EASTERN JOURNAL OF EUROPEAN STUDIES Volume 12, Issue 2, December 2021
DOI: 10.47743/ejes-2021-0207

Interaction between business and financial cycles: evidence from Turkey

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Abstract

This study investigates the relationship between the business and financial cycles in Turkey. While gross domestic product represented business cycles, nine different indices including real effective exchange rate in addition to credit and stock markets indicators were calculated for financial cycles. Initially, Bry-Boschan quarterly algorithm was used for defining cycle characteristics such as turning points, duration, amplitude, slope and cumulative loss. Subsequently, the series detrended through Hodrick-Prescott filter were subjected to Hacker and Hatemi-J (2006) symmetric and Hatemi-J (2012) asymmetric causality tests. In addition to the fact that the number of financial cycles is higher than the number of business cycles, financial cycles follow a more sloped and rapid cycle than business cycles. Findings also point out that there is significant synchronization between the two cycles especially during contraction phases. Furthermore, there is the presence of a symmetric and asymmetric causality relationship running from financial cycles to business cycles in Turkey. These evidences outline that policy makers should take into account the role played by financial cycles on the output.

Keywords: business cycle, financial cycle, Bry-Boschan quarterly algorithm, symmetric causality, asymmetric causality

Introduction

The history of the cycles in economy goes back to the Jewish tribes. It is known that Israel had developed economically in periods when law and justice were maintained and the orders of the God were followed, while economic and social crises had occurred when behaviours to the contrary were exhibited (Sedlacek, 2017, pp. 65-69). In the literature of economy, the concept of cycle has begun to be used

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together with various panic, depression and crisis events experienced in market economies at the beginning of the 19th century. What was meant by the term cycle herein are business cycles (Altug, 2010, p. 1). Business cycles essentially indicate the oscillations occurring throughout the overall economic activity. A cycle comprises of recession, stagnation and recovery phases that occur almost synchronously but not periodically within many economic activities (Burns and Mitchell, 1946, p. 3).

Each economic event brings along different views and opinions and different lessons are learned from each new event. Financial factors entered the radar of very few economists during the aftermath of the Second World War and were mostly disregarded. However, the 2008 Global Financial Crisis unsettled almost all world economies and led to the economists steering towards various pursuits. In recent years, economists have made efforts towards including the financial factors into macroeconomic models and thus the financial cycles have entered the agenda (Borio, 2014). Existing theories on business cycles did not properly consider the interaction between debt, input-output, asset prices and the other variables that may replace them. This situation exhibits one of the reasons behind why many developed economies' foundations remain weak. In the name of ensuring that economies are sure-footed, it is of importance that the role of debt, leverage and risk-taking channels in steering economic and financial developments is investigated and the point maintained in regard to financial cycles is evaluated. However, while doing so, it is necessary not to think of financial cycles as independent from business cycles (Chorafas, 2015, p. 5). To put it all in simple terms, while business cycles represent cyclical movements in real indicators in the economy, financial cycles state cyclical movements in financial markets. Although they are distinct phenomena in terms of their cyclical components such as duration and length as Drehmann *et al.* (2012) pointed out, they have interacted quite closely with each other owing to the effect of increasing financialization.

The increasing importance of the role of financial factors on business cycles and the fact, discerned with the last crisis, that the instabilities within financial markets may have more destructive impacts especially in developing countries such as Turkey have become the motivation source of this study. The Turkish economy has a fragile structure like many emerging economies. Therefore, it becomes attractive to analyse real and financial connections in Turkey and other similar economies. However, it should be known that during the sample period the Turkish economy has experienced global and national economic crises in which real and financial factors strongly interacted. This is why detailed analysis of the relationship between business cycles and financial cycles is so important especially for the Turkish economy. Eventually, the results of this study have a potential to be a strategic road map for policy makers to overcome economic crises. Besides being periodically different from other studies on the Turkish economy, this study provides a more detailed framework in terms of the characteristics of the cycles. One of the important differences of this study is the use of indices created from different financial market indicators to represent financial cycles. Moreover, both symmetric and asymmetric perspectives are presented here when examining the relationship between cycles. Thus, this study is expected to contribute to the relatively limited number of asymmetric studies on this issue and to create new insights for future researches. In this direction, it is aimed through this study to reveal comprehensively the relationship between business and financial cycles for the emerging economy of Turkey. To that end, the relevant literature was reviewed, followed by the analysis stage. In this stage, initially nine financial indices comprising different financial market indicators were obtained, and then the turning points, durations, amplitudes, slopes and cumulative losses of the cycles were investigated by way of BBQ (Bry-Boschan Quarterly) method. After obtaining cycles series by use of HP (Hodrick-Prescott) filter, the relationship between the two cycles was analysed through Hacker and Hatemi-J (2006) symmetric and Hatemi-J (2012) asymmetric causality tests.

1. Related literature

Studies on the interactions between financial cycles and business cycles have become popular after the last great crisis experienced. These two cycles were subjected to comparisons from different angles such as duration, amplitude and synchronization degrees. Actually, the main reason for the occurrence of such studies is the investigation of whether or not financial factors have impact on the real economy. Again, in connection with this, the aim is tracking the behaviours of cycles especially during recession periods and thus becoming informed of potential crises beforehand and developing new policy recommendations against such events. In this sense, many studies conducted have revealed that financial cycles had important impacts on real economy (Claessens *et al.*, 2011; Borio *et al.*, 2016; Oman, 2019). The strong relationship and high synchronization between the two cycles (Claessens *et al.*, 2011; Akar, 2016; Grinderslev *et al.*, 2017; Skare and Porada-Rochon, 2020), become especially stronger during crisis periods compared to other periods (Haavio, 2012; Antonakakis *et al.*, 2015; Akar, 2016; Shen *et al.*, 2019). However, there are also evidences that indicate such relationship between the cycles to be weak at country basis (Schüler *et al.*, 2015). Another comparison is related to the durations of the cycles. Empirical findings provide evidence that financial cycles usually endure longer than business cycles (Drehmann *et al.*, 2012; Gonzalez *et al.*, 2015; Bhatta, 2018). Among the studies that provided evidence to the causality relationship between the two cycles, Gomez-Gonzalez *et al.* (2014), Shen *et al.* (2019) and Aravalath (2020) have found a unidirectional causality relationship from financial cycles to business cycles. On the other hand, Sala-Rios (2016) and Ahmad and Sehgal (2017) underlined the presence of a limited interaction between the two cycles; they have found the direction of causality from business cycles to financial cycles like Yan and Huang (2020). Bartoletto *et al.* (2019) have reached the evidence pointing out the presence of a unidirectional causality relationship from financial cycles to business cycles and also an asymmetric causality relationship in the same direction. Detailed information on some of the studies that investigated the relationship between financial cycles and business cycles are summarized in Table 1.

Table 1. Summary of related literature

Author(s)	Period	Countries	Method	Results
Claessens *et al.* (2011)	1960-2007	44 advanced and emerging countries	BBQ algorithm and concordance index	Financial cycles tend to be longer, deeper, and sharper than business cycles. Cycles in output tend to display a high degree of synchronization with cycles in credit and house prices.
Drehmann *et al.* (2012)	1960-2011	Australia, Germany, Japan, Norway, Sweden, United Kingdom, United States	Christiano and Fitzgerald filter and BBQ algorithm	Financial cycle is much longer than the business cycle. Business cycle recessions are much deeper when they coincide with the contraction phase of the financial cycle.
Haavio (2012)	1980-2010	17 OECD countries	BBQ algorithm and concordance index	There is a tighter connection between business and financial cycles during recessions than expansions.
Apostoaie & Percic (2014)	2000-2012	20 European countries	Baxter and King filter, Cross-correlation, Granger Causality	There is no causality relationship between business and financial cycles but there is evidence of a short-term lead-lag relationship.
Gomez-Gonzalez *et al.* (2014)	1978-2012	Chile, Colombia and Peru	Christiano and Fitzgerald filter, Frequency domain causality	There are the highest correlations between two cycles and financial cycle (Granger cause of business cycle).
Antonakakis *et al.* (2015)	1957-2012	G7	HP filter and Spillover index approach	The link between business and financial cycles particularly tightens during crises periods and there are bidirectional spillovers of shocks between the two cycles.
Gonzalez *et al.* (2015)	1996-2013	28 countries	HP filter, Singular Spectral Analysis, Bayesian	Financial cycles could indeed be longer than business cycles.

			structural time series	
Schüler *et al.* (2015)	1970-2013	13 European Union countries	Christiano and Fitzgerald filter, Spectral analysis	Financial cycles tend to be longer than business cycles.
Akar (2016)	1998-2014	Turkey	HP Filter, BBQ algorithm and dynamic conditional correlations	Financial and business cycles are highly synchronized. There are positive and high correlations between two cycles.
Borio *et al.* (2016)	1980-2012	USA	HP and Kalman filter, State-Space Model	Financial cycles play a key role in explaining business cycles.
Sala-Rios (2016)	1970-2014	Spain	HP Filter, BBQ algorithm, cross-correlation Granger causality	Business cycle is Granger cause of financial cycle.
Ahmad & Sehgal (2017)	1975-2013	South Asian Association for Regional Cooperation	Dynamic spillover	There is a limited interdependence between business and financial cycles.
Grinderslev *et al.* (2017)	1970-2016	Denmark	Christiano and Fitzgerald filter, Frequency domain analysis	There is a strong synchronization between business and financial cycles on the medium term.
Bhatta (2018)	1991-2017	Nepal	Frequency domain filter	Financial cycles are longer and deeper than business cycles.
Bartoletto *et al.* (2019)	1861-2013	Italy	BB algorithm, concordance index, Christiano and Fitzgerald filter, Granger Causality and VAR model	Business cycle is leading financial cycle. Financial cycle shocks are much more intense than business cycle shocks in the recession phase.
Oman (2019)	1971-2015	EA11	Christiano and Fitzgerald filter, concordance index	Financial cycles are less synchronized than business cycles. Business cycle synchronization has increased while financial cycle synchronization has decreased.
Shen *et al.* (2019)	2001-2015	China (regional)	BBQ algorithm, Panel dynamic logit	Financial cycle leads business cycle. The leading effect is stronger in rich provinces than in poor areas.

