TÜRKİYE CUMHURİYET MERKEZ BANKASI

Synchronization, Concordance and Similarity between Business and Credit Cycles: Evidence from Turkish Banking Sector

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Synchronization, Concordance and Similarity between Business and Credit Cycles: Evidence from Turkish Banking Sector

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Abstract

In this study, we provide a comprehensive quantification of the co-movement between credit and business cycles in the Turkish case for the period 2007-2020. To this end, we construct synchronization, concordance and similarity index, which aim to measure the time-varying degree of coherence between credit and output dynamics. In specific, these indices are designed to capture the location, momentum and size aspects of the cyclical correlation respectively. Our empirical analysis also covers the cyclical association of 13 different loan sub-categories with the course of the output gap by employing disaggregated data. Overall, index results show that credit-output nexus in the Turkish case present heterogeneities across loan types, sample episodes and cyclical characteristics (location, momentum, and size). We also examine the impact of local and global macroeconomic and financial factors on cyclical coherence by utilizing Tobit regressions. The empirical results indicate that movements in local financial conditions, fluctuations in macroeconomic volatilities, and the course of capital flows are influential determinants of cyclical co-movements.

Özet

Bu çalışmada Türkiye örneğinde 2007-2020 dönemi için kredi ve iş çevrimleri arasındaki ortak hareketlerin sayısallaştırılması hedeflenmektedir. Bu bağlamda, zamana göre değişen kredi piyasası-ekonomik aktivite ilişki derecesini ölçen senkronizasyon, uyuşma ve benzerlik endeksleri hesaplanmaktadır. İlgili endeksler çevrimsel ilişkinin sırasıyla konum, faz ve boyut özelliklerini yakalamaktadır. Sektör geneli toplam kredi gelişmelerine ek olarak, 13 alt kredi kategorisinin de çıktı açığıyla çevrimsel uyumu incelenmektedir. Genel olarak endeks sonuçları Türkiye ekonomisi özelinde krediler ile iktisadi faaliyet arasındaki çevrimsel ilişkinin kredi türü, örneklem dönemi ve çevrim karakteristikleri (konum, faz ve boyut uyumu) açısından önemli heterojenlikler taşıdığını göstermektedir. Çalışma kapsamında ayrıca yerel ve küresel makro-finansal faktörlerin çevrimsel uyuma olan etkisi Tobit regresyon modelleriyle araştırılmıştır. Ampirik bulgular finansal koşullardaki hareketlerin, makroekonomik oynaklıkların ve sermaye akımlarının seyrinin kredi-iş çevrimi uyumunu anlamlı şekilde etkilediğini ortaya koymaktadır.

JEL Classification: G21, E32, C35, C38

Keywords: Credit Cycle, Business Cycle, Synchronization, Filtering, Tobit Regression

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Non-Technical Summary

This study aims to analyze the co-movement between credit and business cycles in Turkey from 2007 to 2020. Initially, the time-invariant relationship is examined with the help of a simple correlation measure and distance indicators. Furthermore, to measure the time-varying degree of coherence between credit and output dynamics, we construct synchronization, concordance, and similarity indices. These indices are designed to capture the position, momentum, and size aspects of the cyclical correlation between credit and output gap series, respectively. In the following step, we investigate how macro-financial factors impact the degree of co-movements. On top of aggregate loans, our analyses are conducted for retail loans as a whole and its subcomponents of general-purpose, vehicle, housing loans and credit cards; and commercial loans broken down to investment, foreign trade, business, SME and large firm loans.

The empirical results on the static measures suggest that there exists a lead-lag relationship between credit and output dynamics for which fluctuations in output growth cycle precedes credit cycle and more prominent co-movements seem to occur with 3-4 months as elapsed time. In addition to the static analysis, investigation of the dynamic relationship between credit and output series with the synchronization index reveals that, on average, the perfect synchronization is observed for 80% of the sample period, which demonstrates that total credit and economic activity stand in the same front with respect to the trend, for the majority of the sample period. The highest synchronizations with the output gap are observed for total, housing, and consumer loans; while the lowest ones are found in credit cards, investment, and business loans. The analysis with the concordance index proposes that on average, there is a perfect phase coherence between credit and output gap in nearly 60% of the sample period. Looking at the loan breakdowns, the highest level of concordance is achieved by retail loans mainly driven by housing loans while the lowest concordance with economic activity is observed in credit card and foreign trade loans. The similarity index results measuring the coherence of cyclical sizes suggest that the least discrepancy in the amplitudes of the credit and output gap is observed in consumer and housing loans, and the highest discrepancy is observed in credit cards and investment loans.

Our empirical investigation on the determinants of the co-movement between credit and output gap series indicates that financial conditions significantly influence the position coherence for commercial loans (especially foreign trade, business, and SME loans). Similarly, macroeconomic volatilities are detected to affect position-wise suitability between credit and output gap mainly for commercial, general-purpose, investment, SME, and large firm loans. Synchronization seems to be elevated during the episodes characterized by stronger capital inflows for the total loans as well as sub-segments of commercial loans. Estimation results using the concordance index as the dependent variable show that tightening in local financial conditions is significantly stimulating phase coherence for consumer, housing, vehicle, business, and SME loans. On the other hand, in contrast to synchronization, macroeconomic volatilities seem to have a reversed impact on concordance, particularly for sub-components of retail loans. Moreover, capital flows tend to improve phase coherence in a statistically significant way, both for retail and commercial loans. Lastly, Tobit estimation results provide less information for the extent of cyclical similarity between credit and output dynamics.

1. Introduction

Even in the current conjuncture characterized by well-developed and integrated equity and bond markets on a global scale, bank loans remain the most preferred method of financing in emerging market (EM) economies (Dorucci et al., 2009). Following the regulatory and monetary policy-related measures taken in the recent decade to overcome the repercussions of the Global Financial Crisis, the overall improvement in global liquidity conditions and capital outlook in domestic banking systems shored the credit growth in emerging countries (Eickmeier et al., 2014; Dahir et al., 2019). For households, traditionally, mortgage financing in EMs constitutes a considerable amount of liabilities (in household balance sheets) and they are generally arranged in the form of bank loans (Warnock and Warnock, 2008; Badarinza et al., 2019). While the impact is more pronounced in SMEs, non-financial firms operating in EM economies can face challenges given financing constraints and the availability of collateral as the bank financing is the most important external funding in those countries (Beck et al., 2006; Kira, 2013; Dong and Men, 2014). In this context, bank credit emerges as the most representative indicator for the domestic financial cycle and its compatibleness with economic activity should be inherently highlighted as a proxy of imbalances regarding financial stability.

Another factor contributing to the importance of this issue is related to the monetary policy transmission mechanism. Apart from traditional interest rate channel and expectations channel, firm credits and bank lending effectuate important bases of how monetary policy stance is transmitted to macroeconomic aggregates including growth and inflation. Particularly in EMs, credit channel is determined to function considerably so it is expected that the periods, during which credit-business cycle is strongly associated, can also potentially be seen as periods with the more efficient monetary transmission (Caballero and Krishnamurthy, 2004; Çatık and Karakuça, 2012). This issue holds importance for authorities dealing with the estimation of the effect of monetary policies on financial/macroeconomic outcomes. Furthermore, there is rooted empirical evidence in the previous literature asserting the indicative nature of drastic credit movements for the occurrence of banking/financial and real economic crises (Slingenberg and De Haan, 2011; Feldkircher, 2014; Krishnamurthy and Muir, 2017). Hence, analyzing the credit-business cycle coherence might improve forecasting practices. Perhaps, more relevant to the Turkish case, countercyclical financial policies aiming to tackle the deceleration in economic activity might directly focus on selective credit extension. In fact, loosening of macroprudential and reserve requirement policies as well as the introduction of new credit facilities including Treasury-backed Credit Guarantee Fund (CGF) guarantees and affordable housing loans) to enhance the credit growth in the Turkish banking sector are observed after 2016. Having a quantitative proxy of the coherence between credit and output cycles can provide better information about the effectiveness of such policies.

Turkish banking sector serves as a proper case to examine the time-varying nature of business and financial cycle co-movements. Figures 1 and 2 present the credit market outlook across three distinct periods in which economic growth sharply deteriorated from its long-term trend.[2] Such periods are especially unique from each other regarding the source, cause, and duration of economic shocks as well as the level of financial development and the policy measures taken afterward.

Top-left charts in Figures 1 and 2 take January 2009 as the bottom point of the economic slowdown in the wake of the Global Financial Crisis and represent the fluctuations in main loan categories in terms of both normalized level and month-on-month changes. This period was characterized by decaying external demand, contraction in global liquidity, deteriorated global investor sentiment and abnormal portfolio outflows in emerging markets, which all abridge the financial health of the non-financial companies by tightening the financial conditions and limiting the growth realizations in emerging countries (Frank and Hesse, 2009; Coulibaly et al., 2013; Dimitriou et al., 2013). The case of Turkey is subject to similar results for economic activity, particularly for the real sector firms. Alp and Elekdağ (2011) estimate a structural model to analyze the role of possible factors on the recession in the Turkish economy during this period. Their results confirm that foreign demand and financial uncertainty constitute important parts of the slump in economic growth. Demirhan and Ercan (2018) analyze the export behavior of Turkish manufacturing firms by employing firm-level data and they conclude that this period reduced the export propensity as well as the volume of exports. On the other hand, macroeconomic fundamentals in Turkey were strong before the crisis period as indicated by the relatively lower levels of dollarization, anchored inflation expectations, and subdued external debt (Kılınç et al., 2012). This background combined with expansionary fiscal policy allowed the domestic demanded to rebound considerably aftermath the crisis. The abovementioned divergence between economic agents in terms of the exposure to the economic downturn was reflected in the credit developments. Given the size of the shock, the recovery in total loans took longer compared to other crisis episodes in the recent decades. More importantly, the behavior of loan sub-categories differed in the sense that while the momentum of the commercial loan extensions was stronger than that of retail loans before the peak point, they performed relatively poorly after the point of interest. The stagnation in commercial activities together with

[2] We use both annual growth rate and cyclical component of the industrial production index to identify these periods.

depressed export transactions and investment growth are argued to play important role in this plateau observed in commercial loan growth.

