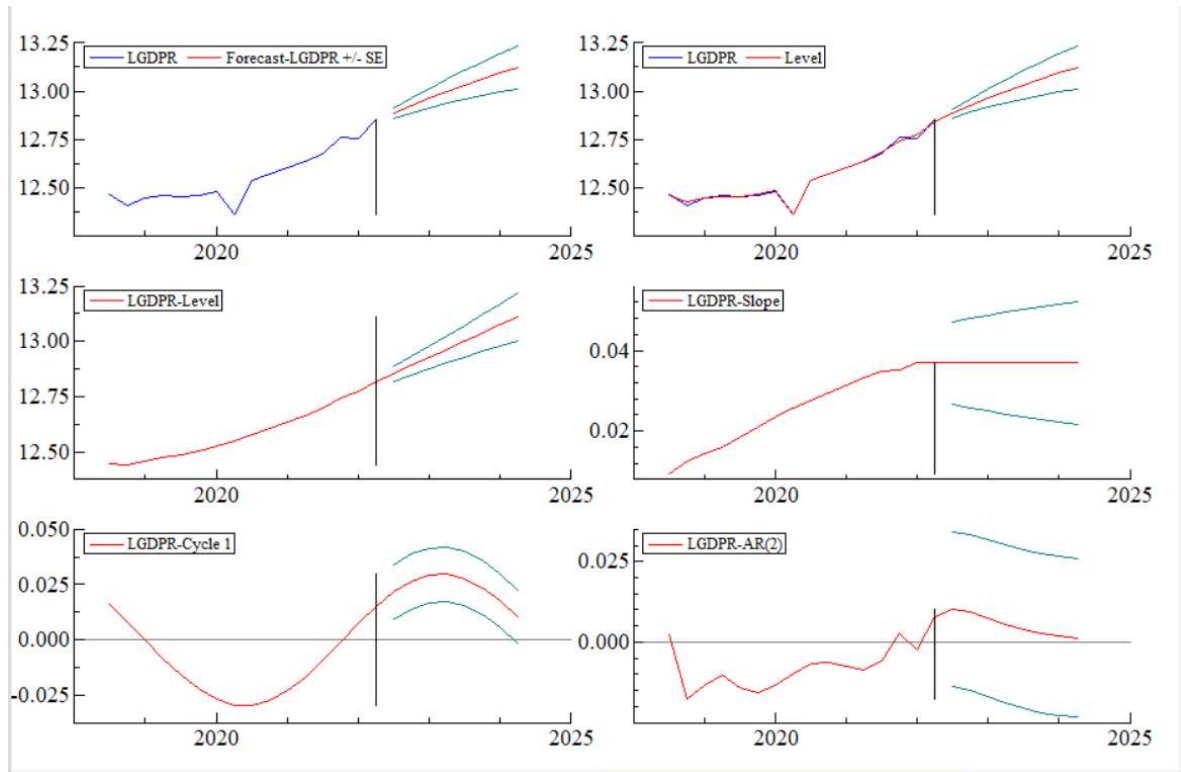


Figure 3.18 LGDPR- UCM forecasts (Model 1)

As for financial cycle, credit cycle and credit to GDP cycles are computed by univariate models. The model 2 and Model 3 are the decomposition of the trend and cycles of credit and credit to GDP respectively.

The credit cycle model is specified as follows¹⁶:

Model 2: LCREDR= Trend + Irregular + Cycle 1 + AR(2) + Interventions

¹⁶ Several interventions are selected automatically by STAMP.

The plots of Model 2 (CREDR) are given at Figure 3.19 and the residuals for diagnostic checking and model results are given at Table 3.14.

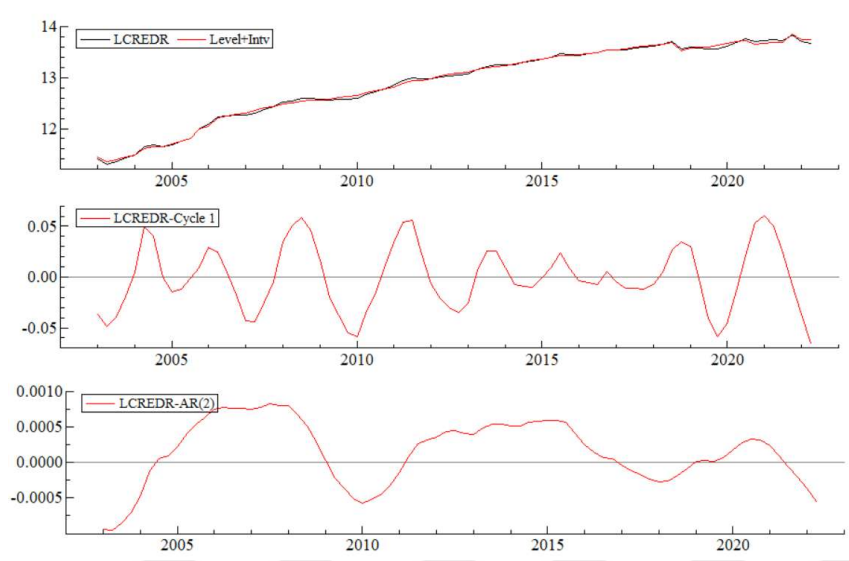


Figure 3.19 CREDR UCM spots (Model 2)