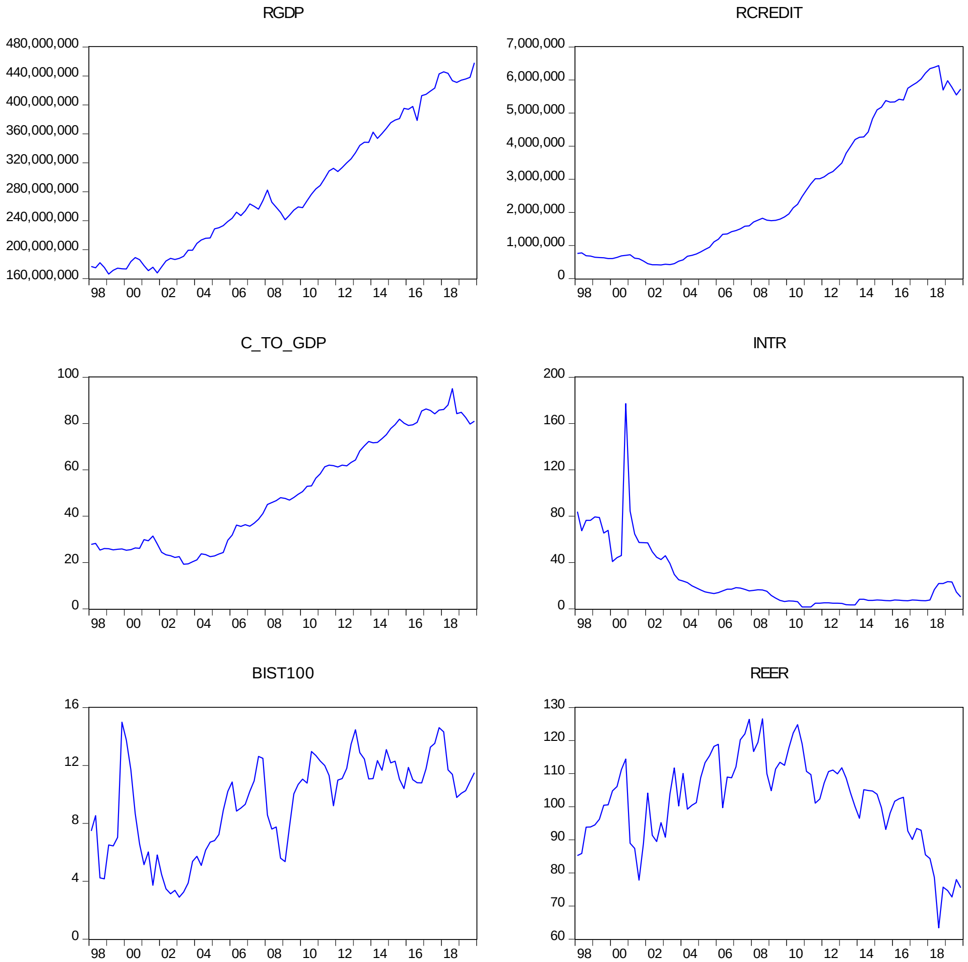
Aravalath (2020)	1990-2019	India	Wavelet analysis, BBQ algorithm, Toda-Yamamato causality	Financial cycle is Granger cause of business cycle.
Skare and Porada-Rochon (2020)	1270-2016	United Kingdom	Spectral Granger Causality	Financial and business cycles move along over medium-term spectrum and there is a strong link between two cycles.
Yan and Huang (2020)	1970-2018	USA	Wavelet Power Spectrum and VAR model	Financial cycles are closely related to the business cycles especially on the medium-term. Business cycles lead the financial cycles with a high positive correlation.

Source: Authors' representation

2. Data

The relationship between business cycles and financial cycle were analysed based on the data belonging to the 1998Q1 - 2019Q4 period. Although variables such as industrial production index (Aravalath 2020), consumption expenditures (Akar, 2016) and employment rates (Cagliarini and Price, 2017) are used in literature for representing business cycles, the more commonly used and generally accepted variable is GDP (Gross Domestic Product) (Skare and Stjepanovic, 2016). Thus, Real GDP was used in this study to represent business cycles and shown with *rgdp*. In regard to financial cycles, there is not one variable generally accepted. However, data pertaining to three different markets, namely credit, stock and housing markets, may be used to that end (Claessens *et al.*, 2011; Drehmann *et al.*, 2012). In line with this, real credit volume (CPI adjusted) - *rcredit; credit/GDP ratio* - *c_to_gdp* and interbank interest ratio - *intr* variables were used as credit market indicators and real (CPI adjusted) BIST100 (Borsa Istanbul 100) return index - *bist100* was used for representing stock markets. As the recording of real estate market indicators in the Turkish economy happened to commence on a more recent date, no direct variable could be used regarding this market. Instead, the foreign exchange variable (Binici *et al.*, 2016) - real effective rate of exchange, which employs important impacts upon the overall economy by way of production, consumption and trade channels, was included in the *reer* analysis. Interbank rate was obtained from the OECD (Organization for Economic Co-operation and Development) database, while the other variables were obtained from the Central Bank of the Republic of Turkey Electronic Data Delivery System. The time series graphs of the seasonally adjusted series produced through Moving Average Method are shown in Figure 1.

Figure 1. Time series graphs of variables



Source: Authors' representation

Instead of investigating each of the relations between financial cycles and business cycles one by one, financial cycle indices were calculated in order to see market impacts altogether, as pointed out in studies such as Ma and Zhang (2016) and Krznar and Matheson (2017).

As the variables used while formulating the financial cycle indices vary by type and units, Min-Max normalization method, one of the many normalization methods, was used when converting these into the index. Min-Max normalization realizes a linear conversion on the original data (Amiri *et al.*, 2014).

$$V'_{it} = \frac{V_{it} - min(V_i)}{max(V_i) - min(V_i)} \qquad (1)$$

V_{it}, included in Equation 1 represents the value of the variable *i* during the *t* period; *min(V*$_i$*)* and *max(V*$_i$*)* represent, respectively, the minimum and maximum values of the variable *i* during the sampling period; and V'_{it} represents the normalized value of the variable. Through normalization, the values of all variables were converted into the interval of [0, 1]. The normalized variables were then integrated in the indices through the formula below.[1]

$$FC = \sum_{i=1}^{3} w_i x_i \qquad (2)$$

In Equation 2, w_i represents the weight of variable *i*; while x_i represents the normalized values of the variables. Although there are five separate normalized variables to be used in the financial cycle indices (credit market indicators: nrcredit, nc_to_gdp and nintr, stock market indicator: nbist100, and beside them: nreer), three different indices were formulated that included each credit market indicator separately. When formulating indices, three different methods used in the studies of Goodhart (2001) and Ma and Zhang (2016) were preferred. The first one among these is the weighting of each variable by use of the correlation coefficients[2] between them and the real GDP. The second one is weighting of each variable through identical weight (1/3). The third one is weighting the variables by use of inverse variance method. This last method allows for higher rate weighting of variable that is relatively more stable due to weighting each variable reversely proportional with its volatility. Therefore, three different indices were subjected to three different weightings and a total of nine different financial cycle indices[3] were calculated.

Descriptive statistics for all variables are presented in Table 2.