[Insert Figure 1 and 2]

Top-right charts in Figures 1 and 2 present the credit market outlook around July 2016 during which economic activity slowed down as well. Although global and local geopolitical risks have been prominent during that time, in addition to the relatively milder size of the shock, policy measures taken to enhance the financial inclusion and credit channel helped credit growth rates to be less susceptible to adverse economic conditions (Bilgin et al., 2019; Mansour-Ichrakieh and Zeaiter, 2019). Similar to many emerging markets, the lack of adequate collateral stands as a major obstacle against non-financial entities in Turkey to reach credit-based financing (Beck et al., 2008; Yıldırım et al., 2015; Yoshino and Taghizadeh-Hesary, 2019). Thus, policymakers responded by introducing the Treasury-backed credit guarantee scheme aiming to neutralize any possible impacts on credit demand and supply conditions. This appeared to be the reason behind the strong recovery in total loans aftermath the crisis driven by commercial loans. More recently, financial market volatilities and tightening in financial conditions put downward risks on economic activity becoming more visible around December 2018. However, both the relaxations in macroprudential measures and the decline in cost of financing supported by decreases in loan rates on the back of the disinflation process paved way for an improvement in credit market outlook, mainly caused by retail loans as the momentum in this category exceeded that of commercial loans. Overall, the descriptive data indicate that the Turkish case provides a suitable framework to analyze the cyclical coherence between economic activity and credit growth through indexation methods, considering the heterogeneities in the extent of growth shock, the macroeconomic background, and policies implemented to contain the macro-financial results of the crises.

In this study, we provide a comprehensive analysis of co-movement between output and credit cycles in the Turkish case by constructing three different indices each of which captures different aspects of common evolvement. As the most basic indexation method, we choose the technique named as synchronization index which is utilized by Mink et al. (2012) and Samarina et al. (2017). This index basically captures whether or not business and credit gaps carry the same sign at a specific time period. Although it is a simple method, it has a particular advantage over static correlation as it can be calculated in a time-varying manner. Secondly, as initiated by Harding and Pagan (2006) and preferred by many empirical studies, we proceed with the concordance index.[3] It monitors the suitability of the positions of output and business cycle over expansion and contractions. Hence, the concordance index can measure conformity in the momentums of credit and business cycle in addition to position-wise analysis. As the third measure, we employ the similarity index covered by Mink et al. (2012) and Samarina et al. (2017) which provides continuous information about the size differences of two cyclical series.

There are few previous studies aiming to quantify the behavior of credit and financial cycles using Turkish banking sector data. Akar (2016) investigates the co-movement between financial and business cycle in Turkey and reveal that the credit cycle is the leading factor of GDP cycle. However, that study is conducted in quarterly frequency lacking the evidence for higher frequency and only concordance index is calculated which excludes the abovementioned aspects of the association. Binici et al. (2016) also work on the relationship between credit and business cycle on the Turkish case, but they only focus on concordance index and analysis was limited to total credits. Our paper contributes to the existing literature on several fronts. Firstly, as mentioned before, our indexation mechanism quantifies location, momentum, and size aspects of cyclical correlation. Secondly, we focus on disaggregated credit data and provide empirical results for 13 different sub-categories of total loans ranging from general-purpose loans to credit cards, from SME loans to foreign trade loans. Thirdly, we extend our empirical analysis to reveal the impact of local and global macroeconomic/financial factors on indices describing the output/credit cycle correlation by utilizing Tobit regressions.

The rest of the paper is organized as follows. Section 2 conducts a literature review about finance-growth nexus and some empirical methods to measure the joint movement between credit and output growth. Section 3 provides detailed information about methodological aspects of the study, while section 4 briefly mentions about utilized data sets. Section 5 discusses the empirical results and the last section makes conclusive remarks of the paper.

2. Literature Review

The interaction between financial and economic aggregates has been a major interest in academic and policy-based analysis. Earlier literature considers this issue within finance-growth nexus describing a long term relationship stemming from financial development and economic growth (Hicks, 1969). Although there were critics like Lucas (1988) claiming that the role of financial factors are over-emphasized, developed banking sector and capital markets are thought to lift output growth by accommodating the capital allocation and facilitating investment. This strand of the literature also states that causality can function from the demand side cultivating

[3] For the implementation of the concordance index in cross-country settings, please see Meller and Metiu (2015), Oman (2019) among many others.

the influence of economic activity on financial development. Credit booms followed by credit busts are regarded as results of the self-feeding feedback mechanism between the real and financial side of the economy (Minsky, 1977). As mentioned by Gomez-Gonzalez et al. (2015), this "instability" hypothesis asserts that prolonged periods of economic stability induce risk-seeking behavior among firms and households who assume an increasing level of debt, whereas credit standards are loosened given less frequent default realizations. In turn, such a boom outlook paves way for financial instability and associated output losses in the case of crises.[4]

Earlier theoretical explanations for common cyclical credit and output movements are rooted in "financial accelerator" framework established by Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Bernanke et al. (1999). Assuming that credit creation mostly depends on the banking sector, bank lending should have real effects and serves as a significant source of macroeconomic fluctuations. In other words, in the presence of financial market frictions and asymmetric information, credit and asset prices shape the business cycle by propagating the shocks to the economy through borrower and bank balance sheet channel. Financial accelerator mainly works through the cost of borrowing faced by economic agents that is inversely related to net wealth. Negative wealth shocks caused by the collapse in asset prices reduce the collateral values and exacerbate the external finance premium leading to higher borrowing costs. Kiyotaki and Moore (1997) and Kiyotaki (1998) stress a borrower-lender agency problem which drives the external finance premium as net worth declines are transformed into prominent agency costs. Hence, negative financial shocks accompanied by worsened creditworthiness would decrease credit demand and ultimately result in lower investment and economic activity.

In this process, frictions caused by the pro-cyclical nature of net worth would amplify the magnitude and persistence of output variations. On the other hand, rebound in economic activity coupled with inflated collateral values can incline relaxation in credit restrictions and contribute to boosted credit and output growth. On top of the borrower balance sheet channel, another element of the financial accelerator mechanism is the bank balance sheet channel. Any deterioration of bank balance sheets would deepen the negative shocks coming to asset prices. For instance, Bernanke and Blinder (1988) indicate that monetary policy tightening would influence asset formation of banks and create stronger than anticipated decreases in credit supply. Based on general equilibrium models, several studies investigate the output fluctuations by incorporating financial frictions in model setting.[5]

[4] Studies like Minsky (1995) and Goodhart (2010) document the findings that minor business cycles are the sources of increasing indebtedness, whereas major business cycles drive severe financial crises.

[5] Please see Christiano et al. (2010), Gertler and Kiyotaki (2010), Jermann and Quadrini (2012) among many others.

The abovementioned mechanism operates primarily by amplifying business investment fluctuations. However, as conceptualized by Mian and Sufi (2018), a credit-driven household demand channel is also effective in establishing the link between financial and business cycles. It is argued that, apart from boosting firm production capacities, the expansionary phase of the credit cycle would also support household spending demand and increase the household debt excessively. Once credit supply is contracted due to financial difficulties, a sharp drop is observed in spending by the households, especially the ones with considerable indebtedness. Aggregate demand will ultimately drop as savers cannot sufficiently raise the spending, while supply-side is also depressed severely given nominal rigidities and disruptions. In short, household demand is also a part of the endogenous credit/output cyclical movements.

The contemporary global economic system is characterized with a stronger relationship between output and credit dynamics. By using a comprehensive historical data from advanced economies, Jorda et al. (2016) show that co-movement of consumption and investment with loan growth has increased considerably in recent decades, possibly due to increasing financing opportunities. The recent financial crisis and accompanied uncertainties about the course of credit growth have rekindled the interest in credit cycle-business cycle relation mostly from policymaking and financial stability perspectives since recent economic downturns coincided with financial market volatilities, substantial drop in asset prices, dried up liquidity in sovereign debt markets, and most importantly slowdown in loan growth (Jorda et al., 2011). To prevent the build-up of financial imbalances, monetary authorities are advised to include credit cycle monitoring in policy design (Claessens et al., 2012). Thus, the overwhelming majority of empirical works in recent time has evaluated the predictive power of credit growth for signaling the economic crisis episodes. By using a historical data set belonging to developed countries, Schularick and Taylor (2012) find that credit booms serve as powerful predictors of economic crises characterized by sizeable output losses, compared to alternative measures like monetary aggregates. Drehmann et al. (2017) utilize a wide panel of countries to attain the rising indebtedness preceding economic slowdowns. Drehmann et al. (2012) and Claessens et al. (2011) also assert that the duration and intensity of economic recessions are determined by the nature of financial cycle movements. Furthermore, financial cycles are seen as predictors of banking crises more often followed by severe recessions (Drehmann et al., 2012). Borio and Drehmann (2009) propose deviations of credit and asset prices from their respective long-term trends as best-performing early warning indicators of crises. Giannone et al. (2019) examine the relationship between the business cycle and financial intermediation and they identify that while short term loan dynamics did not differentiate in the post-crisis period, economic recession associated with sovereign debt crisis in Euro Zone has depressed the long-term credits. In the context of forecasting practices, involving credit and financial variables in the estimation processes are also thought to improve the prediction accuracy of drastic changes in business cycles (Erdem and Tsatsaronis, 2013; Borio et al., 2014).