The model 2 meets the diagnostic conditions (normality, heteroscedasticity and autocorrelation) at the significance level at 0.05. The variation of the irregular component is zero, and that indicates the model variation can be explained with trend component (level+ fixed slope trend) and cycle component. The q ratio of the components indicate that the model contains trend (level), cycle and AR(2) process. The estimated average real credit gap period (including AR(2)) is found as 10.5 quarters (2.6 years) and its frequency is 0.60. This finding is similar to Güney et al. (2018) as they find the average credit cycle length as 35 months (2.9 years) for the period of 2007:1-2018:3.

Table 3.14 CREDR UCM results (Model 2)**Summary statistics**

p	8.0000
Normality	0.16218 [5.991]*
H(23)	0.55547 [2.050]*
DW	1.3376
r(1)	0.16366
q	15.000
r(q)	-0.15884
Q(15,7)	15.122 [15.507]*

Variances of disturbances:

	Value (q-ratio)
Level	0.000668740 (1.000)
Slope	0.000000 (0.0000)
Cycle	0.000209441 (0.3132)
AR(2)	3.91452e-005 (0.05854)
Irregular	0.000000 (0.0000)

Cycle other parameters:

Variance	0.00156
Period	10.45319
Period in years	2.61330
Frequency	0.60108
Damping factor	0.93052
Order	1.00000
AR(1) coefficient	1.50822
AR(2) coefficient	-0.56587

State vector analysis at period 2022(2)

	Value Prob
Level	13.91264 [0.00000]
Slope	0.03205 [0.00000]
Cycle 1 amplitude	0.06263 [.NaN]

Goodness of Fit

Log-Likelihood	233.526 (-2 LogL = -467.052)
P.e.v:	0.00103327
std.error (p.e.v)	0.032145
Rd^2	0.68300

*Implies significance at the %5 level

The model 2 forecasting spots for the next 8 quarters horizon is also given at Figure 3.20.

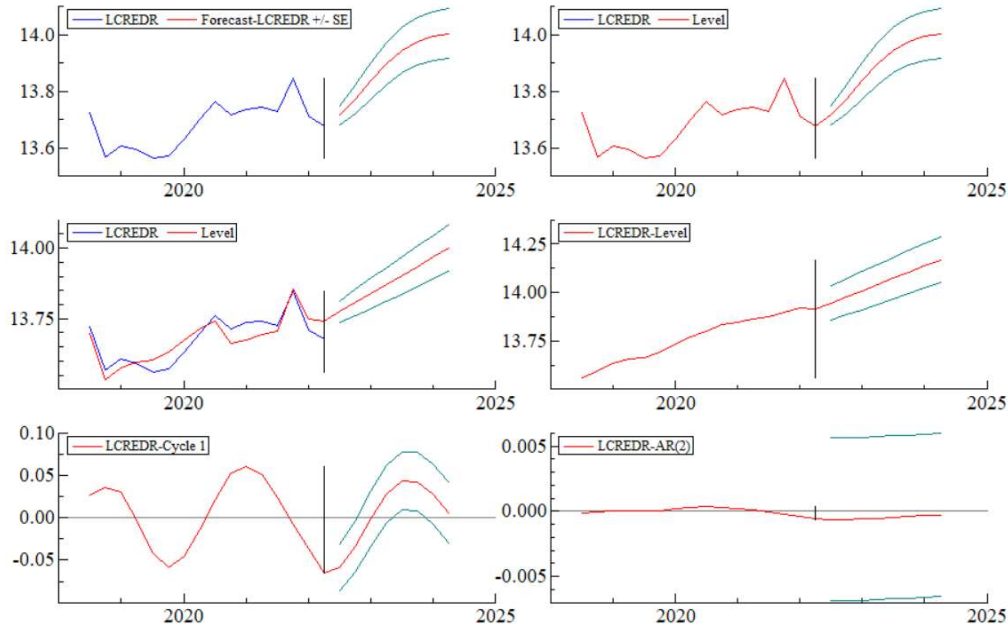


Figure 3.20 CREDR UCM forecasts (Model 2)

The credit to GDP cycle model is specified as follows¹⁷:

Model 3: $C_GDP = \text{Trend} + \text{Irregular} + \text{Cycle 1} + \text{AR}(2) + \text{Interventions}$

The model 3 (C_GDP UCM) meets the diagnostic conditions (normality, heteroscedasticity and autocorrelation) at the significance level at 0.05. The variation of the irregular component in the model is very close to zero, and that indicates the model variation can be explained with trend component (including fixed level+slope) and cycle component. The q ratio of the components indicate that the model contains trend (including fixed level and slope), cycle and AR(2) process. The estimated credit to GDP cycle period (including AR(2)) is found 7 quarters (1.8 years) and its frequency is 0.90.