Table 2. Descriptive Statistics

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Obs.**
RGDP	2.83E+08	2.59E+08	4.58E+08	1.66E+08	90572463	0.4117	1.8695	88
RCREDIT	2583240.	1765917.	6435344.	406306.8	2046034.	0.5923	1.8167	88
C_TO_GDP	50.08543	47.33292	95.01958	19.24157	23.80261	0.2634	1.5545	88
INTR	24.97642	15.24873	177.1728	1.538167	28.23138	2.4133	11.229	88
BIST100	9.397928	10.32755	14.99178	2.892842	3.227092	-0.4229	2.0821	88
REER	101.7929	103.3262	126.5741	63.38837	13.34958	-0.4861	2.9189	88
NRGDP	0.400798	0.318937	1.000000	0.000000	0.310008	0.4117	1.8695	88
NRCREDIT	0.361075	0.225510	1.000000	0.000000	0.339363	0.5923	1.8167	88
NC_TO_GDP	0.407029	0.370706	1.000000	0.000000	0.314110	0.2634	1.5545	88
NINTR	0.133449	0.078063	1.000000	0.000000	0.160739	2.4133	11.229	88
NBIST100	0.537658	0.614493	1.000000	0.000000	0.266725	-0.4229	2.0821	88
NREER	0.607804	0.632071	1.000000	0.000000	0.211275	-0.4861	2.9189	88

Source: Authors' representation

[1] *rgdp* will not be used in any index calculation but it was subjected to normalization for the purpose of having it comparable with the financial cycle indices.

[2] See Appendix A for correlation coefficients.

[3] When forming indices, the positive and negative signs of the correlation coefficients were considered, and all indices were weighted in regard to these signs obtained from the correlation matrix.

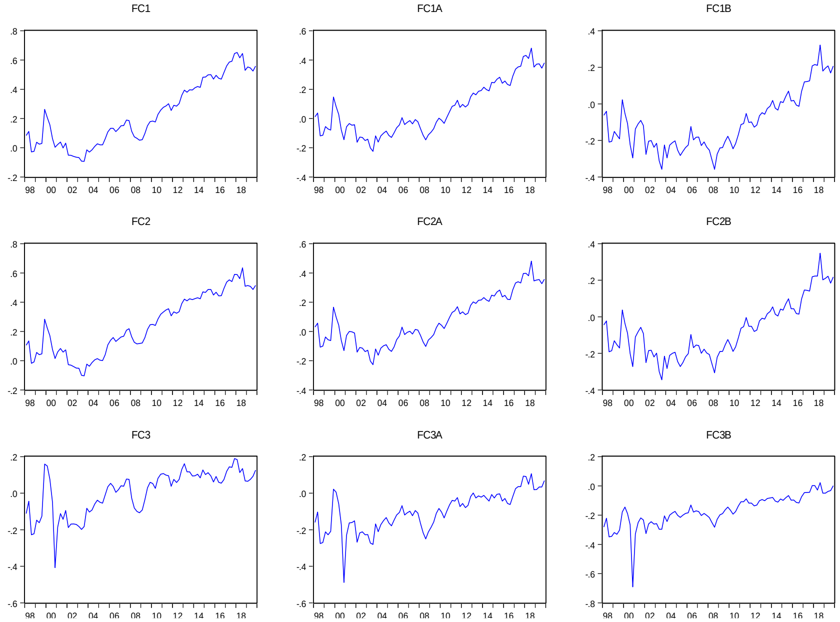
In Table 3, weightings calculated for the financial cycle indices are presented. According to this, *fc1*, *fc2* and *fc3* represent indices weighted by correlation coefficients; *fc1a*, *fc2a* and *fc3a* represent indices weighted by same rated variables; and *fc1b*, *fc2b* and *fc3b* represent indices weighted by variables with reverse variance method.

Table 3. Calculated weights for financial cycle indices

INDICES	NRCREDİT	NC_TO_GDP	NİNTR	NBİST100	NREER
FC1	0.50	-	-	0.34	-0.16
FC1A	0.34*	-	-	0.33	-0.33
FC1B	0.19	-	-	0.31	-0.50
FC2	-	0.49	-	0.34	-0.17
FC2A	-	0.34*	-	0.33	-0.33
FC2B	-	0.22	-	0.30	-0.48
FC3	-	-	-0.38	0.42	-0.20
FC3A	-	-	-0.33	0.34*	-0.33
FC3B	-	-	-0.51	0.19	-0.30

* While weighting the variables with the same rate, the 0.34 high value was assigned to the variable with the highest correlation with nrgdp for avoiding the repetitive number problem.
Source: Authors' representation

Figure 2. Financial cycle indices



Source: Authors' representation

The calculated financial cycle indices are shown altogether in Figure 2. It is observed through the graphs that index groups with different weighting using the same variables displayed similar trends.

3. Methodology and results

Dating of cycles and defining the turning points is of considerable importance for policymakers in order to comprehend the course of economy and adopt an attitude accordingly. Significant money policy steps need to be taken in order to balance the conservative behaviours during economy's contraction periods and the wasteful behaviours during economy's expansion periods and to reduce the instability of economy. Thus, dating the cycle characteristics in an appropriate manner may be the basis for efficient and practical policy decisions (Luvsannyam *et al.*, 2019, p. 59).

3.1. Characteristics of cycles: BBQ algorithm

There are various approaches in literature for defining the characteristics of cycles. One of the most commonly known among these is the Markow Switching model. However, the most traditional method in this field is the BB algorithm developed by Bry and Boschan (1971) (Harding and Pagan, 2002). This algorithm that allows for defining the cycles' turning points adopting a non-parametric approach creates more useful results for defining the cycle characteristics. This algorithm that is relatively simple to apply is preferred due to being more transparent compared to other methods. Therefore, it provides consistent results even when the sampling period changes (Harding and Pagan, 2003). When this algorithm, which was applied over monthly observations by Bry and Boschan (1971), is applied by integrating certain censoring rules and by using quarterly data, is referred to as the BBQ algorithm (Harding and Pagan, 2002). The BBQ algorithm includes two fundamental steps: (i) defining the local maximum and the local minimum values of the sample and (ii) using censoring rules for providing the cycles' (consequent two peaks or two trough points) and each phase's (from peak to trough or from trough to peak) minimum lengths (Drehmann *et al.*, 2012). As this study will focus on the determination of shorter-term cycles, as in Drehmann *et al.* (2012), the censoring rules were defined in the manner pointed out by Harding and Pagan (2002). Thus, the censoring rules to be applied in the analysis are as follows:

- One cycle should continue for at least five quarters;
- One phase should continue for at least two quarters.

Together with the censoring rules, the peak and trough points of the series are defined through the following conditions:

$$t = [(y_{t-2}, y_{t-1}) < y_t > (y_{t+1}, y_{t+2})] \qquad (3)$$

$$t = [(y_{t-2}, y_{t-1}) > y_t < (y_{t+1}, y_{t+2})] \qquad (4)$$

Equation 3 displays the series' peak point condition, while Equation 4 displays the series' trough point condition. Satisfaction of the censoring rules is possible with the peak and trough points satisfying the conditions above.

Table 4. Turning points of cycles

Variables	Number of Cycles	Turning Points	
		Peaks	***Troughs***
NRGDP	3	1998Q3, 2000Q3, 2008Q1, 2018Q1	1999Q1, 2001Q4, 2009Q1, 2018Q4
FC1	4	1999Q4, 2001Q2, 2007Q3, 2015Q3, 2018Q1	1998Q3, 2000Q4, 2003Q3, 2008Q4, 2016Q3
FC1A	7	1994Q4, 2001Q2, 2004Q4, 2006Q2, 2009Q4, 2014Q1, 2015Q3, 2018Q3	1998Q3, 2000Q4, 2003Q3, 2005Q2, 2008Q3, 2010Q2, 2014Q3, 2016Q3
FC1B	8	1994Q4, 2001Q3, 2004Q4, 2006Q2, 2009Q4, 2011Q3, 2014Q1, 2015Q3, 2018Q3	1998Q3, 2000Q4, 2003Q3, 2005Q2, 2008Q3, 2010Q2, 2012Q2, 2014Q3, 2016Q3
FC2	5	1999Q4, 2001Q2, 2004Q4, 2007Q4, 2015Q3, 2018Q3	1998Q3, 2000Q4, 2003Q3, 2005Q2, 2008Q3, 2016Q2
FC2A	8	1999Q4, 2001Q2, 2004Q4, 2006Q2, 2009Q4, 2011Q3, 2014Q1, 2015Q3, 2018Q3	1998Q3, 2000Q4, 2003Q3, 2005Q2, 2008Q3, 2010Q2, 2012Q2, 2014Q3, 2016Q3
FC2B	8	1999Q4, 2001Q3, 2004Q4, 2006Q2, 2009Q4, 2011Q3, 2014Q1, 2015Q3, 2018Q3	1998Q3, 2000Q4, 2003Q3, 2005Q2, 2008Q3, 2010Q2, 2012Q2, 2014Q3, 2016Q3
FC3	9	1999Q4, 2001Q4, 2004Q4, 2006Q1, 2007Q3, 2009Q4, 2011Q1, 2013Q1, 2017Q4	1998Q3, 2000Q4, 2003Q2, 2005Q2, 2006Q3, 2008Q4, 2010Q2, 2011Q4, 2016Q3, 2019Q1
FC3A	8	1994Q4, 2001Q4, 2004Q4, 2006Q2, 2009Q4, 2011Q3, 2013Q1, 2015Q3, 2018Q3	1998Q3, 2000Q4, 2003Q3, 2005Q2, 2008Q3, 2010Q2, 2012Q2, 2014Q3, 2016Q3
FC3B	9	2000Q1, 2001Q3, 2004Q4, 2006Q2, 2009Q4, 2011Q3, 2014Q1, 2015Q3, 2018Q3	1998Q3, 2000Q4, 2002Q1, 2005Q2, 2008Q3, 2010Q2, 2012Q2, 2014Q3, 2016Q3, 2019Q1

Source: Authors' representation

In Table 4 that included the initial results obtained from the BBQ algorithm, the numbers of cycles and their turning points are provided for each variable representing the cycle. The numbers of business cycles are lower compared to the numbers of financial cycles. A total of three business cycles were defined for the 1998 - 2019 period. It is observed that these cycles represent the 2000 - 2001

Economic Crisis, the 2008 Global Crisis and the 2018 - 2019 Foreign Currency Crisis. Such crisis periods are also reflected as turning points for financial cycles, while financial cycles also have a presence outside of such periods. Another issue worthy of remark at this point is that indices including interbank rate covered more cycles compared to indices including real credit volume and credits/GDP ratio among the variables used as credit market indicators.