More relevant to our paper, another branch of the recent empirical literature directly aims to quantify the degree of correlation between output and credit growth. Claessens et al. (2012) analyze financial-business cycle interactions for a panel of 44 countries during the period 1960-2007. They find that output and credit cycles appeared to be highly synchronized with the finding that about 80% of all the sample period, they are indeed in the same phase of the cyclical movement. However, this finding is not uniform across country classes as developed countries are found to have higher co-movement compared to emerging counterparties. Kurowski and Rogowicz (2018) also report the higher degree of co-movement between financial and output cycle, especially around crisis time with global impacts. By utilizing Spanish data during the period 1970-2014, Sala-Rios et al. (2016) quantify the level of divergence between credit and business cycle and they demonstrate that the business cycle mostly leads total credit, particularly the credits extended to the non-financial sector. Although it does not distinguish different credit types, Gomez-Gonzalez et al. (2015) choose to analyze the co-movement across different frequencies and they identify that interdependence is more pronounced across medium and long-term.

There exist alternative methods for extracting the degree of movements between credit and output growth. By considering the cyclical behavior on time and frequency domain, Wavelet coherence analysis can be used to explain credit-economic activity nexus. Scharnagl (2011) applies this method to real GDP growth and loans extended to households and firms in Germany for the period 1971-2011. It is found that the Wavelet coherence between GDP and loans given to non-financial firms is significant over a relatively longer horizon (4-8 years interval). Scharnagl and Mandler (2015) extend a similar method to core European countries to evaluate the association between firm loans and real GDP growth. In a similar spirit, Caraiani (2012) evaluate the relationship between money and output growth in the US economy through the Wavelet coherence method. Kim and In (2003) investigate the predictive power of financial variables over real economic activity in the US economy by using spectral and Wavelet analysis. Zhang et al. (2020) explain the dynamic correlation between financial structure and economic growth in the US and China through continuous Wavelet analysis. Although it is implemented to assess business cycle synchronization in a cross-country setting (not directly credit-business cycle relationship), Akkoyun et al. (2014) put spectral analysis to use. Notwithstanding, Wavelet analysis does not provide a continuous measure over time-dimension with ordinal ranking properties. Since our aim is to construct a proxy, which is expected to present an ordinal ranking for the business/credit cycle synchronization in Turkey over the sample period, we abstain to use Wavelet analysis in this paper. It can also not differentiate between different dimensions of cyclical co-movements. Besides, this particular method is sort of cumbersome and is not widely utilized in finance/economics topics.[6] In line with a simpler framework, some papers choose to use basic measures like standard deviation and correlation to monitor the synchronization. Despite the fact that it is only conducted to analyze business cycle synchronization across Euro Area countries, simple correlation is chosen as the method in Gächter et al. (2012). Our time-varying methodology aims to capture what is not identified with a simple correlation.

3. Methodology

Our empirical setting is initiated with the retrieval of business and credit cycles. To this end, the Hodrick-Prescott (HP) filter is utilized to extract de-trended versions of output and loan series, which will be termed as output and credit gaps.[7] The filtering technique developed by Hodrick and Prescott (1997) seeks to minimize the variance of examined series around trend component, which also includes a penalty term governing the second difference of the trend. In specific, cyclical components are obtained by evaluating the following optimization problem:

$$min_{\tau_1 \dots \tau_T} \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} ((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2 \qquad (1)$$

where λ controls the smoothness of the series such that larger values of the parameter correspond to less volatile trend component with the extreme case embodying linear trend, subtending λ being equal to infinity. Since our analysis is conducted in monthly frequency, we choose to implement HP filter with $\lambda = 14440$ as suggested by Hodrick and Prescott (1997).[8] Individual gap indicators are created from industrial production (IP) index and 13 sub-categories of credits through recursive filtering.

The next step of the empirical setting is to calculate descriptive measures over the sample period to assess the time-invariant degree of correlation between business cycles and credit cycles. Apart from simple correlation over lag and lead values of credit cycles and the contemporaneous business cycle, we innovate on the front of measurement by composing distance indicators, which are robust to any time differentials. In other words, once variables are standardized, we

6 Çepni et al. (forthcoming) implement the Wavelet coherence technique to analyze the credit-business cycle relationship in the Turkish economy.

7 Throughout the text we use terms like cycle, gap, deviation from trend, cyclical movements interchangeably.

8 We prefer to use a one-sided recursive version of this filter to avoid any forward-looking bias that might be caused by future observations during the implementation of a two-sided filtering procedure.

benefit from traditional Euclidean and Manhattan metrics which display how far business and credit cycle observations are located in distance z-score terms.[9] For each credit type and metric definition, 12246 distance calculations are performed paving way for richer information compared to static correlation. Then, in the following step, simple averaging is done to compose what we call "composite distance indicators". These measures are created for all the pairs of output and credit gaps including total, retail, commercial, consumer, housing, vehicle, credit card, general-purpose, foreign trade, investment, business, SME, and large firm loans. Lower values of created measures show that the descriptive resemblance between credit and business cycles is higher, when all combinations of time and size differences are accounted for. Regarding technical representation, Euclidean and Manhattan distance values are calculated as the followings:

$$First\ Distance\ Indicator = \frac{1}{N(N+1)/2}\sum_{i=1}^{N-1}\sum_{j=2}^{N} Euclidean\ Distance(Output\ Gap_i, Credit\ Gap_j) \tag{2}$$

$$Euclidean\ Distance\ (\ell 2\ \text{Norm}): d(Output\ Gap, Credit\ Gap) = \sqrt{(Output\ Gap_1 - Credit\ Gap_1)^2 + (Output\ Gap_1 - Credit\ Gap_2)^2 + \cdots}$$

$$Second\ Distance\ Indicator = \frac{1}{N(N+1)/2}\sum_{i=1}^{N-1}\sum_{j=2}^{N} Manhattan\ Distance(Output\ Gap_i, Credit\ Gap_j) \tag{3}$$

$$Manhattan\ Distance\ (\ell 1\ Norm): d(Output\ Gap, Credit\ Gap) = |Output\ Gap_1 - Credit\ Gap_1| + |Output\ Gap_1 - Credit\ Gap_2| + \cdots$$

$$Composite\ Distance\ Indicator = (0.5 * First\ Distance\ Indicator) + (0.5 * Second\ Distance\ Indicator) \tag{4}$$

On top of overall measures of relevance among cycles, we extend the empirical analysis by referring to the recent literature to derive time-variant measures, which are synchronization index, concordance index, and similarity index capturing different dimensions of co-movements. Firstly, by following the method preferred by Mink et al. (2012) and Samarina et al. (2017), we focus on the synchronicity between output and credit cycles in the reference period:

$$Synchronization_t = \frac{Output\ Gap_t * Credit\ Gap_t}{|Output\ Gap_t * Credit\ Gap_t|} \tag{5}$$

This synchronization index is defined on a $[-1,1]$ scale in which the value of 1 shows that the business cycle has the same sign as the credit cycle, while -1 indicates that gap measures have opposite signs. This basic measure only considers the location of cyclical movements regarding

[9] We implement the Stata module named "DISTAN" operationalized by Saez (1998) to derive distance values for all combinations of time differences for the abovementioned metrics.

positive/negative fronts while ignoring other aspects of the relationship. Its most important advantage over the correlation coefficient is that it is dynamic and can be created for each time point. Moreover, as argued by Mink et al. (2012), while correlation can provide misleading results in the case of heteroscedastic distribution of cycles, the synchronization index presents more accurate results in such cases.

The second measure is concordance index suggested by Harding and Pagan (2006) and utilized by several empirical works to assess the compatibility of cycle positions in output and credit dynamics in cross-country and single country settings (Claessens et al., 2012; Kurowski and Rogowicz, 2018; Meller and Metiu, 2015, 2017; Oman, 2019). This index is created as follows:

$$Concordance_t^{BC} = (B_t * C_t) + (1 - B_t) * (1 - C_t) \tag{6}$$

$$B_t = \begin{cases} 1 & if\ Output\ Gap\ is\ in\ upturn\ phase \\ 0 & if\ Output\ Gap\ is\ in\ downturn\ phase \end{cases} \tag{7}$$

$$C_t = \begin{cases} 1 & if\ Credit\ Gap\ is\ in\ upturn\ phase \\ 0 & if\ Credit\ Gap\ is\ in\ downturn\ phase \end{cases} \tag{8}$$

where B_t and C_t are dummy variables tracking the relative position of gap measures regarding historical tendencies. In other words, these dummies take the value of 1 when underlying de-trended series are increasing, while the value of 0 is assigned when cyclical components are decreasing. To create dummies, similar to Harding and Pagan (2006), we identify turning points of cycles then “peak-to-trough” and “trough-to-peak” segments of time series are associated with binary classifications.[10] Concordance (or phase synchronization) evaluates to what extent business and credit cycle accelerate and decelerate jointly so that it is informative for the momentum of transmission mechanisms. Concordance index either takes the value of 1 indicating perfect pro-cyclicality between business and credit cycle or it assumes the value of 0 corresponding to perfect misalignment and counter-cyclicality, as argued by Claessens et al. (2012), Meller and Metiu (2017).