¹⁷ Several interventions are selected automatically by STAMP.

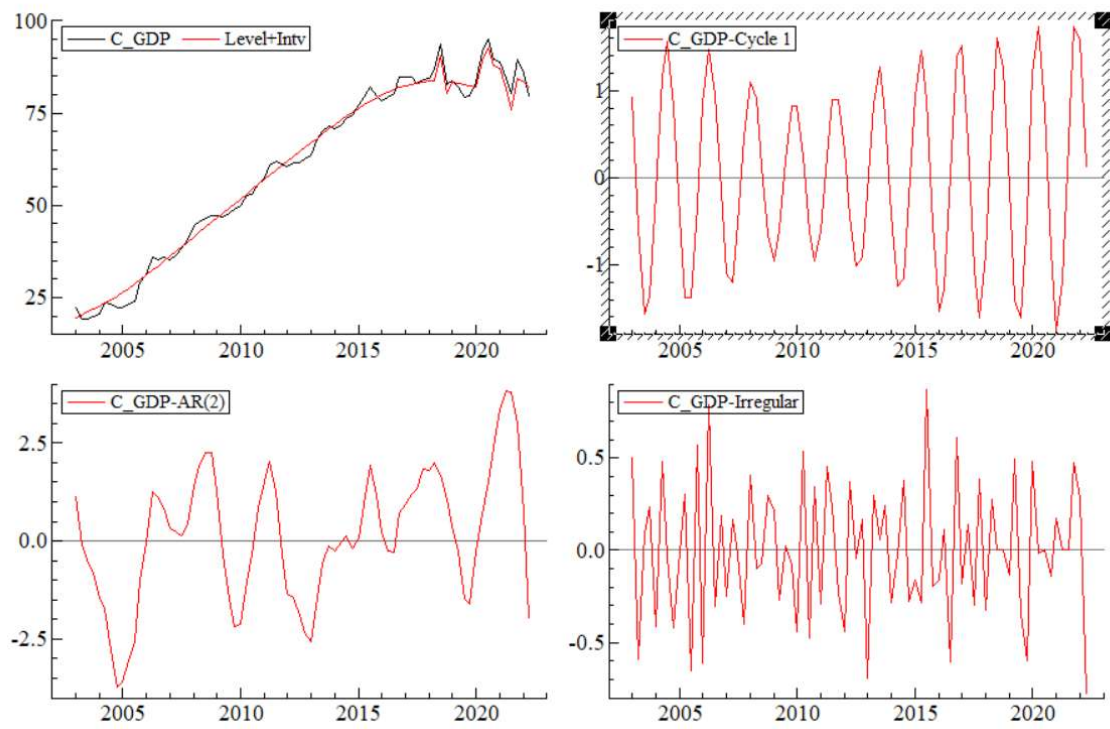


Figure 3.21 C_GDP - UCM spots (Model 3)

Table 3.15 C_GDP UCM results (Model 3)**Summary statistics**

p	8.0000	
Normality	3.5481	[5.991]*
H(23)	1.8452	[2.050]*
DW	1.5963	
r(1)	0.12412	
q	15.000	
r(q)	-0.11330	
Q(15,7)	12.636	[15.507]*

Variances of disturbances:

	Value	(q-ratio)
Level	0.000000	(0.0000)
Slope	0.0244908	(0.06918)
Cycle	0.0416346	(0.1176)
AR(2)	6.26012	(17.68)
Irregular	0.354026	(1.000)

Cycle parameters:

Variance	1.72546
Period	6.96771
Period in years	1.74193
Frequency	0.90176
Damping factor	0.98786
Order	1.00000
AR(1) coefficient	1.33505
AR(2) coefficient	-0.44549

State vector analysis at period 2022(2)

	Value	Prob
Level	74.27134	[0.00000]
Slope	-1.17471	[0.00699]
Cycle 1 amplitude	1.81628	[.NaN]

Goodness of Fit

Log-Likelihood	-40.6746 (-2 LogL = 81.3493).
P.e.v:	2.56984
std.error (p.e.v)	1.6031
Rd^2	0.73173

*Implies significance at the %5 level.

The model 3 forecasting spots for the next 8 quarters horizon is also given at Figure 3.22.