Table 5. Characteristics of cycles

Variables	Duration		Amplitude (%)		Slope/Violence		Cumulative loss (%)
	Expansion	***Contraction***	***Expansion***	***Contraction***	***Expansion***	***Contraction***	
NRGDP	22.33	3.50	38.98	-7.92	1.75	-2.26	-19.70
FC1	11.20	5.50	24.79	-13.96	2.21	-2.53	-49.02
FC1A	6.00	4.57	17.44	-11.36	2.90	-2.48	-35.59
FC1B	5.11	4.25	18.99	-14.72	3.71	-3.46	-46.97
FC2	9.83	4.20	21.13	-12.32	2.14	-2.93	-40.87
FC2A	5.00	4.37	16.32	-11.02	3.26	-2.52	-34.88
FC2B	5.11	4.25	18.85	-14.47	3.68	-3.40	-47.13
FC3	4.77	4.33	17.18	-13.93	3.60	-3.21	-39.55
FC3A	4.77	4.62	16.18	-13.43	3.39	-2.90	-34.02
FC3B	5.88	3.22	15.49	-12.18	2.63	-3.78	-23.69

Source: Authors' representation

In Table 5, the characteristics of business and financial cycles in terms of duration, amplitude, slope/violence and cumulative loss, as obtained from the BBQ algorithm are shown. For the 1998Q1 - 2019Q4 period, the average expansion phase of business cycles covers 22.3 quarters, while the average contraction phase of financial cycles covers 3.5 quarters. For the same period, the average expansion phase durations of financial cycles occur to be below that of business cycles, while the average contraction phase durations of financial cycles occur to be above that of business cycles. In general sense, it is observed that the average expansion phases of cycles occur to be longer than the average contraction cycles; which means that the contraction periods of the economy last shorter while the expansion periods last longer. Another characteristic in Table 5 is the amplitude of cycles. In this respect, while the average expansion phase amplitude of business cycles occurs to be 38.98%, their average contraction phase amplitude occurs to be 7.92%. In regard to financial cycles, while the average expansion phase amplitude is at lower levels compared to business cycles, the average contraction phase amplitude is usually at higher levels. In terms of the cycle's slope, or the amplitude to period ratio, it is observed that financial cycles displayed a more acute (faster) cycle compared to business cycles in all of the average expansion phases and most of the average contraction phases. Another indicator included in the table is cumulative loss, which expresses the average losses during contraction phases. This loss that occurs to be 19.70% for business cycles is higher in the case of financial cycles. This finding points out that financial cycles are costlier compared to business cycles during the given period.

3.2. Detrending: HP filtering

While investigating the cycles in the economy, one of the most important stages is adjusting the trend component in the series (detrending). Detrending the series for analysis may have both advantages and disadvantages. For instance, the productivity shocks in traditional growth models are defined by both the long-term trend and the cycles surrounding such a trend. On the other hand, detrending the series may be beneficial for policymaking purposes by allowing more robust analysis of the expansion and contraction cycles in the series. Recent studies on cycles separate trend and cycle components and use filtering methods to that end (Rand and Trap, 2002). HP filtering, the method used in this study, was preferred for the comparability it provided due to its frequent use in relevant studies. Hodrick and Prescott (1997) indicated that any time series dependent on t comprised the sum of the trend component (g_t) and the cycle component (c_t) (Equation 5).

$$y_t = g_t + c_t \qquad (5)$$

When detrending the cycle series by way of HP filter, an optimization problem is solved. To that end, the following calculation is made, with the assumption that $c_t = y_t - g_t$:

$$Min_{(g_t)_{t=-1}^{T}}\{\sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=1}^{T}[(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2\} \qquad (6)$$

The λ smoothing parameter in Equation 6 is a positive value that penalizes the variables in the trend. Although there is no absolute rule for what this value should be, Hodrick and Prescott (1997) proposed the value 1,600 for three-month observations. Smoothing a parameter taking on zero value means that no cycle component is included in the series, while the parameter taking on infinite value means that there is a linear trend in the series.

Table 6. Filtered series with HP filter

Cycles	Weights	Components
NRGDP → BC	-	Real GDP
FC1 → FC11	Correlation coefficient	Real credit volume – BIST100 – Real effective exchange rate
FC1A → FC12	Identical weight	
FC1B → FC13	Inverse volatility	

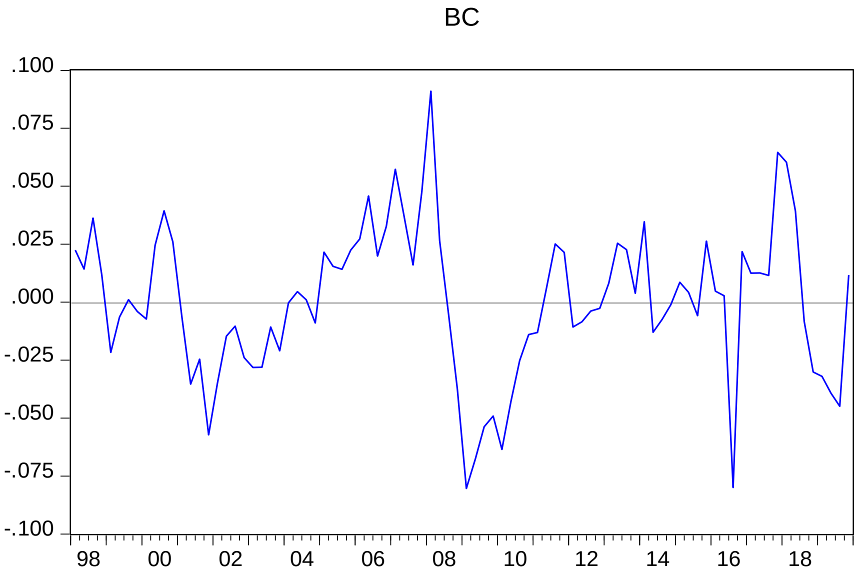
FC2 → FC21	Correlation coefficient	Credit/GDP – BIST100 – Real effective exchange rate
FC2A → FC22	Identical weight	
FC2B → FC23	Inverse volatility	
FC3 → FC31	Correlation coefficient	Interbank rate – BIST100 – Real effective exchange rate
FC3A → FC32	Identical weight	
FC3B → FC33	Inverse volatility	

Source: Authors' representation

Real GDP and the indices previously weighted were detrended; and the names of the new series are presented in Table 6 together with the indices' weighting types and the components included in the indices. Throughout the cycles, a course over the trend is observed especially during pre-crisis periods, while crisis periods displayed a course below the trend.

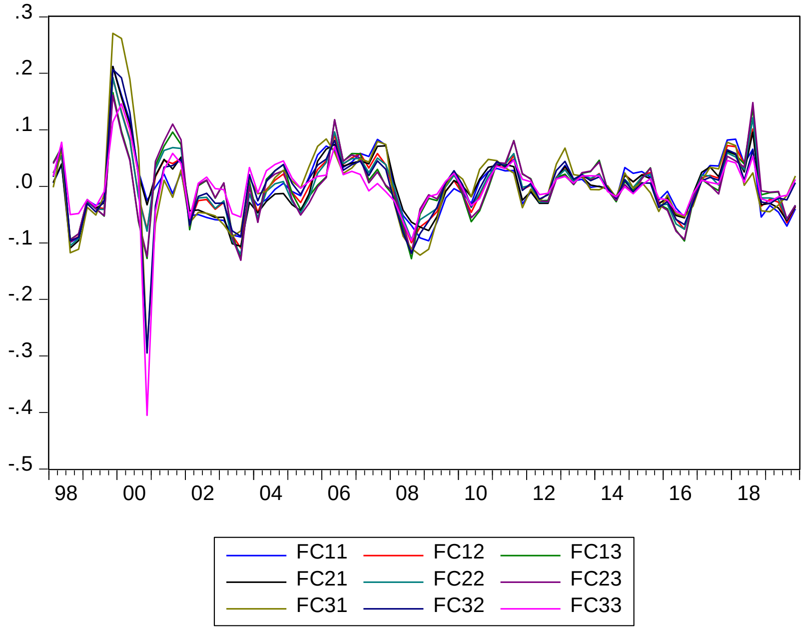
In Figure 3, the business cycles series detrended through HP filter is shown. According to this, the contractions experienced in Turkey's economy during the year 1999, the 2000-2001 Crisis, the 2008 Global Crisis, the second quarter of 2014, the third quarter of 2016 and the 2018 - 2019 Foreign Currency Crisis may be seen clearly reflected in the graph.