The third and last measure of compatibility in this paper is the similarity index. As covered by Mink et al. (2012) and Samarina et al. (2017), it is capable of capturing the difference in amplitudes of business and credit cycle. Since other measures are agnostic in assessing the heterogeneity in the size of cycles, such a measure is included in the study given the fact that perfectly correlated series might have drastic amplitude differences. The index is retrieved as follows:

[10] The peak and through points of the all cycle series are determined manually by analyzing the data. Although in literature, several algorithms such as BBQ are proposed in the determination of turning points in the cycle series, they are mainly designed for annual and quarterly series.

$$Similarity_t = 1 - \frac{|Output\ Gap_t - Credit\ Gap_t|}{0.5 * (|Output\ Gap| + |Credit\ Gap_t|)} \tag{9}$$

where it can take continuous values on a [-1,1] scale depending on to what extent amplitudes of cycles are coherent. When the index is assigned with the value of 1, we can conclude that sizes of the output and credit gaps are identical with perfect synchronization at the reference sample period. On the other hand, value of -1 is associated with similar amplitudes in imperfect phase synchronization. Again, index is retrieved for the relation of each 13 loan sub-categories with business cycle dynamics.

In the last step, we aim to investigate the possible determinants of synchronization, concordance, and similarity indices. The explanatory power of macroeconomic and financial factors can lead to policy inferences taking the association between business and credit cycle in Turkey into consideration. In this context, we are inspired by the method embraced by Samarina et al. (2017) which attempt to evaluate possible determinants of credit cycle synchronization and similarity among Eurozone countries with ordered Probit and Tobit models. In this paper, we follow a similar approach in estimating the probability of embodying better synchronization, concordance and similarity between output and credit dynamics. As a notable difference from other studies, since we try to create indices in higher frequency (monthly rather than quarterly frequency), we utilize 12-months moving average trend indicators of indices as dependent variables. Given the fact that created indices are right and left-censored, moving averages are continuous series and dependent variables represent ordinal ranking, Tobit regression method is chosen. In sum, the following specification is estimated for different indices:

$$Index\_Trend_t{}^* = X'\beta + \varepsilon = \beta_0 + \beta_1 LF_t + \beta_2 MV_t + \beta_3 CF_t + \beta_4 GF_t + \varepsilon_t \tag{10}$$

$$Index\_Trend_t = \begin{cases} Index\_Trend_t{}^* & if \quad L \leq Index\_Trend_t{}^* \leq U \\ observed\ to\ be\ missing & if \quad Index\_Trend_t{}^* < L \\ observed\ to\ be\ missing & if \quad Index\_Trend_t{}^* > U \end{cases} \tag{11}$$

$$\varepsilon \sim N(0, \sigma^2) \tag{12}$$

Here, $Index\_Trend_t{}^*$ refers to latent dependent variable for which $Index\_Trend_t$ stands for incompletely observed values corresponding to moving trends of synchronization, concordance and similarity indices, which represent different dimensions of co-movements and utilized as dependent variables. Censoring from above and below is derived from highest and lowest values that trend component of indices can take, due to construction process. LF_t and GF_t represent series obtained from the principal component analysis (PCA) applied on pre-determined groups of individual financial indicators representing the financial conditions on country-level and aggregate global scales. PCA is employed to compose these explanatory variables, as we want to mitigate possible disruptive effects on model selection induced by the existence of the high number of potential covariates (representing the financial conditions) and the low number of observations given relatively shorter sample period imposed by data availability, in other words, the curse of dimensionality. The upcoming section elaborates on this issue more by describing the individual financial series used to come up with factors. Furthermore, MV_t stands for another explanatory variable created to monitor the level of macroeconomic uncertainty in the Turkish economy obtained by the two-step process. In the first step, pre-determined group of macroeconomic variables is processed by subtracting the sample mean and re-scaling the transformed versions by the respective averages. In the second step, these implied variances are aggregated by the calculating the standard deviation from combined series in each period. CF_t shows Treasury bond, equity, and corporate bond flows incoming/outgoing Turkish economy, whereas ε_t is the error term.

4. Data

The sample period is determined to cover January 2007-January 2020 interval. The decision for the sample period is based on the fact that the pre-2007 period was not characterized by relatively prominent financial deepening and inclusion of that time window will misguide the credit gap indicators due to base effects and volatile credit series. To proxy for economic activity in monthly frequency, IP index (adjusted for seasonal and calendar effects) from TurkStat is used and filtering techniques are applied to separate the cyclical component.

Nominal credit volume data is retrieved from the Banking Regulation and Supervision Agency (BRSA) database. Apart from the main credit types which are total, retail, and commercial loans, a variety of sub-categories are included to see whether or not the nature of credits has a profound role in shaping the association with growth tendencies. In other words, our empirical quest aims to decipher the heterogeneity among credit types in expansion and depression phases. To this end, as the sub-categories of retail loans, consumer loans, housing loans, vehicle loans, general-purpose loans and credit card loans are separately taken.[11] Similarly, as sub-components of the commercial segment, foreign trade loans, investment loans, and business loans are collected. Depending on the firm size, SME and large firm classifications are also added. The fraction of loan data denominated in non-TRY currencies is adjusted for FX effects whenever deemed necessary by utilizing currency basket which is constructed with 70% and 30% weights

[11] Retail loans are the sum of consumer loans and credit card loans; and consumer loans consist of housing, vehicle and general-purpose loans.

for US dollar (USD) and euro (EUR), respectively. FX-adjusted credit series are handled with logarithmic transformation and filters are applied to create credit gaps.

[Insert Table 1]

We employ multiple data series (from sources such as Bloomberg, TurkStat, and CBRT) to create covariates in Tobit estimations as briefly described in the previous section (Table 1). In this context, 11 series representing the conditions tracking FX market, risk premium, bond market, and equity market are considered. Transformed series are normalized to produce z-scores before being aggregated by PCA. The first principal component is named as local financial factor. Likewise, the bottom-up approach is preferred to construct macroeconomic volatility covariate. A broad range of macroeconomic series is chosen to stand for inflation, economic activity, foreign trade, and public finance outlook. Transformed versions displaying the divergence from the sample means are then integrated by constructing ultimate period-wise standard deviation to produce volatility proxy. On the other hand, the explanatory variable proxying capital flows is directly created by adding up normalized net capital flows for local bond and equity instruments. Lastly, we derive the global financial factor from PCA implemented on global financial data about the bond, equity, and FX markets. The stationarity properties of all series subject to analysis are investigated with ADF unit root tests.

We further implemented diagnostics tests for the PCA conducted to create local and global financial factors (Table 2). Bartlett's test of sphericity aiming to detect whether or not the observed correlation matrix is equivalent to an identity matrix is performed. For both of the cases, the null hypothesis that variables are not inter-correlated can be rejected at conventional significance levels. Besides, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is retrieved. KMO measure takes values between 0 and 1 for which smaller values point out that examined variables have too little in common to apply PCA. However, in our cases, KMO values are found to be relatively high indicating the appropriateness of utilized series for PCA setting. In addition to these, we evaluated the criterion like percentage of total variance explained, factor loadings, and eigenvalues before proceeding with first principal components as explanatory variables.

[Insert Table 2]

5. Empirical Results

In the benchmark case, HP filtered credit cycles and business cycle indicators are depicted in Figure 3. As expected, economic activity has fallen below the long-term trend during periods like the Global Financial Crisis, and recent years caused by temporary uncertainties and volatilities. While the deterioration in 2008-2009 is more sizeable, all of the economic downturns are followed by a boost in economic activity which brings the cycle component into positive territory. Similarly, recent weakening in business conditions, clarified especially towards the end of 2018, has been overcome with the help of coordinated efforts to preserve the functioning of credit channel as manifested by the recent coincident rise in credit cycles across sub-categories.

[**Insert Figure 3**]

When we examine credit cycle series, a striking finding is that, in contrast to developed countries, credit movements in the Turkish banking sector have rather shorter durations and they have similar sizes compared to the business cycle. This finding can be explained through the high share of banking sector loans in household and firm financing. In other words, loan demand outlook which is highly dependent upon consumption demand by households and investment demand by firms resembles closely with the course of economic activity. Regarding credit types, commercial loans seem to be more associated with the total loan movements, whereas retail loans display mildly larger fluctuations. In fact, the last year in the sample validates a divergence between these groups as retail loans recorded a stronger rebound. In other words, cycle values in that category are higher than that of commercial and total loans towards the end of 2019. This inclination turns out to be mainly driven by general-purpose and vehicle loan cycles, whereas credit cards do not show a similar trend.

5.1 Correlation and Distance Analyses

Notwithstanding the limitations of the graphical analysis, the first set of formal empirical findings contains the time-invariant measures. Table 3 exhibits the pairwise correlations between the lag values of credit gap indicators retrieved from different loan categories and the business cycle, and the subsequent table shows the correlation of the lead values of credit gap indicators with the business cycle. It is evident from Table 3 that, as time lag increases, the correlation with output gap worsens for all loan types. Contemporaneous correlations have the highest value compared to the all lags of credit gap indicators and the second-largest correlation is achieved with the first lag among all up-to-six lags of credit gap indicators. In other words, rising loan volume corresponds with the rising economic activity in the current period more profoundly than the future periods.