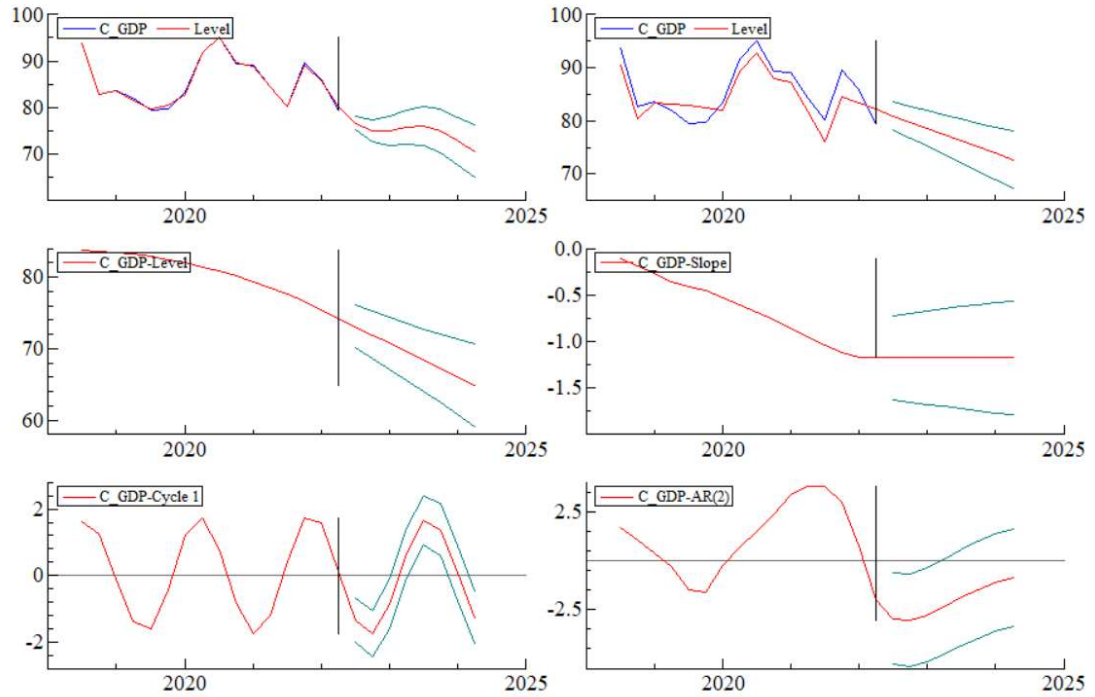


Figure 3.22 C_GDP UCM forecasts (Model 3)

When the average cycle periods and frequencies of the cycles are compared, it is found that the average duration of business cycle has the longest with a value of 22.2 quarters. On the other hand, the duration of the credit cycles and credit to GDP cycles are found as 10.5 quarters and 7 quarters respectively. Moreover, it is found that the business cycles have a lower frequency when compared to financial cycles including credit cycle and credit to GDP cycle.

4. CONCLUSION

After the Global Financial Crisis (GFC), the studies focusing on financial cycles have become popular. Still it is not as popular as business cycle literature, however, business cycles have also been explored with its macrofinancial linkages and interaction with financial cycles.

While the pioneering studies of the financial cycle claims that financial cycles are longer than business cycles (Borio, 2014; Aikman et al., 2015; Claessens et al., 2011; Galati et al., 2016; Schuler et al., 2015; Farrell & Kemp 2017), following studies reveals that the duration and amplitude of the financial cycles may differ across the countries. The studies show that there is a synchronicity between financial cycles and business cycles, and financial cycles lead to business cycles. Thus, the financial cycle has a significant role in macroeconomics and analyzing financial cycles and their macro financial linkages is crucial. However, the financial cycle literature is not extensive as business cycle literature in Turkey.

To contribute the financial cycle literature of Turkey, the financial cycles are analyzed for the period of 2003Q1-2022Q2. The proxies of financial cycles are determined as real credit volume, credit to GDP, real BIST100 return index, real effective exchange rate and REIDIN Residential Property Price Index (adjusted for inflation, TR7, June 2007=100). The residential property prices has been limitedly included to financial cycle literature due to data gap and quality issues so far, thus this dissertation helps to extend the analysis by housing market. Global cycle (proxied by VIX Index) is also taken into account in order to see implications.

Despite ongoing reaches and analysis, currently there is no consensus on a standard definition and method for measuring financial cycles. Additionally, a comprehensive theoretical understanding of the financial cycle remains elusive. The financial cycles are identified by different approaches and various methods borrowed from business cycle literature. Generally financial cycles are determined by not only one method but also a combination of various methods at the literature. Selected three methods are discussed in this thesis.