Figure 3. Business cycle



Source: Authors' representation

Figure 4. Financial cycles



Source: Authors' representation

The graphical display of financial cycles is presented in Figure 4. It is observed that financial cycles had higher volatility compared to business cycles and thus they covered more frequently repeating cycle periods. In addition to this, it is seen that all 9 different financial cycle series calculated followed mostly the same course. Therefore, indices that included different credit market indicators and weighted by use of correlation (*fc11*, *fc21* and *fc31*) were used hereinafter in this study for representing financial cycles.

3.3. Analysis of relationship between business and financial cycles

The relationship between business cycles and financial cycles was analyzed through causality tests. The first step in this stage that includes time series analysis is defining the stationarity levels of variables. Moreover, Hodrick and Prescott (1997) proposed that there may be certain instances that breach the assumption that cycle components cannot include unit root and is thus stationary. Thus, the stationarity tests of variables were investigated by use of traditional unit root tests[4] prior to the causality tests.

[4] The augmented version of the DF test originally developed by Dickey and Fuller (1979), namely Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1981), Phillips-Perron (PP)

Table 7. Traditional unit root tests results

Variables	Include in Test Equation	Test Statistics	ADF	PP	KPSS
BC	With constant	Calculated test stat.	-4.164*	-4.183*	0.046*
		Critical value	-2.895	-2.895	0.463
	Without constant and trend	Calculated test stat.	-4.189*	4.207*	-
		Critical value	-1.944	-1.944	-
FC11	With constant	Calculated test stat.	-4.086*	-5.245*	0.034*
		Critical value	-2.895	-2.895	0.463
	Without constant and trend	Calculated test stat.	-4.111*	-4.268*	-
		Critical value	-1.944	-1.944	-
FC21	With constant	Calculated test stat.	-4.384*	-4.491*	0.035*
		Critical value	-2.895	-2.895	0.463
	Without constant and trend	Calculated test stat.	-4.410*	-4.517*	-
		Critical value	-1.944	-1.944	-
FC31	With constant	Calculated test stat.	-4.950*	-5.065*	0.028*
		Critical value	-2.895	-2.895	0.463
	Without constant and trend	Calculated test stat.	-4.979*	-5.093*	-
		Critical value	-1.944	-1.944	-

* According to Schwarz Information Criteria (SIC), it indicates stationarity [I(0)] at 5% significance level.
Source: Authors' representation

In Table 7, the results from the traditional unit root tests are shown. In order to provide more robust findings, ADF, PP and KPSS tests were used together. Because the variables subjected to unit root tests were previously detrended by way of HP filter, the tests' trended forms were not used. The results of all three tests provide supporting evidence, and *bc*, *fc11*, *fc21* and *fc31* variables are stationary at that level.

test (Phillips and Perron, 1988) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski *et al.*, 1992) are the traditional unit root tests used in variables' stationarity testing.

Hacker and Hatemi-J (2006) symmetric causality test

Hacker and Hatemi-J (2006) causality test is based on the causality test developed by Toda and Yamamato (1995). In Toda and Yamamato's (1995) causality test, the presence of rules such as cointegration between variables and variables being stationary at the same levels are deemed to be among the superior aspects of the test. There are known approaches to apply the Granger causality test on stationary variables according to the causality test developed first by Granger (1969) and the Vector Autoregressive (VAR) models developed by Sims (1980). In such a case, long term information losses may occur in analyses conducted by taking the differences of non-stationary series. These tests also necessitate that the cointegration tests are conducted initially and long-term relations are defined in the event the variables are stationary at the same level. However, there is no such requirement for the Toda and Yamamato (1995) and Hacker and Hatemi-J (2006) causality tests (Erdoğan *et al.*, 2019). The relationship expected between the variables according to Toda and Yamamato (1995) causality test is as follows:

$$\begin{bmatrix} bc_t \\ fc_t \end{bmatrix} = \vartheta_0 + \vartheta_1 \begin{bmatrix} bc_{t-1} \\ fc_{t-1} \end{bmatrix} + \cdots + \vartheta_{p+d_{max}} \begin{bmatrix} bc_{t-p+d_{max}} \\ fc_{t-p+d_{max}} \end{bmatrix} + w_t \qquad (7)$$

In Equation 7[5], it is seen that the Toda and Yamamato (1995) causality test is VAR based. The ϑ_0 in the model is the constant term vector, while $\vartheta_1 \ldots \vartheta_{p+d_{max}}$ are parameter vectors. The 'p' included in parameter vectors is the optimal leg length relevant to the model, which is defined by use of the information criteria in a VAR model while d_{max} maximum integration degree is defined by the stationarity levels of the variables. After the definition of such values, the below hypotheses are tested:

H_0: $\vartheta_1 = \vartheta_2 = \ldots = \vartheta_p = 0$, "$fc_t$ is not the cause of bc_t" or "bc_t is not the cause of fc_t"

H_1: At least one $\vartheta \neq 0$, "fc_t is the cause of bc_t" or "bc_t is the cause of fc_t"

In the Granger causality, the hypotheses are tested through Wald F-statistic by applying a constraint to the coefficients as a whole. Toda and Yamamato (1995) developed this test into the MWALD test statistic. If the MWALD statistic calculated is higher than the critical value of χ^2, the zero hypothesis is rejected. This means that there is a causality relationship between the variables while the contrary result means no causality relationship between the variables. However, Hacker and Hatemi-J (2006) proposed that the MWALD test included χ^2 distribution and that this assumption is not valid when the model contains heteroscedasticity problems. Applying the bootstrap

[5] The fc variable in the equation represents the fc11, fc21 and fc31 variables.

method towards solving the heteroscedasticity problem, Hacker and Hatemi-J (2006) defined the critical value of the causality test in accordance with this.

Table 8 presents the Hacker and Hatemi-J (2006) causality test findings estimated for the entire 1998 - 2019 period. According to this, no causality relationship was defined from *bc* to *fc11*, *fc21* and *fc31* due to the calculated MWALD test statistics being lower than the critical value. On the other hand, a causality relationship was defined at 5% significance level from *fc11* and *fc31* to *bc*, and at 10% significance level from *fc21* to *bc* due to the calculated MWALD test statistics being higher than the critical value. This means that there is unidirectional Granger causality from financial cycles to business cycles.

Table 8. Hacker and Hatemi-J (2006) symmetric causality test results

H_0	MWALD	Critical V.	H_0	MWALD	Critical V.
$fc11 \nrightarrow bc$	19.108*	4.152	$bc \nrightarrow fc11$	0.296	4.064
$fc21 \nrightarrow bc$	3.369**	2.323	$bc \nrightarrow fc21$	0.430	4.116
$fc31 \nrightarrow bc$	14.705*	4.324	$bc \nrightarrow fc31$	0.342	4.013

* and ** indicate, respectively, significance levels of 5% and 10%.
Note: The optimal lag length (p) for all causality relationships was defined as 1 according to Hatemi-J Information Criteria and the maximum integration degree (d_{max}) was defined as 0 according to unit root test results. Bootstrap simulation was determined as 10000.
Source: Authors' representation

Hatemi-J (2012) asymmetric causality test

Hatemi-J (2012) asymmetric causality test is based on the Hacker and Hatemi-J (2006) symmetric causality test. However, Hacker and Hatemi-J (2006) assumes that the positive and negative shocks in variables creates the same impacts in the causality relationship between the variables, while Hatemi-J (2012) realizes the asymmetric causality analyses by taking into account the positive and negative components of the variables. Such a distinction provides a broader perspective for the variables between which there is no symmetric causality relationship but only an asymmetric causality relationship and for being able to observe which shock is the cause of the existing symmetric causality relationship.