Besides, as Table 4 suggests, there exists a lead-lag relationship between credit and output dynamics for which fluctuations in output growth cycle precedes credit cycle and more prominent co-movements seem to occur with 3-4 months as elapsed time. While this finding is applicable for almost all loan breakdowns, the time differentials where the strongest association is detected for credit cards and investment loans are relatively larger. As a general finding, these results confirm the procyclicality of bank credits in the Turkish case as the overwhelming majority of loan breakdowns are attached with larger positive correlation coefficients with exceptional cases of credit cards and investment loans. Previous empirical literature documents the procyclical nature of credits by referring to the market imperfections and financial sector-real sector interactions under which credit conditions can exacerbate the output fluctuations (Athanasoglou et al., 2014; Bouvatier et al., 2014). Particularly, the positive correlation is accepted as an inclination of the banking sector to behave in a procyclical manner in empirical works, whereas the impact might be varied depending on the competition level of the banking sector and whether the credit is secured (Azariadis et al., 2016; Leroy and Lucotte, 2019). Moreover, regulatory frameworks aiming to establish a link between capital buffers and output fluctuations might also alter the procyclicality (Jacques, 2010).

A within-group comparison among loan breakdowns with positive correlation values shows that the highest correlation with output gap is observed for total loans. It is followed by the credit gap indicators created from commercial, retail, consumer, housing, and SME loans. On the other hand, the lowest correlations are found when we evaluate credit cards and investment loans. Although credit card spending is expected to increase when the economy booms, consumers also tend to fully pay their credit card debt balances as quickly as possible during positive economic activity. Conversely, during downturns where financial conditions tighten and credits squeeze, people utilize their credit cards more to create cash for consumption spending and tend to delay their repayment due to slowing income growth. Also, the drop in income level during downturns often leads households to use their credit cards to finance the repayment of other debts. Hence, the role of credit cards to generate additional income when economic activity slowdowns makes credit card loans less procyclical with economic activity compared to other loan breakdowns. For investment loans, a relatively lower correlation with output gap emerges from the specific characteristics of this loan type. Firstly, investment demand is dependent more on the long-term macroeconomic outlook rather than short-term cyclical movements in the business cycle since the return on investment might take several years to break even. Hence, investment loans are expected to rise when the long-term expectations of investors are positive, irrespective of the current economic situation. Secondly, investment loans have very long maturities (more than 10 years) and large amounts, and nearly 85% of the loans are FX denominated in the Turkish banking sector. This makes investment loan usage associated with several other factors, some of which are the level of the exchange rate and interest rate, global financial conditions, and banks’ non-core financing. Finally, the majority of private sector investments are subject to various government incentives granted via investment incentive certificates, which raise the firm's access to investment loans in Turkey. And the fact that these incentives do not decline, or even increase, in economic downturns due to the countercyclical motives of the government mitigates a procyclical drop in investment loans when economic activity slowdowns. Overall, since investment loans are dependent more on long-term macroeconomic outlook and exogenous government stimulus, it has a less procyclical pattern with the output gap among other loan types.

[Insert Table 3 and 4]

On top of correlation analysis, we focus on the composite distance indicators, which take into account all possible combinations for time differentials as well as the size differences to construct an average static measure for the association between output and credit gap. Results depicted in Figure 4 indicate that breakdowns including large firm, SME, commercial and total loans are subject to the shorter distance to growth cycle compared to other categories. Although the stronger correlations for these categories certainly contribute to the abovementioned findings, comparably lower variances for the examined breakdowns are also assessed to reduce the distance indicators.

[Insert Figure 4]

5.2 Synchronization, Concordance and Similarity between Cycles

Next, we cover results belonging to indices that are designed to monitor the coherence between credit and output developments. Figure 5 provides the synchronization index examining whether the credit gap and output gap contain the same sign at a specified time. Even through this group of indices is binary by construction and can take either -1 or 1 as the value, we also present the 12-month moving average as the trend indicator to assess the time-varying properties of cyclical position in a basic way. The fact that synchronization index trend values stay broadly on the positive front (and closer to 1) across loan breakdowns points out that coherence between credit and output dynamics are mostly similar regarding the cyclical positions, except for investment loans. The trends of synchronization indices also assert that the position-wise compatibility between credit and business cycles has been robust during the earlier phases of the sample period including the Global Financial Crisis since both loan extension and economic activity have shrunk and have coordinately been reduced into negative territory. However, the episode from 2012 till 2016 witnessed weakened conformity in cyclical positions, especially for total, consumer, vehicle, and general-purpose loans as well as the credit cards. A striking finding is that this period is also related to the wave of macroprudential measures designed to contain the excessive credit movements diverging from credit demand and supply forces. Hence, the utilization of a broad set of macroprudential measures including reserve requirements, loan-to-value ratios, installment restrictions, and FX debt limitations all contribute to the decline in cyclical position suitability.

Furthermore, it is detected that credit guarantee mechanisms improved by the policymakers since the beginning of 2017 help increasing the synchronization between credit and business cycle. This finding is strongly observed for commercial loans and sub-components such as SME loans, foreign trade loans, and business loans. The main rationale behind this relationship is that, after the introduction of new credit guarantee scheme, credit gap indicators calculated from commercial loans accelerated to higher levels, eventually reaching to positive territory and they resemble the course of economic activity which had started to display signs of a rebound in the same period. The results derived from synchronization indices also contain insights for the more recent conjuncture, specifically the period after the financial market turbulence in August 2018. At the beginning of this phase, the sharp devaluation of TL against foreign currencies led to insolvency issues for highly FX-indebted firms, balance sheets worsened and asset quality of the banking sector deteriorated. This caused economic activity to lose momentum, which was accompanied by tightening financial conditions and a significant credit crunch (Çolak et al., 2019). Hence, from the third quarter of 2018 till the second quarter of 2019, we observed that both the output gap and credit cap in nearly all loan types are in the negative territory, which is also a sign of perfect synchronization between two series. Nevertheless, credit card loans and foreign trade loans are two exceptions in this overall pattern. Credit card loans did not collapse as much as other loan types, supporting our previous argument on the income-generating role of credit cards in downturns. Foreign trade loans did not also accompany the general downtrend in the overall credit market because real exchange rate depreciation gained exporter firms a significant competitive advantage in global markets. Although the banking sector contracted overall credit supply in this period due to asset quality concerns, they maintained extending loans to firms dealing with foreign trade due to their improving business activities. This situation is also consistent with the finding of earlier literature that, in crisis times, banks incline to provide more finance for the tradable sectors than non-tradable sectors (Krueger and Tornell, 1999 and Borensztein and Lee, 2002).

Following the second quarter of 2019, the improvement in economic agents' expectations coupled with expansion in financial conditions has brought joint increases in credit and consumption demand. This allowed the economic activity to exceed the trend in the third quarter of 2019, while most loan types were still behind the trend due to the reluctance of private banks to provide credit. Finally, in the last quarter of 2019, particularly retail and consumer loans synchronized with the output growth owing to the realization of pent-up spending together with easing financial conditions. Whereas positional harmonization between commercial credit and business cycles continues to decrease mainly because of the subdued investment tendencies and credit risk concerns towards SMEs.

[**Insert Figure 5**]

After the analysis of how the synchronization index has changed over time, investigating the overall synchronization of all loan sub-categories with the output gap for the whole sample period would give us an aggregate picture of the differentiation among loan types. The last graph of Figure 5 depicts the number of months where perfect synchronization (index being equal to 1) occurred as a percentage of the total number of months in the sample for each loan category. The graph suggests that while aggregate loan volume and total output are in the same position with respect to the trend for nearly 80% of the whole sample period, credit card loans are in the same position with output growth for around half of the sample period. The highest synchronizations with the output gap are attained by total, housing, and consumer loans; while the lowest ones are found in credit cards, investment and business loans. On average, perfect synchronization is observed for 70% of the sample period, which demonstrates that the credit market and economic activity stand in the same front with respect to the trend, most of the time, in the context of the Turkish economy. Finally, the cyclical position of retail loan sub-categories is more synchronized with the business cycle compared to sub-types of commercial loans.

Next, we discuss the concordance index results and short term tendencies of indices presented in Figure 6. By construction, the value of 1 refers to perfect phase conformity in which both credit and output gap indicators are on the same phase over the cycle. In other words, they jointly stand-in "peak-to-trough" or "trough-to-peak" phases at a specific point in time. Naturally, the lack of conformity regarding the cycle phase results in the value of 0 attached to concordance indices. Similar to synchronization, on average, prominent concordance relationships are also manifested in different loan breakdowns. In parallel with the 3-6 months lag/lead structure, which has already been evident in static analysis of correlations and distances, we expect weaker concordance around the Global Financial Crisis during which the duration and amplitude of the shocks to economic activity were sizeable. The concordance indices actually document declines around that period and support this view in almost all loan breakdowns. In particular, the rebound in growth cycles has started earlier than those of credit cycles which continued to decelerate. This process led to temporary contradictions in terms of phase conformity. Concordance indices hovered around values closer to 1 aftermath the first half of 2016 during which another growth shock occurred. As there existed a consensus between downward movements in the credit and output gap in this period, both indicators have aligned in the "peak-to-trough" phase.