First, the traditional turning point analysis is applied which is based on a dating algorithm firstly introduced by Bry and Boschan (1971) and extended by Harding and Pagan

(2002). After the turning points of financial cycles and their phases are detected via BBQ algorithm, the characteristics of each phase are identified. Then the characteristics of financial cycle phases are compared with those of business cycles and global cycles. In order to assess synchronization between the cycles, the co-movements of expansion and contraction phases are measured by the concordance index.

According to turning point analysis results, the numbers of business cycles and global cycles are lower when compared to those of financial cycles. It is found that financial cycles of Turkey have a higher frequency than the business cycles. On the other hand, the credit cycle and business cycles have similar frequencies. The duration of expansions is higher than the duration of contractions for both business cycle and financial cycles. The average duration of credit cycles takes longer than business cycles for expansion phase, while duration of business cycles takes longer than credit cycles for contraction phase. Stock market index, real effective exchange rate and credit to GDP cycles seem to be occur more frequent but take shorter than those of others. The average amplitudes of all financial cycles are higher than those of the business cycles in contraction phase. As for expansion phase, credit, credit to GDP and BIST100 cycles have higher amplitude than those of business cycles. Among financial cycles, credit to GDP has the highest amplitude for both phases. On the other hand, the cumulative loss of financial cycles are found higher than the business cycles, meaning that recessions of financial cycles are more costly.

According to concordance index analysis findings, credit cycle has the highest concordance with business cycle. CI between business cycle and credit gap cycle (CGDP) as well as CI between business cycle and housing cycle (REIDINR) are found relatively higher than the CI between the business cycle and equity cycle. On the other hand, CI between the global (volatility) cycle and business cycle indicates a weak countercyclical relationship. However, CI analysis show that there is no systematic relationship in the dynamics of business cycle and real effective rate cycle.

In order to see the synchronization between the lagged values of financial cycles and business cycles, CI is also computed by the lagged values of financial cycles and business cycles (level). According to analysis results, it is found that CI between business and credit cycle is very high for all lagged quarters of credit cycles. It is also found that equity prices cycles and house prices tend to act as pioneers to business cycles. According to CI between VIX and business cycle analysis, it is found that global (volatility) cycle tends to act as

pioneers to business cycle turning points in a countercyclical pattern. However, it has been discovered that there is no consistent lagged relationship between the dynamics of REER cycles and business cycles.

Secondly, in order to detect financial cycles, HP Filter is applied as a frequency based filter. The financial variables are detrended by HP Filter by using different smoothing parameters (1,600 and 400,000) in line with literature. In order to see the relationship between financial and business cycles, Granger Causality analysis is applied to de-trended cycles by HP Filter. According to the results of Granger causality analysis of the cycles (with BIS proposed $\lambda=400,000$), equity markets, residential property prices and credit represent Granger-cause business cycles. However, real effective rate cycle is not the Granger cause of business cycles. On the other hand, business cycles do not Granger-cause of financial cycles or global cycle.

Thirdly, an univariate model-based approach is applied in order to detect cycles by using unobserved components time series models. It is categorized as a “structural model” in the time series literature, and formulated by unobservable components such as trend, cyclical, seasonal, and irregular and interventions. Thus, first, an univariate UCM model is applied in order to extract business cycles. The estimated average business cycle period is found 22.2 quarters (5.6 years). Then, real credit cycles and BIS supposed credit to GDP cycles are also modelled by UCM. The estimated average period credit to GDP cycle is found 7 quarters while it is found 10.5 quarters as for credit cycle. According to model estimations, it is found that the duration of financial cycles (credit to GDP cycles and real credit cycles) are less than those of business cycle regardless of phase of the economy. Moreover, it is found that the business cycles have a lower frequency when compared to financial cycles including credit cycle and credit to GDP cycle.

In order to take crucial future policy decisions that have to be taken immediately to mitigate the effects of macroeconomic crises and systemic risks, further research on the linkages between financial and macroeconomic cycles is needed. Thus, extending to a larger set of different explanatory variables and different methods will contribute to policy makers on macro finance.

While BIS advises the use of credit-to-GDP gap as reference variable in setting the CCB, it also recommends employing additional indicators such as credit, equity prices and

housing prices. These indicators should be closely monitored during the design and application of macroprudential policies. As for Turkish economy, the concordance index and Granger Causality test results indicate that there is no concordance or causality between real effective exchange rate and business cycles. However this dissertation claims that credit, equity prices and house prices can be employed individually or by a composite index including those as additional indicators besides credit to GDP.

The findings are crucial in formulating prudent strategies for proactively monitoring and promoting stability within the banking sector. This is especially significant for effectively managing the countercyclical capital buffer as outlined in Basel III .