While splitting the variables into positive and negative components, the method used by Granger and Yoon (2002) in their hidden cointegration analyses was followed. According to this, the bc_t ve fc_t[6] variables tested for asymmetric causality relationship are defined as below in the framework of random walk (Hatemi-J, 2012, p. 449):

[6] As in the symmetric causality test, the fc variable represents the variables fc11, fc21 and fc31.

$$bc_t = bc_{t-1} + e_{1t} = bc_0 + \sum_{i=1}^{t} e_{1i,} \qquad (8)$$
$$fc_t = fc_{t-1} + e_{2t} = fc_0 + \sum_{i=1}^{t} e_{2i,} \qquad (9)$$

In Equation 8 and Equation 9, the terms bc_t and fc_t indicate the initial values of the variables, while the terms e_{1i} and e_{2i} indicate the residual value causing deviation from white noise, or the shocks inside the variables. These shocks are defined as follows:

$$e_{1i}^{+} = \max(e_{1i}, 0)\,, e_{2i}^{+} = \max(e_{2i}, 0) \qquad (10)$$
$$e_{1i}^{-} = \min(e_{1i}, 0)\,, e_{2i}^{-} = \min(e_{2i}, 0) \qquad (11)$$
$$e_{1i} = e_{1i}^{+} + e_{1i}^{-},\ e_{2i} = e_{2i}^{+} + e_{2i}^{-} \qquad (12)$$

The positive shocks belonging to variables are defined in Equation 10, and the negative shocks belonging to variables are defined in Equation 11. In Equation 12, it is shown that the sum of the shocks for each variable comprised positive and negative shocks. In the light of this information, the variables bc_t and fc_t are defined again as follows:

$$bc_t = bc_{t-1} + e_{1t} = bc_0 + \sum_{i=1}^{t} e_{1i}^{+} + \sum_{i=1}^{t} e_{1i}^{-} \qquad (13)$$
$$fc_t = fc_{t-1} + e_{2t} = fc_0 + \sum_{i=1}^{t} e_{2i}^{+} + \sum_{i=1}^{t} e_{2i}^{-} \qquad (14)$$

Thus, the new variables that represent the positive and negative shocks for each variable are shown as follows:

$$bc_t^{+} = \sum_{i=1}^{t} e_{1i}^{+}\,,\ bc_t^{-} = \sum_{i=1}^{t} e_{1i}^{-}\,,\ fc_t^{+} = \sum_{i=1}^{t} e_{2i}^{+}\,,\ fc_t^{-} = \sum_{i=1}^{t} e_{2i}^{-} \qquad (15)$$

In Equation 15; bc_t^{+} represents the cumulative positive shocks belonging to the business cycles variable, and bc_t^{-} represents the cumulative negative shocks belonging to the business cycles variable, while fc_t^{+} represents the cumulative positive shocks belonging to the financial cycle variables, and fc_t^{-} represents the cumulative negative shocks belonging to the financial cycle variables. The causality relationship between the cycles is tested via the model shown below:

$$\begin{bmatrix} bc_t^{+/-} \\ fc_t^{+/-} \end{bmatrix} = \begin{bmatrix} \varphi_0^{+/-} \\ \varphi_0^{+/-} \end{bmatrix} + \begin{bmatrix} \varphi_{11,1} & \varphi_{12,1} \\ \varphi_{21,1} & \varphi_{22,1} \end{bmatrix} \begin{bmatrix} bc_{t-1}^{+/-} \\ fc_{t-1}^{+/-} \end{bmatrix} + \cdots +$$
$$\begin{bmatrix} \varphi_{11,p+d_{max}} & \varphi_{12,p+d_{max}} \\ \varphi_{21,p+d_{max}} & \varphi_{22,p+d_{max}} \end{bmatrix} \begin{bmatrix} bc_{t-p}^{+/-} \\ fc_{t-p}^{+/-} \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \end{bmatrix} \qquad (16)$$

In Equation 16, a VAR(p) model expression, the φ_0 indicates the constant term vector, $\varphi_1, \ldots, \varphi_p$ indicate parameter vectors; and v_t indicates the error term. The following process proceeds as in the Hacker and Hatemi-J (2006) symmetric test. In this context, the following zero hypotheses are tested:

i. H_0: *There is no causality from positive financial cycle shock* (fc_t^+) *to positive business cycle shock* (bc_t^+)*;*
ii. H_0: *There is no causality from negative financial cycle shock* (fc_t^-) *to negative business cycle shock* (bc_t^-)*;*
iii. H_0: *There is no causality from negative financial cycle shock* (fc_t^-) *to positive business cycle shock* (bc_t^+);
iv. H_0: *There is no causality from positive financial cycle shock* (fc_t^+) *to negative business cycle shock* (bc_t^-)*;*
v. H_0: *There is no causality from positive business cycle shock* (bc_t^+) *to positive financial cycle shock* (fc_t^+)*;*
vi. H_0: *There is no causality from negative business cycle shock* (bc_t^-) *to negative financial cycle shock* (fc_t^-)*;*
vii. H_0: *There is no causality from negative business cycle shock* (bc_t^-) *to positive financial cycle shock* (fc_t^+)*;*
viii. H_0: *There is no causality from positive business cycle shock* (bc_t^+) *to negative financial cycle shock* (fc_t^-).

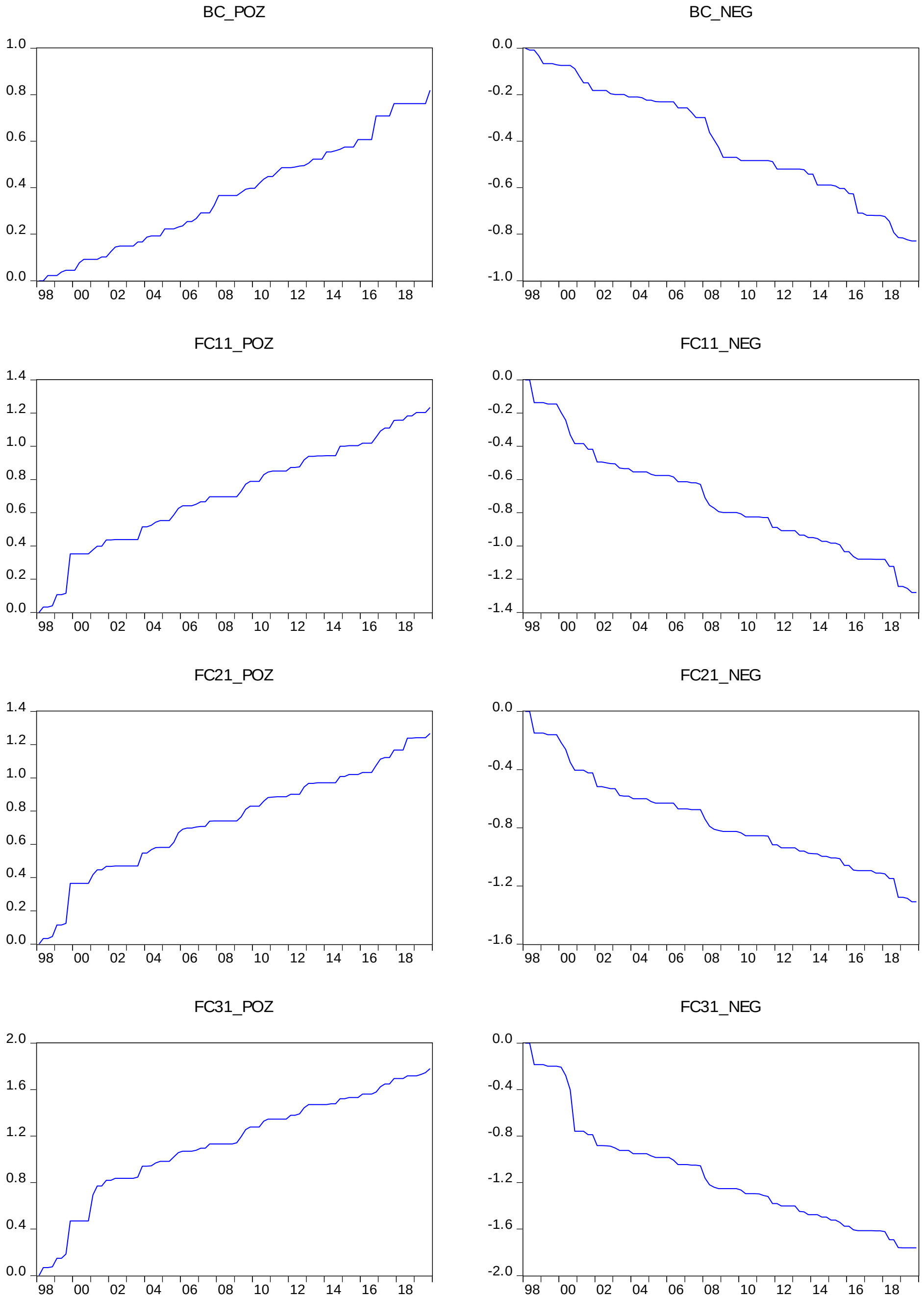
In the event the above hypotheses are rejected, the sub-hypotheses indicate the presence of causality relationship between the shocks.

Each variable subjected to Hatemi-J (2012) asymmetric causality test were initially split into their positive and negative components and the graphs of these components are shown in Figure 5. Following this, these components obtained were subjected to unit root test.

ADF unit root test was used for the variables' stationarity testing, and these results are shown in Table 9. According to the test findings, the positive and negative components belonging to all variables are I (1).

In Table 10, Hatemi-J (2012) asymmetric causality analysis findings are presented. Causality relationships at 5% significance level were found out from the financial cycles' negative shocks ($fc11^-$, $fc21^-$ and $fc31^-$) to the negative shock of business cycles (bc^-). There is also a causality relationship at 10% significance level from the negative shock of business cycles (bc^-) to the negative shock of financial cycles ($fc11^-$). No causality relationship was found between the positive and negative components other than these.