Besides, after the financial volatilities in 2018 and accompanied stagnation in economic activity, a joint drop has been observed among loan categories. The "peak-to-through" phase in the business cycle has started at the beginning of 2018, while credit gaps had been in the expansion phase, which resulted in a sharp drop in the concordance index. Following the third quarter of 2018, the majority of loan movements took place in the "peak-to-through" phase jointly with the output gap, resulting in steadiness in terms of 12-month moving average concordance index. From the first quarter of 2019, the output gap started its through-to-peak phase jointly with commercial loans and retail loans picked them up from the third quarter of 2019. Concordance index constructed for commercial loans stayed in relatively higher levels in this period mainly driven by larger firm loans. One reason behind this fact is that, during downturns, banks are more inclined to restructure the loans extended to larger firms than the SMEs because their loan balances are large enough to create a systemic risk. Hence, they seem to treat these firms as "too-big-to-fail". Also, the credit risk of SMEs has sharply risen in the recent turmoil, which entailed private banks to be more prudent in restructuring the existing credits or extending new credits to SMEs. Henceforth, similar to the case in the global financial crisis, the concordance index for large firms has been higher than the SMEs since the second half of 2018. Besides, since the "trough-to-peak" movement in economic activity has started earlier than that of retail loans, a discrepancy was observed for the phase coherence between retail loan sub-types and business cycle throughout 2019.

The last graph of figure 6 shows the percentage of the number of months where the concordance index takes the value of 1 in the whole sample for each credit gap indicator. On average, we observe a perfect phase coherence between the credit and output gap in nearly 60% of the sample period. Looking at the loan breakdowns, the highest number of concordance is achieved by retail loans mainly driven by housing loans while the lowest concordance with economic activity is observed in credit card and foreign trade loans. These findings are similar to the results of the synchronization index where housing loans possessed the second-highest positional coherence with output gap and credit cards had the lowest.

[**Insert Figure 6**]

As the last set of index-based findings, similarity index results are given in Figure 7. This particular index is designed to monitor the size conformity between credit and business cycles. Although there were variations in the earlier parts of the sample period, we observe that the sizes of credit and business cycles had differed heavily between 2012 and 2015, across almost all loan categories. This finding is more visible for the credit card, vehicle, investment, business, foreign trade, and SME loans. This period was characterized by less sizeable movements in the business cycle accompanied by more sizeable fluctuations in the credit cycles. However, the credit growth initiated by the credit guarantee scheme in 2017 particularly supported the size compatibility between commercial credit and business cycles. During the recent period, possibly due to exacerbated credit risk and weak investment appetite, we have experienced another wave of disintegration between commercial credit and business cycles in terms of the size, which is more prominent in SME and business loans.

Finally, we constructed the average similarity index values covering the whole sample period for each cycle indicator in loan sub-categories, which could be monitored in the last chart of Figure 7. The chart suggests that the least discrepancy in the amplitudes of the credit and output gap is observed in consumer and housing loans, and the highest discrepancy is observed in credit cards and investment loans. This result also confirms our previous findings on the synchronization and concordance indices that credit card loans were among the least pro-cyclical category in terms of positional and phase coherence while housing loans have the most pro-cyclical pattern with the output.

[Insert Figure 7]

5.3 Determinants of Cyclical Coherence

After constructing and examining the cyclical conformity indices based on position, phase, and size dimensions, we proceed by assessing the determinants of cyclical coherence between the credit and output gap. The empirical results from Tobit regressions taking synchronization indices as dependent variables are given in Table 5.

Neither of the local or global factors is found to be significantly effective in explaining the synchronization of retail loan sub-types with the output gap, while some of the factors are significant for commercial loan sub-types. The rationale might be that, historically, households in Turkey are not highly indebted relative to their income and assets (compared to counterparties in other EM and developed countries), which enables them to borrow when needed without much regard to the local or global macro-financial environment.[12] Also, households have a sound credit risk profile, evidenced by historically low NPL ratios, which accommodates robust tendencies of banks in extending retail loans even if the output gap is in negative territory. The credit demand of households in Turkey in our sample period is mostly

[12] According to BIS database, as of 2019, the households credit/GDP ratio for Turkey stands around 15%, which is relatively lower than the EM average of 43%.

formed by their current consumption needs as well as the nominal level of interest rates. For instance, when the output gap is negative, a fall in nominal rates might spur retail loan demand, even if the global or macro-financial environment does not imply a favorable outlook for credit markets. Besides, macroprudential policies to curb excessive indebtedness when the economy is in the boom phase have commonly been designed for retail loans in Turkey. Examples are loan-to-value ratio in housing and vehicle loans, maturity restrictions on general-purpose and credit card loans and increasing the risk weights of consumer loans. These policies exogenously mitigate the retail credit gap to stay at the negative front for a long time when the output gap is already positive. This implies that the role of macro-financial factors on the positional coherence of retail credit and output gap is hindered by regulations and policies as well.

Local financial factor is found to be significant in explaining the synchronization of commercial, foreign trade, business, and SME loans. Since local financial factor consists of the variables representing the financial outlook in the short-term perspective such as the level of exchange rates and interest rates or implied FX volatility, one should expect this factor to be significantly effective in shorter-maturity loans. Among commercial loan sub-types, SME, business and foreign trade loans have a relatively shorter duration compared to investment and large firm loans. Also, business and foreign trade loans are used mainly for the purpose of working capital financing or trade payments, which are most likely to be affected by the tightening financial conditions in the short-term.

The macroeconomic volatility indicator represents a rather longer-term outlook on the state of the economy since it consists of structural macro indicators. Hence, the synchronization in the long-maturity commercial loan-types, which are investment and large firm loans, are significantly affected by the macro volatility indicator, while relatively shorter-term commercial loan types reveal insignificant results. The positive coefficients of the macro-volatility factor also inform us about the direction of the impact; rising volatility means more positional coherence between economic activity and investment and large-firm loans. As macro-volatilities soar, it is more likely that both economic activity and investment loan demand by large-firms have a negative gap. Similarly, as macro volatilities deflate, both investment demand and output should have a positive gap.

Capital flows are found as an influential determinant of cyclical synchronization between credit and economic activity. This result is significant for total loans and different sub-categories of commercial loans. It is known that in emerging markets with savings-investment imbalances, which utilize extensive foreign financing, strong capital flows initiate an additional source of funds for banks, amplify the credit supply, and boost the asset prices (Lane and McQuade, 2014; Gozgor, 2014; Samarina and Bezemer, 2016). Hence, capital inflows enhance access to finance (as well as the cost of financing) and investment tendencies so that positional synchronization is supported. Nevertheless, the crucial discrepancy on the role of capital inflows among loan types is that it is statistically significant in the sub-categories of commercial loans, while we obtain insignificant results in the sub-categories of retail loans. This result might be linked to the prohibition of FX-denominated consumer loan usage by the amendment taken place in 2009. Also, the same amendment promoted the real sector firms to use more FX denominated commercial loans, which resulted in a steep rise in FX commercial loan balance after 2009. This gave the banking sector advantage to directly place their foreign currency funding as FX loans to firms without needing to swap them to TL. Therefore, we expect that rising capital inflows, in the form of syndication and securitization loans or Eurobonds, have a more profound positive impact on commercial loan sub-types than the consumer loan sub-categories.

Global financial conditions have an insignificant impact on the synchronization of all loan types with the business cycle. We believe that this statistical finding occurs because its indirect impact is captured by other factors, most notably local financial conditions and capital flow indicators. Although the expectation is that global conditions, to some extent, influence the positional coherence of credit and output gap, the channel of the influence should be more indirect compared to other factors. The global conditions explain the credit-output relationship in the Turkish economy to the extent of their impact on local financial and macroeconomic variables.[13]

[**Insert Table 5**]

Estimation results presented in Table 6 explain how concordance index measuring phase coherence responds to the macro-financial outlook. The results suggest that local financial factors are the significant determinants of the phase coherence of consumer, housing, vehicle, business, and SME loans with the economic activity. Similar to previous results on the synchronization index, tightening in the local financial conditions is reflected in a higher tendency for phase compatibility between credit and growth cycles. Tightening in financial conditions is, in general, associated with economic activity being in the peak-to-through phase since tighter local financial conditions, identified mainly by the rise in interest and exchange rate variables, have also negative influences on economic activity through macroeconomic expectations, credit pricing, and demand channels. Also, the overheating economy at the peak-phase often leads to adjustments in the exchange rate and hikes in the interest rates in the Turkish economy after which output growth moves towards the peak-to-through phase. Among retail loan types, housing and vehicle loans are the types of loans that are mostly dependent on the interest rates

[13] Also, our control for multicollinearity reveals that global factors have less than 0.5 correlation with other explanatory factors and Variance Inflation Factor (VIF) results demonstrate no significant concern for multicollinearity. Henceforth, it would be better to treat the global factor variable as a control variable factoring in the effect of global financial market indicators on credit demand.

since consumers' demand for these goods is shaped by the installment payments relative to their income. A rise in interest rates increases the volume of installments and also a jump in exchange rate worsens their overall expectations, which all lead to subdued demand for these loans. Nevertheless, credit card and general-purpose loan demands are mainly shaped by the short-term needs of the households without much dependence on the local financial conditions. Among the sub-categories of commercial loans, the coherence of SME and business loans, which are mostly denominated in TL, with the business cycle is significantly impacted by the local financial factor. The large share of TL denomination in these loan categories makes them vulnerable to local financial shocks. Also, during tightened financial conditions accompanied by the declining economic activity in the peak-to-through phase initially impacts the SME loan balances due to the credit risk concerns and worsening risk appetite of the banks. This makes SME loans to be in the "peak-to-through" phase similar to the output gap. Nevertheless, since investment, foreign trade, and large firm loans are extensively allocated in FX, the local financial conditions have an insignificant impact on the coherence of these loan categories.