Since the public housing data (Residential Property Price Index) has been publishing by CBRT since May 2010 and past data gap limits the empirical analysis, in the near future, it can be included as an indicator to be assessed to develop macroprudential tools accordingly.

Modelling financial cycles by UCM may contribute the literature as the analysis can be extended by applying multivariate models. Furthermore, the explanatory variables can be extended by including IMF Financial Soundness Indicators and alternative models can also be developed.

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APPENDIX 1

Turning points for LBIST100:

peaks	troughs
2006Q1	2006Q3
2007Q4	2009Q1
2010Q4	2011Q4
2013Q1	2014Q1
2014Q4	2015Q4
2017Q4	2018Q4
2019Q3	2020Q1
2020Q4	2021Q3

Duration:

expansion	4.9
contraction	3.5

Amplitudes:

expansion	0.4
contraction	-0.3

Cumulation:

expansion	1.4
contraction	-0.8

Excess:

expansion	8.8
contraction	-5.5

Turning points for

C_GDP:

peaks	troughs
2004Q2	2004Q4
2006Q2	2007Q1
2008Q4	2009Q2
2011Q3	2012Q1
2015Q3	2016Q1
2017Q1	2017Q3
2018Q3	2019Q3
2020Q3	2021Q3

Duration:

expansion	6.9
contraction	2.6

Amplitudes:

expansion	13.6
contraction	-4.8

Cumulation:

expansion	51.4
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contraction	-12.2
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Excess:

expansion	-17.5
contraction	-6.1

Turning points for

LCREDR:

peaks	troughs
2008Q4	2009Q2
2015Q3	2016Q1
2018Q3	2019Q3
2021Q4	

Duration:

expansion	14.7
contraction	2.7

Amplitudes:

expansion	0.5
contraction	-0.1

Cumulation:

expansion	4.9
contraction	-0.2

Excess:

expansion	-5.3
contraction	24.4

Turning points for

LREER:

peaks	troughs
2003Q3	2004Q3
2005Q4	2006Q2
2007Q4	2009Q1
2010Q3	2011Q3
2013Q1	2014Q1
2014Q4	2015Q3
2016Q3	2018Q3
2019Q3	2021Q4

Duration:

expansion	4.9
contraction	4.9

Amplitudes:

expansion	0.2
contraction	-0.2

Cumulation:

expansion	0.5
contraction	-0.7

Excess:

expansion	26.9
contraction	-16.2

**Turning points for
LREIDINR:**

peaks	troughs
2005Q1	2006Q3
2007Q3	2009Q1
2009Q3	2010Q3
2016Q2	2017Q1
2017Q3	2020Q1

Duration:

expansion	7.8
contraction	5.8

Amplitudes:

expansion	0.1
contraction	-0.1

Cumulation:

expansion	1.1
contraction	-0.5

Excess:

expansion	4.8
contraction	2.4

Turning points for LVIX:

peaks	troughs
2009Q1	2006Q1
2015Q3	2014Q2
2020Q1	2017Q3
	2021Q2

Duration:

expansion	9.0
contraction	11.3

Amplitudes:

expansion	1.3
contraction	-1.2

Cumulation:

expansion	5.3
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contraction	-9.0
-------------	------

Excess:

expansion	-17.6
contraction	20.6

**Turning points for
LGDPR:**

peaks	troughs
2006Q4	2007Q2
2008Q1	2009Q1
2011Q3	2012Q1
2018Q2	2020Q2

Duration:

expansion	12.7
contraction	4.0

Amplitudes:

expansion	0.2
contraction	-0.1

Cumulation:

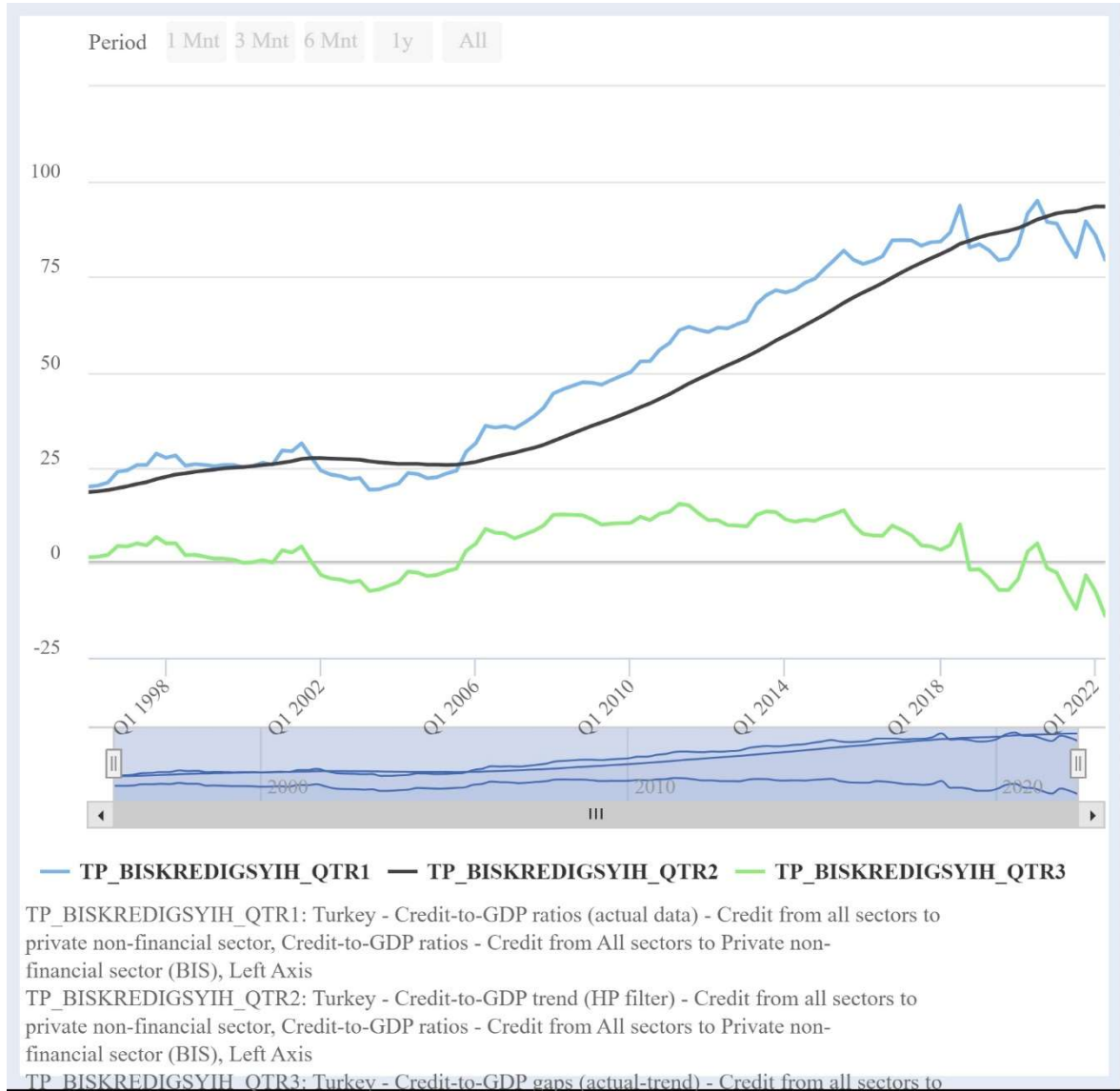
expansion	1.9
contraction	-0.1

Excess:

expansion	-12.8
contraction	-35.3

APPENDIX 2

BIS Credit to GDP Gap (Cycle) Calculation



Source: BIS, CBRT EVDS Dashboard

APPENDIX 3

Granger Causality Test Results– Cycles with $\lambda=1,600$

VAR Granger Causality/Block Exogeneity Wald Tests

Date: 06/25/23 Time: 19:15

Sample: 2003Q1 2022Q2

Included observations: 71

Dependent variable: D(LGDPR_C1)

Excluded	Chi-sq	df	Prob.
D(LBIST100_C1)	5.017346	6	0.5416
D(C_GDP_C1)	11.43931	6	0.0757
D(LCREDR_C1)	2.262452	6	0.8940
D(LREER_C1)	5.339109	6	0.5011
D(LREIDINR_C1)	10.61184	6	0.1011
D(LVIX_C1)	2.565642	6	0.8611
All	91.72656	36	0.0000

Dependent variable: D(LBIST100_C1)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C1)	2.318740	6	0.8882
D(C_GDP_C1)	8.345527	6	0.2139
D(LCREDR_C1)	11.75104	6	0.0678
D(LREER_C1)	4.031110	6	0.6725
D(LREIDINR_C1)	19.92554	6	0.0029
D(LVIX_C1)	13.85993	6	0.0312
All	61.63833	36	0.0049

Dependent variable: D(C_GDP_C1)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C1)	6.597815	6	0.3596
D(LBIST100_C1)	2.218707	6	0.8985
D(LCREDR_C1)	2.399000	6	0.8796
D(LREER_C1)	7.875179	6	0.2474
D(LREIDINR_C1)	6.210272	6	0.4001
D(LVIX_C1)	3.474533	6	0.7474
All	56.73767	36	0.0152

Dependent variable: D(LCREDR_C1)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C1)	6.763174	6	0.3433
D(LBIST100_C1)	3.739026	6	0.7119
D(C_GDP_C1)	7.133454	6	0.3087
D(LREER_C1)	18.86793	6	0.0044
D(LREIDINR_C1)	5.922316	6	0.4319
D(LVIX_C1)	2.840172	6	0.8286
All	82.86814	36	0.0000