Figure 5. Positive and Negative Components of Variables



Source: Authors' representation

Table 9. ADF unit root test results for positive and negative components

Level** Variables	I(0)		I(1)	
	Test statistics	**Probability**	**Test statistics**	**Probability**
bc^+	-3.254	0.0810	-8.702*	0.0000
bc^-	-2.068	0.5559	-8.336*	0.0000
$fc11^+$	-1.864	0.3476	-9.839*	0.0000
$fc11^-$	-1.761	0.3973	-9.239*	0.0000
$fc21^+$	-2.039	0.2697	-9.624*	0.0000
$fc21^-$	-1.986	0.2924	-9.470*	0.0000
$fc31^+$	-2.787	0.0553	-8.816*	0.0000
$fc31^-$	-2.817	0.0601	-7.872*	0.0000

Note: * Indicates stationarity at first difference [I(1)] at 5% significance level according to Schwarz Information Criteria (SIC); ** Model with a constant.
Source: Authors' representation

Table 10. Hatemi-J (2012) asymmetric causality test results

H_0	MWALD	Critical V.	H_0	MWALD	Critical V.
$\boldsymbol{fc11^+ \nrightarrow bc^+}$	0.577	4.223	$bc^+ \nrightarrow fc11^+$	0.123	4.093
$\boldsymbol{fc11^- \nrightarrow bc^-}$	10.019*	7.097	$bc^- \nrightarrow fc11^-$	6.331**	5.426
$\boldsymbol{fc11^- \nrightarrow bc^+}$	0.311	4.275	$bc^- \nrightarrow fc11^+$	0.333	4.704
$\boldsymbol{fc11^+ \nrightarrow bc^-}$	2.946	4.422	$bc^+ \nrightarrow fc11^-$	1.435	4.327
$\boldsymbol{fc21^+ \nrightarrow bc^+}$	0.236	4.227	$bc^+ \nrightarrow fc21^+$	0.183	4.088
$\boldsymbol{fc21^- \nrightarrow bc^-}$	4.989*	4.306	$bc^- \nrightarrow fc21^-$	0.203	4.001
$\boldsymbol{fc21^- \nrightarrow bc^+}$	0.114	4.461	$bc^- \nrightarrow fc21^+$	0.221	4.773
$\boldsymbol{fc21^+ \nrightarrow bc^-}$	2.871	4.295	$bc^+ \nrightarrow fc21^-$	1.084	4.315
$\boldsymbol{fc31^+ \nrightarrow bc^+}$	0.003	4.267	$bc^+ \nrightarrow fc31^+$	0.662	4.163
$\boldsymbol{fc31^- \nrightarrow bc^-}$	10.031*	7.446	$bc^- \nrightarrow fc31^-$	0.062	7.230
$\boldsymbol{fc31^- \nrightarrow bc^+}$	1.385	4.364	$bc^- \nrightarrow fc31^+$	0.046	4.413
$\boldsymbol{fc31^+ \nrightarrow bc^-}$	1.715	4.217	$bc^+ \nrightarrow fc31^-$	0.629	4.327

* and ** indicate, respectively, causality relationships at significance levels of 5% and 10%.
Note: The optimal lag length (p) for all causality relationships was defined as 2 according to Hatemi-J Information Criteria, and the maximum integration degree (d_{max}) was defined as 1 according to unit root test results.
Source: Authors' representation

Conclusions

In this study, the business and financial cycles were initially investigated in regard to fundamental characteristics, then the interaction between the two cycles was revealed. The findings obtained from the BBQ algorithm provide important evidence to the fundamental characteristics of the cycles. The first evidence obtained at this point is that the number of financial cycles is higher than the number of business cycles for the period subject to study. The Turkish economy experienced important economic and financial crises during this period. It was observed in this study that the two cycles behaved simultaneously especially in such crisis periods, as was observed in many other studies (Haavio, 2012; Antonakakis *et al.*, 2015; Shen *et al.*, 2019). However, the financial cycles present a more sloped and rapid cycle compared to business cycles. According to Claessens *et al.* (2011), this situation arises due to financial variables being adjusted faster compared to the real variables. Moreover, the financial cycles occurring in these periods are more costly compared to the business cycles. Claessens *et al.* (2011) highlighted that the high cumulative loss in financial cycles at such point will cause high production loss. According to Hacker and Hatemi-J's (2006) symmetric causality findings, financial cycles are the reason of business cycles, and these findings are in support of the findings obtained by Gomez and Gonzalez (2014), Ahmad and Sehgal (2017), Shen *et al.*, (2019) and Aravalath (2020). According to Hatemi-J (2012) asymmetric causality test findings, there is a strong causality relationship from the negative shocks of financial cycles to the negative shocks of business cycles, while there is a relatively weaker causality relationship from the negative shocks of business cycles to the negative shocks of financial cycles. These findings are similar to that of Bartoletto *et al.* (2019), which is another study investigating the asymmetric relationships between the cycles. This is the most remarkable result of this study. In this respect, it makes a vital contribution to the limited literature which examined the asymmetric relationship between cycles.

When all the findings obtained from the analyses are combined, it becomes apparent that there are impacts of financial cycles on the real economy. The instabilities arising in financial variables induce a considerably high cost for the economies. Acting in synchronization especially during crisis periods, the total impacts of these two cycles increase accordingly and thus this relationship aggravates the crises. Ignoring them means ignoring essential information and this can lead to policy mislead. Drehmann *et al.* (2012) indicated that policies not taking into account the financial cycles may lead to longer term and more sloped stagnation. Macroeconomic models should definitely consider this key role of financial cycles upon business cycles, and policy makers should concentrate on macroprudential policies that include the potential impacts of financial cycles on the output.

This study was limited by the data availability over a long period and it will be interesting to analyse the relationship between business and financial cycles with a larger data range for further studies. These studies should also focus on detailing the asymmetric interactions with different methods between these cycles.

Acknowledgement: This article is derived from the PhD thesis which is written under the supervision of Assoc. Prof. Dr. Burhan DOĞAN by Veysel KARAGÖL in Anadolu University, Eskişehir, Turkey. Title of the Thesis: "Interaction of Business Cycles, Financial Cycles and Monetary Policy in Turkey". This thesis was supported by Anadolu University Scientific Research Projects (BAP) (Project No: 1807E268).

References

Ahmad, W. and Sehgal, S. (2017), Business cycle and financial cycle interdependence and the rising role of China in SAARC, *Journal of Quantitative Economics*, 16, pp. 337-362. https://doi.org/10.1007/s40953-017-0086-3

Akar, C. (2016), Analysing the synchronization between the financial and business cycles in Turkey, *Journal of Reviews on Global Economics*, 5, pp. 25-35. https://doi.org/10.1016/j.physa.2020.124331

Altug, S. (2010), *Business cycles: fact, fallacy and fantasy*, USA: World Scientific.

Amiri, I.S., Akanbi, O.A. and Fazeldehkordi, E. (2014), *A machine-Learning approach to phishing detection and defense*, USA: Syngress.

Antonakakis, N., Breitenlechner, M. and Scharler, J. (2015), Business cycle and financial cycle spillovers in the G7 countries, *The Quarterly Review of Economics and Finance*, 58, pp. 154-162. https://doi.org/10.1016/j.qref.2015.03.002

Apostoaie, C.M. and Percic, S. (2014), Credit cycles and business cycles in twenty EU economies, *Procedia Economics and Finance*, 15, pp. 1055-1064. https://doi.org/10.1016/S2212-5671(14)00669-8

Aravalath, L.M. (2020), Do financial cycles cause business cycles in India? Evidence from wavelet based causality analysis, *Journal of Public Affairs*, e2410. https://doi.org/10.1002/pa.2410

Bartoletto, S., Chiarini, B., Marzano, E. and Piselli, P. (2019), Business cycles, credit cycles, and asymmetric effects of credit fluctuations: Evidence from Italy for the period of 1861–2013, *Journal of Macroeconomics*, 61, 103130. https://doi.org/10.1016/j.jmacro.2019.103130

Bhatta, G.R. (2018), *Estimating Business and Financial Cycles: Case of Nepal*, NRB Working Paper, 4, Nepal Rastra Bank.

Binici, M., Hacihasanoglu, Y.S. and Kutuk, S. (2016). *Turkiye'de Finansal Cevrimler ve Is Cevrimleri: Ne Kadar Farkli, Ne Kadar Baglantili?*, 1626, Research and Monetary Policy Department, Central Bank of the Republic of Turkey.

Borio, C. (2014), The financial cycle and macroeconomics: What have we learnt?, *Journal of Banking and Finance*, 45, pp. 182-198. https://doi.org/10.1016/j.jbankfin.2013.07.031

Borio, C., Disyatat, P. and Juselius, M. (2016), Rethinking potential output: Embedding information about the financial cycle, *Oxford Economic Papers*, 69(3), pp. 655-677. https://doi.org/10.1093/oep/gpw063

Bry, G. and Boschan, C. (1971), Front matter to "Cyclical Analysis of Time Series: Selected Procedures and Computer Programs", in: Bry, G. and Boschan, C.(eds.), *Cyclical analysis of time series: Selected procedures and computer programs*, New York:Columbia University Press, pp. 13-2.