Macroeconomic volatility has significant explanatory power for the majority of loan categories except for vehicle, business, SME, and large firm loans in the case of concordance index. However, in contrast to what is found for synchronization, macroeconomic volatilities degenerate the concordance between credit and growth movements with the exception of credit cards. Rising volatility in the overall economy often coincides with the output gap in the peak-to-through phase. Generally, policymakers' reaction in these periods is to cut interest rates and ease the credit facilities for firms and households. This leads to an overall improvement in the credit cycle while the problems in the macroeconomic outlook still exist. However, as the volatile period persists for a longer period up to the point where the output gap falls into negative territory, the ease in financial conditions will not be sufficient to improve credit demand and the credit gap also becomes negative in synchronization with the output gap. Similarly, the diminishing macro-volatilities generally induce policymakers to take precautionary measures in order to prevent overheating in the economy, which causes the credit cycle to begin a peak-to-through phase. And as this favorable macro environment persists for a longer time sufficient to keep the output gap in positive territory, the rising income level of the agents as well as improving expectations increase the credit demand in the overall economy which makes credit gap stay in positive front as well. This explains why macroeconomic imbalances enhance the synchronization index while deteriorates the phase coherence between credit and output cycles in the majority of loan types.

Capital flows have a significant and positive role in explaining the concordance of the majority of the loan sub-categories with the output gap. Increasing foreign capital flows improves the financing conditions of the banking sector, decreases their funding costs, and eases the credit facilities. In times of rising external financial flows, usually the credit gap indicator moves in the through-to-peak phase such as the period after the global financial crisis till 2012. Similarly, rising external flows are often associated with enhancing economic activity, since external savings have a positive contribution to the structural saving-gap issue of the Turkish economy, and also the resulting stability achieved in the exchange rates improves the expectation and confidence of economic players. Therefore, mounting capital flows in the Turkish economy mean both credit and output gaps are in the through-to-peak phase and worsening flows mean they are in reverse phases. Finally, similar to the findings in the synchronization index, global factors have insignificant explanatory power in the concordance index. The rationale is that the indirect influence of global factors is captured mostly by other indicators without creating a statistically significant multicollinearity issue.

[**Insert Table 6**]

The last set of regression results are obtained for the similarity index proxying the size compatibility in cyclical movements and are presented in Table 7. Contradicting with other indices, the role of global and local macro-financial conditions on the similarity index for all loan types is rather limited with some significance is retained for a few loan types. Local financial conditions reveal mixed results as 10% significance is achieved for housing, foreign trade and business loans and 5% for credit cards. Apart from the previous indices' results, housing and credit card loans gained significance in the similarity index. As financial conditions tighten, due to the high sensitivity of housing loans against interest rates, the housing loan cycle drops similar in size to the fall in the output gap. Nevertheless, credit card balances tend to increase at those times due to consumers' tendency to use credit cards in order to finance their consumption spending when financial conditions tighten. Macroeconomic volatility has a very limited influence on the similarity index except for vehicle, foreign trade, and business loans. The role of capital flows in explaining the similarity index is significant for total commercial loans, foreign trade, and investment loans as observed in the previous two indices. This result might also be linked to the large share of FX denomination in these loans. The period of rising capital flows positively influences the FX loan cycles thanks to the falling funding costs, and this influence is similar in size to the improvement achieved in the business cycle with the help of external savings. All in all, our results propose that global and local macroeconomic and financial factors are not significantly effective in explaining the size coherence of credit cycles with the output gap when compared to position and phase coherence.

[**Insert Table 7**]

6. Conclusion

The recent financial crisis and accompanied uncertainties about the course of credit growth have attracted the interest in credit-business cycle relationship from policymaking and financial stability perspectives, since the recent economic downturns coincided with financial market volatilities, substantial drop in asset prices and most importantly deterioration in credit growth. In this study, we provide a comprehensive quantification of the co-movement between output and credit cycles in the Turkish banking sector by constructing three different indices namely synchronization, concordance, and similarity indices capturing location, momentum, and size aspects of cyclical correlation. We enlarge our analysis with disaggregated credit data and provide empirical results for 13 different sub-categories of total loans ranging from general-purpose loans to credit cards, from SME loans to foreign trade loans. We also aim to examine the impact of local and global macroeconomic and financial factors on the general course of indices by utilizing Tobit regressions.

When we examine the trends of synchronization indices, it is understood that the position-wise compatibility between credit and business cycles has been robust during the earlier phases of the sample period including the Global Financial Crisis since both loan extension and economic activity have shrunk and have been diminished into the negative front. However, the episode from 2012 to 2016 witnessed weakened accordance in cyclical positions, especially for total, consumer, vehicle, and general-purpose loans as well as the credit cards. A striking finding is that this period is also subject to the wave of macroprudential measures, designed to contain the excessive credit movements diverging from credit demand and supply forces. Thus, the utilization of a broad set of macroprudential measures including reserve requirements, loan-to-value ratios, installment restrictions, and FX debt limitations all contribute to the decline in cyclical position suitability. Furthermore, it is detected that credit guarantee mechanisms improved by the policymakers since the beginning of 2017 help increasing the synchronization between credit and business cycle.

Furthermore, regarding the movements of the concordance index showing the phase conformity in credit and output gap indicators, values closer to 1 are captured aftermath the first half of 2016 during which a growth shock occurred. In relation to this finding, we conclude that there existed a consensus between downward movements in the credit and output gap in this period, as both indicators aligned in the “peak-to-trough” phase. When we consider the similarity index which is designed to monitor the size conformity between credit and business cycles, we observe that the sizes of credit and business cycles had differed heavily between 2012 and 2015, across almost all loan categories. However, the credit growth initiated by the credit guarantee scheme in 2017 particularly supported the size compatibility between commercial credit and business cycles.

After constructing the cyclical conformity indices based on position, phase, and size dimensions, we examined the possible determinants of cyclical coherence between the credit and output gap. The empirical results from Tobit regressions taking synchronization indices as dependent variables show that financial conditions significantly influence the position coherence for commercial loans, especially foreign trade, business, and SME loans. Similarly, macroeconomic volatilities are determined to affect position-wise suitability between credit and output gap mainly for commercial, general-purpose, investment, SME, and large firm loans as coherence is improved when macroeconomic volatilities become more pronounced. More strikingly, capital flows turn out to be a significant predictor of total loans as well as the sub-segments of commercial loans. Synchronization seems to be elevated during the episodes characterized by stronger capital inflows. The set of estimations aiming to evaluate phase coherence employed concordance indices as the dependent variable. Estimation results show that tightening in local financial conditions is significantly stimulating the phase coherence for consumer, housing, vehicle, business, and SME loans. On the other hand, in contrast to synchronization, macroeconomic volatilities seem to have a reversed impact on concordance, particularly for sub-components of retail loans. Moreover, capital flows tend to improve phase coherence in statistically significant way, both for retail and commercial loans. Lastly, Tobit estimation results provide inferior explanations for the extent of cyclical similarity between credit and output dynamics.

The analyses in this paper are thought to contribute to the policymaking process through different perspectives. Firstly, in the most general sense, these comprehensive indices can be considered as additions to the wider set of indicators utilized to timely monitor the financial stability. Sizeable divergence of credit cycle behavior from that of the business cycle can potentially be considered as an early warning indicator for the accumulation of financial imbalances. Besides, since separate indices are prepared with a disaggregated credit data (corresponding to sub-segments of retail and commercial loans), outlook regarding different credit segments can be overviewed and their relative contributions to the build-up of overall macro-financial imbalances can be identified. Thus, policies specific to that credit segment can be designed. Secondly, in the context of the credit channel, one can infer the efficiency of the monetary transmission mechanism by evaluating the index results. In other words, episodes characterized by stronger cyclical coherence can be defined as the time intervals when monetary policy transmission to macroeconomic aggregates is more pronounced. Thirdly, the timing of implementation for macroprudential measures as well as incentivized credit policies can also benefit from this empirical exercise. The divergence in the credit-business cycle inherently hints the need for appropriate macroprudential measures aiming to sustain the credit growth level suitable with macroeconomic fundamentals. Policies should be designed in a flexible manner to respond to the needs of both expansionary and contractionary episodes, depending on the phase of the cycle. For example, macroprudential measures might be put in place when the economy is in the boom cycle; on the other hand, subsidized credit initiatives might be beneficial during bust periods. The results relevant to the possible determinants of cyclical coherence are also valuable as they reveal that enhancing robust capital inflows and containing macroeconomic volatilities emerge as possible ways of improving the association between credit and business cycles.