Dependent variable: D(LREER_C1)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C1)	2.957281	6	0.8142
D(LBIST100_C1)	10.30421	6	0.1124
D(C_GDP_C1)	9.241078	6	0.1605
D(LCREDR_C1)	10.47044	6	0.1062
D(LREIDINR_C1)	9.535338	6	0.1456
D(LVIX_C1)	2.091793	6	0.9111
All	45.46423	36	0.1341

Dependent variable: D(LREIDINR_C1)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C1)	5.916113	6	0.4327
D(LBIST100_C1)	4.952008	6	0.5500
D(C_GDP_C1)	8.931697	6	0.1775
D(LCREDR_C1)	3.890648	6	0.6915
D(LREER_C1)	2.203001	6	0.9001
D(LVIX_C1)	2.756033	6	0.8388
All	54.23182	36	0.0261

Dependent variable: D(LVIX_C1)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C1)	11.53628	6	0.0732
D(LBIST100_C1)	6.860688	6	0.3339
D(C_GDP_C1)	8.574648	6	0.1990
D(LCREDR_C1)	7.519231	6	0.2755
D(LREER_C1)	11.60932	6	0.0713
D(LREIDINR_C1)	6.647484	6	0.3547
All	54.15256	36	0.0265

APPENDIX 4

Granger Causality Test Results– Cycles with $\lambda = 400,000$

VAR Granger Causality/Block Exogeneity Wald Tests

Date: 06/25/23 Time: 20:01

Sample: 2003Q1 2022Q2

Included observations: 76

Dependent variable: D(LGDPR_C2)

Excluded	Chi-sq	df	Prob.
D(C_GDP_C2)	0.986425	1	0.3206
D(LBIST100_C2)	4.088856	1	0.0432
D(LCREDR_C2)	4.900668	1	0.0268
D(LREER_C2)	0.521900	1	0.4700
D(LREIDINR_C2)	25.76687	1	0.0000
D(LVIX_C2)	7.323891	1	0.0068
All	56.64351	6	0.0000

Dependent variable: D(C_GDP_C2)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C2)	0.818042	1	0.3658
D(LBIST100_C2)	0.016318	1	0.8984
D(LCREDR_C2)	3.227239	1	0.0724
D(LREER_C2)	10.55817	1	0.0012
D(LREIDINR_C2)	1.941433	1	0.1635
D(LVIX_C2)	3.390961	1	0.0656
All	24.05370	6	0.0005

Dependent variable: D(LBIST100_C2)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C2)	1.546564	1	0.2136
D(C_GDP_C2)	0.504961	1	0.4773
D(LCREDR_C2)	0.001440	1	0.9697
D(LREER_C2)	0.019119	1	0.8900
D(LREIDINR_C2)	0.011770	1	0.9136
D(LVIX_C2)	0.198736	1	0.6557
All	4.226503	6	0.6461

Dependent variable: D(LCREDR_C2)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C2)	0.424229	1	0.5148
D(C_GDP_C2)	0.769077	1	0.3805
D(LBIST100_C2)	0.461930	1	0.4967
D(LREER_C2)	24.78614	1	0.0000
D(LREIDINR_C2)	1.13E-05	1	0.9973
D(LVIX_C2)	0.434934	1	0.5096
All	49.79159	6	0.0000

Dependent variable: D(LREER_C2)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C2)	0.074445	1	0.7850
D(C_GDP_C2)	0.011879	1	0.9132
D(LBIST100_C2)	2.938962	1	0.0865
D(LCREDR_C2)	2.261581	1	0.1326
D(LREIDINR_C2)	0.219839	1	0.6392
D(LVIX_C2)	0.040385	1	0.8407
All	7.723646	6	0.2591

Dependent variable: D(LREIDINR_C2)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C2)	0.015538	1	0.9008
D(C_GDP_C2)	4.803719	1	0.0284
D(LBIST100_C2)	3.580896	1	0.0584
D(LCREDR_C2)	5.251051	1	0.0219
D(LREER_C2)	8.508444	1	0.0035
D(LVIX_C2)	0.671274	1	0.4126
All	34.40101	6	0.0000

Dependent variable: D(LVIX_C2)

Excluded	Chi-sq	df	Prob.
D(LGDPR_C2)	0.145102	1	0.7033
D(C_GDP_C2)	0.859334	1	0.3539
D(LBIST100_C2)	0.018641	1	0.8914
D(LCREDR_C2)	0.421755	1	0.5161
D(LREER_C2)	0.193106	1	0.6603
D(LREIDINR_C2)	0.020181	1	0.8870
All	2.364546	6	0.8833

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