Burns, A.F. and Mitchell, W.C. (1946), *Measuring Business Cycles*, New York: National Bureau of Economic Research.

Cagliarini, A. and Price, F. (2017), Exploring the link between the macroeconmic and financial cycles, RBA Annual Conference Volume (Discontinued), in: Hambur, J. and Simon, J. (eds.), *Monetary Policy and Financial Stability in a World of Low Interest Rates*, Reserve Bank of Australia.

Chorafas, D.N. (2015), *Financial cycles: Sovereigns, Bankers, and Stress Tests*, New York: Palgrave Macmillan.

Claessens, S., Kose, M.A. and Terrones, M.E. (2011), Financial cycles: what? how? when?, in: Clarida, R. and Giavazzi, F. (eds.), *NBER International seminar on Macroeconomics*, Chicago, IL: University of Chicago Press, pp. 303-344. https://doi.org/10.1086/658308

Dickey, D.A. and Fuller, W.A. (1979), Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American statistical association*, 74(366), pp. 427-431. https://doi.org/10.1080/01621459.1979.10482531

Dickey, D.A. and Fuller, W.A. (1981), Likelihood ratio statistics for autoregressive time series with a unit root, *Econometrica: journal of the Econometric Society*, 49(4), pp. 1057-1072. https://doi.org/10.2307/1912517

Drehmann, M., Borio, C.E. and Tsatsaronis, K. (2012), *Characterising the financial cycle: don't lose sight of the medium term!*, Bank for International Settlements Working Paper, 380.

Erdoğan, S., Gedikli, A. and Kırca, M. (2019), A note on time-varying causality between natural gas consumption and economic growth in Turkey, *Resources Policy*, 64, 101504. https://doi.org/10.1016/j.resourpol.2019.101504

Gómez-González, J.E., Ojeda-Joya, J.N., Zárate, H.M. and Tenjo-Galarza, F. (2014), Testing for causality between credit and real business cycles in the frequency domain: an illustration, *Applied Economics Letters*, 21(10), pp. 697-701. https://doi.org/10.1080/13504851.2014.884689

Gonzalez, R.B., Lima, J. and Marinho, L.S.G. (2015), *Business and Financial Cycles: An Estimation of Cycles'; Length Focusing on Macroprudential Policy*, 385, Banco Central do Brasil.

Goodhart, C. (2001), What weight should be given to asset prices in the measurement of inflation?, *The Economic Journal*, 111(472), pp. 335-356. https://doi.org/10.1111/1468-0297.00634

Granger, C.W. (1969), Investigating causal relations by econometric models and cross-spectral methods, *Econometrica: journal of the Econometric Society*, 37(3), pp. 424-438. https://doi.org/10.2307/1912791

Granger, C.W. and Yoon, G. (2002), *Hidden cointegration*, Department of Economics, Unpublished Working Paper, University of California, San Diego (retrieved from https://escholarship.org/content/qt9qn5f61j/qt9qn5f61j.pdf).

Grinderslev, O.J., Kramp, P.L., Kronborg, A.F. and Pedersen, J. (2017), *Financial cycles: What are they and what do they look like in Denmark?*, Danmarks Nationalbank Working Papers, 115, Danmarks Nationalbank, Copenhagen.

Haavio, M. (2012), *Financial cycles and business cycles: some stylized facts*, Bank of Finland Online, pp. 1-20.

Hacker, R.S. and Hatemi-J, A. (2006), Tests for causality between integrated variables using asymptotic and bootstrap distributions: theory and application, *Applied Economics*, *38(13*), pp. 1489-1500. https://doi.org/10.1080/00036840500405763

Harding, D. and Pagan, A. (2002), Dissecting the cycle: a methodological investigation, *Journal of monetary economics*, 49(2), pp. 365-381. https://doi.org/10.1016/S0304-3932(01)00108-8

Harding, D. and Pagan, A. (2003), A comparison of two business cycle dating methods, *Journal of Economic Dynamics and Control*, 27(9), pp. 1681-1690. https://doi.org/10.1016/S0165-1889(02)00076-3

Hatemi-J, A. (2012), Asymmetric causality tests with an application, *Empirical Economics*, 43(1), pp. 447-456. https://doi.org/10.1007/s00181-011-0484-x

Hodrick, R.J. and Prescott, E.C. (1997), Postwar US business cycles: an empirical investigation, *Journal of Money, credit, and Banking*, pp. 1-16. https://doi.org/10.2307/2953682

Krznar, M.I. and Matheson, M.T.D. (2017), *Financial and business cycles in Brazil*, International Monetary Fund Working Paper, 17/12, pp. 1-27. https://doi.org/10.5089/9781475571042.001

Kwiatkowski, D., Phillips, P.C., Schmidt, P. and Shin, Y. (1992), Testing the null hypothesis of stationarity against the alternative of a unit root, *Journal of econometrics*, 54(1-3), pp. 159-178. https://doi.org/10.1016/0304-4076(92)90104-Y

Luvsannyam, D., Batmunkh, K. and Buyankhishig, K. (2019), Dating the business cycle: Evidence from Mongolia, *Central Bank Review*, 19(2), pp. 59-66. https://doi.org/10.1016/j.cbrev.2019.06.001

Ma, Y. and Zhang, J. (2016), Financial cycle, business cycle and monetary policy: evidence from four major economies, *International Journal of Finance & Economics*, 21(4), pp. 502-527. https://doi.org/10.1002/ijfe.1566

Oman, W. (2019), The Synchronization of Business Cycles and Financial Cycles in the Euro Area, *International Journal of Central Banking*, 15(1), pp. 327-362.

Phillips, P.C. and Perron, P. (1988), Testing for a unit root in time series regression, *Biometrika*, 75(2), pp. 335-346. https://doi.org/10.1093/biomet/75.2.335

Rand, J. and Tarp, F. (2002), Business cycles in developing countries: are they different?, *World development*, 30(12), pp. 2071-2088. https://doi.org/10.1016/S0305-750X(02)00124-9

Sala-Rios, M., Torres-Solé, T. and Farré-Perdiguer, M. (2016), Credit and business cycles' relationship: evidence from Spain, *Portuguese Economic Journal*, 15(3), pp. 149-171. https://doi.org/10.1007/s10258-016-0124-7

Schüler, Y.S., Hiebert, P. and Peltonen, T.A. (2015), *Characterising the financial cycle: a multivariate and time-varying approach*, ECB Working Paper, 1846.

Sedlacek, T. (2017), *İyi, Kötü & Ekonomi: Gılgamış'tan Wall Street'e İktisadi Anlam Arayışı*, Çev. Alpogan Sabri Erdoğan, İstanbul: Türkiye İş Bankası Kültür Yayınları.

Shen, C.H., Shi, J.G. and Wu, M.W. (2019), Is finance a veil? Lead-and-lag relationship between financial and business cycles: The case of China, *European Financial Management*, 25(4), pp. 978-1012. https://doi.org/10.1111/eufm.12193

Sims, C.A. (1980), Macroeconomics and reality, *Econometrica: journal of the Econometric Society*, pp. 1-48. https://doi.org/10.2307/1912017

Skare, M. and Porada-Rochoń, M. (2020), The synchronisation between financial and business cycles: a cross spectral analysis view, *Technological and Economic Development of Economy*, 26(4), pp. 907-919. https://doi.org/10.3846/tede.2020.12567

Skare, M. and Stjepanović, S. (2016), Measuring business cycles: a review, *Contemporary Economics*, 10(1), pp. 83-94.

Toda, H.Y. and Yamamoto, T. (1995), Statistical inference in vector autoregressions with possibly integrated processes, *Journal of econometrics*, 66(1-2), pp. 225-250. https://doi.org/10.1016/0304-4076(94)01616-8

Yan, C. and Huang, K.X. (2020), Financial cycle and business cycle: An empirical analysis based on the data from the US, *Economic Modelling*, 93, pp. 693-701. https://doi.org/10.1016/j.econmod.2020.01.018

Appendix A: correlation matrix

Correlation (Probability)	NRGDP	NRCREDIT	NC_TO_GDP	NINTR	NBIST100	NREER
NRGDP	1.000000					

NRCREDIT	0.982844	1.000000				
	(0.0000)	-----				
NC_TO_GDP	0.966540	0.982485	1.000000			
	(0.0000)	(0.0000)	-----			
NINTR	-0.608937	-0.522845	-0.564462	1.000000		
	(0.0000)	(0.0000)	(0.0000)	-----		
NBIST100	0.668931	0.657713	0.689296	-0.536656	1.000000	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	-----	
NREER	-0.322789	-0.398609	-0.318605	-0.219196	0.127633	1.000000
	(0.0022)	(0.0001)	(0.0025)	(0.0402)	(0.2360)	-----

Source: Authors' representation