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Figure 1: Credit Market Outlook Across Growth Shocks (Level, FX-Adjusted, Crisis Period: t=0)

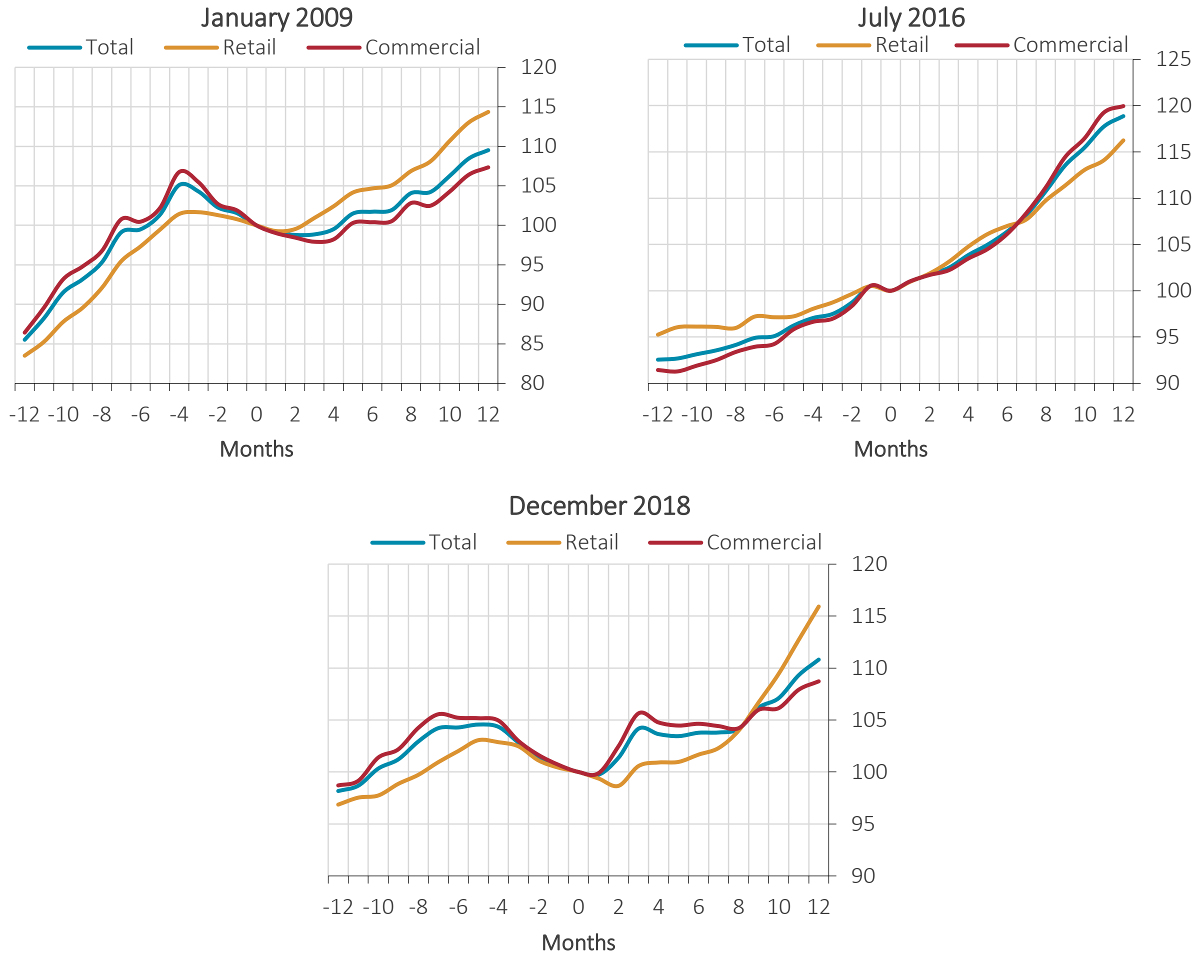


Figure 2: Credit Market Outlook Across Growth Shocks (MoM Percentage Change, Crisis Period: t=0)

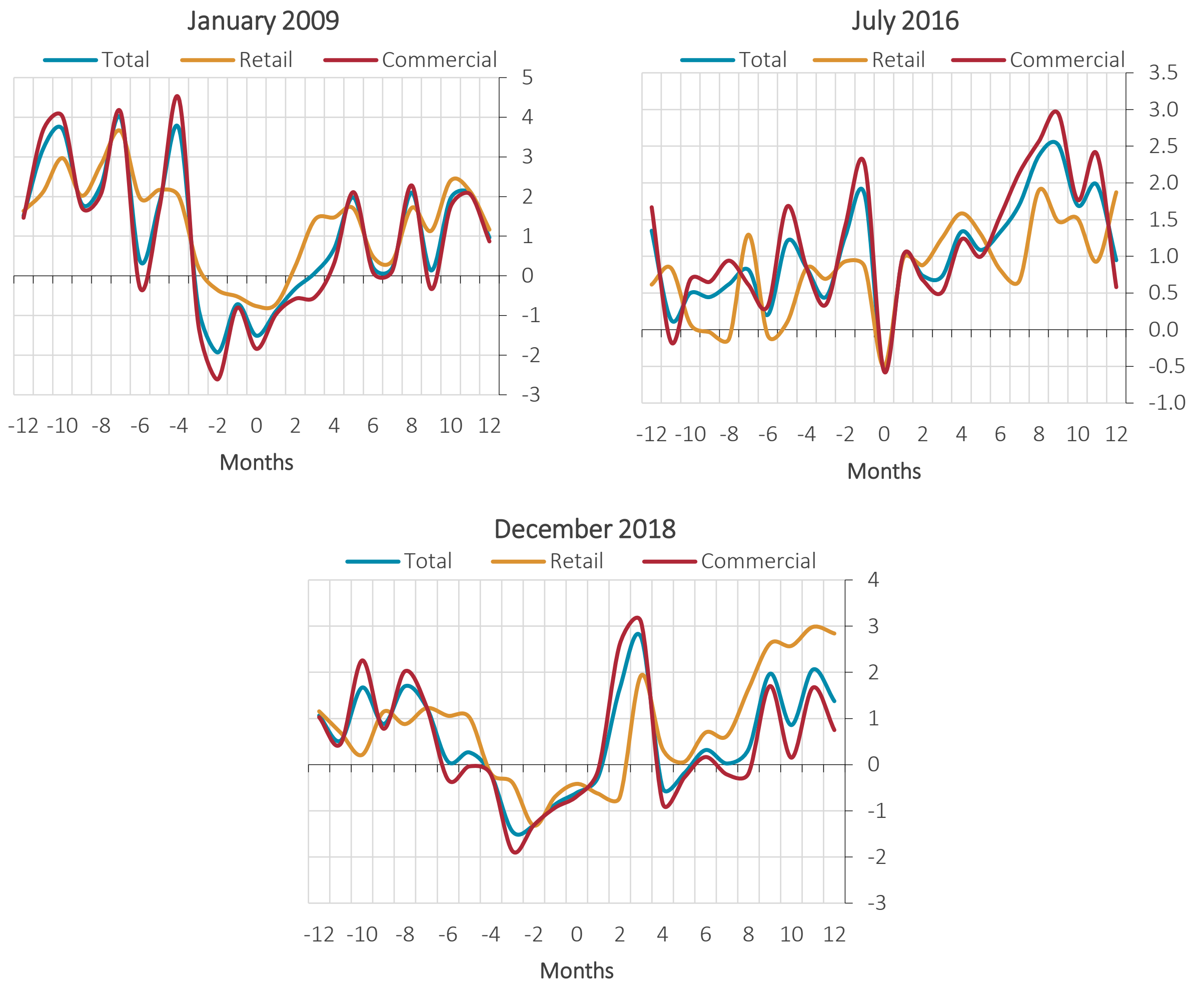


Table 1: Data Series for PCA

Series Name	Transformation	Covariates	ADF Test Resuls
USDTRY Spot Exchange Rate	Logarithmic Change	Local Financial	-8.825***
EURTRY Spot Exchange Rate	Logarithmic Change	Local Financial	-9.659***
USDTRY 1 Month Implied Volatility	Difference	Local Financial	-12.996***
USDTRY 3 Month 25 Delta Risk Reversal	Difference	Local Financial	-10.252***
Turkey CDS Premium	Difference	Local Financial	-10.890***
2 Year Treasury Bond Yield	Difference	Local Financial	-8.292***
5 Year Eurobond Yield	Difference	Local Financial	-10.152***
3 Month Money Market Rate	Difference	Local Financial	-7.776***
Turkey EMBIG Spread	Difference	Local Financial	-10.477***
MSCI Turkey Index	Difference	Local Financial	-9.955***
CPI Inflation Rate	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-2.718*
PPI Inflation Rate	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-3.057**
Unemployment Rate	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-3.823***
Capacity Utilization Rate	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-3.167**
Real Sector Confidence Index	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-3.938***
Consumer Confidence Index	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-2.718*
Export Growth Rate	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-5.193***
Import Growth Rate	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-3.266**
Budget Revenues Growth Rate (Annualized)	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-3.222**
Budget Expenditures Growth Rate (Annualized)	Deviation from sample average, Re-scaled by sample average	Macro Volatility	-2.922**
Equity Flows to Turkey	Level, Normalized	Capital Flows	-10.515***
Sovereign Bond Flows to Turkey	Level, Normalized	Capital Flows	-9.890***
Private Sector Bond Flows to Turkey	Level, Normalized	Capital Flows	-8.128***
TED Spread	Difference	Global Financial	-14.407***
US 10 Year Treasury Bond Yield	Difference	Global Financial	-11.866***
Emerging Market Corporate Bond Index	Difference	Global Financial	-8.862***
US Corp BBB/Baa-Treasury 10 Year Spread	Difference	Global Financial	-7.336***
US Libor-OIS Spread	Difference	Global Financial	-11.378***
S&P US Equity Risk Premium Index	Difference	Global Financial	-11.915***
EURUSD 1 Month Implied Volatility	Difference	Global Financial	-14.370***
Crude Oil 3 Month Implied Volatility	Difference	Global Financial	-14.505***
VIX Index	Difference	Global Financial	-12.978***
MOVE Index	Difference	Global Financial	-15.138***
V2X Index	Difference	Global Financial	-14.465***

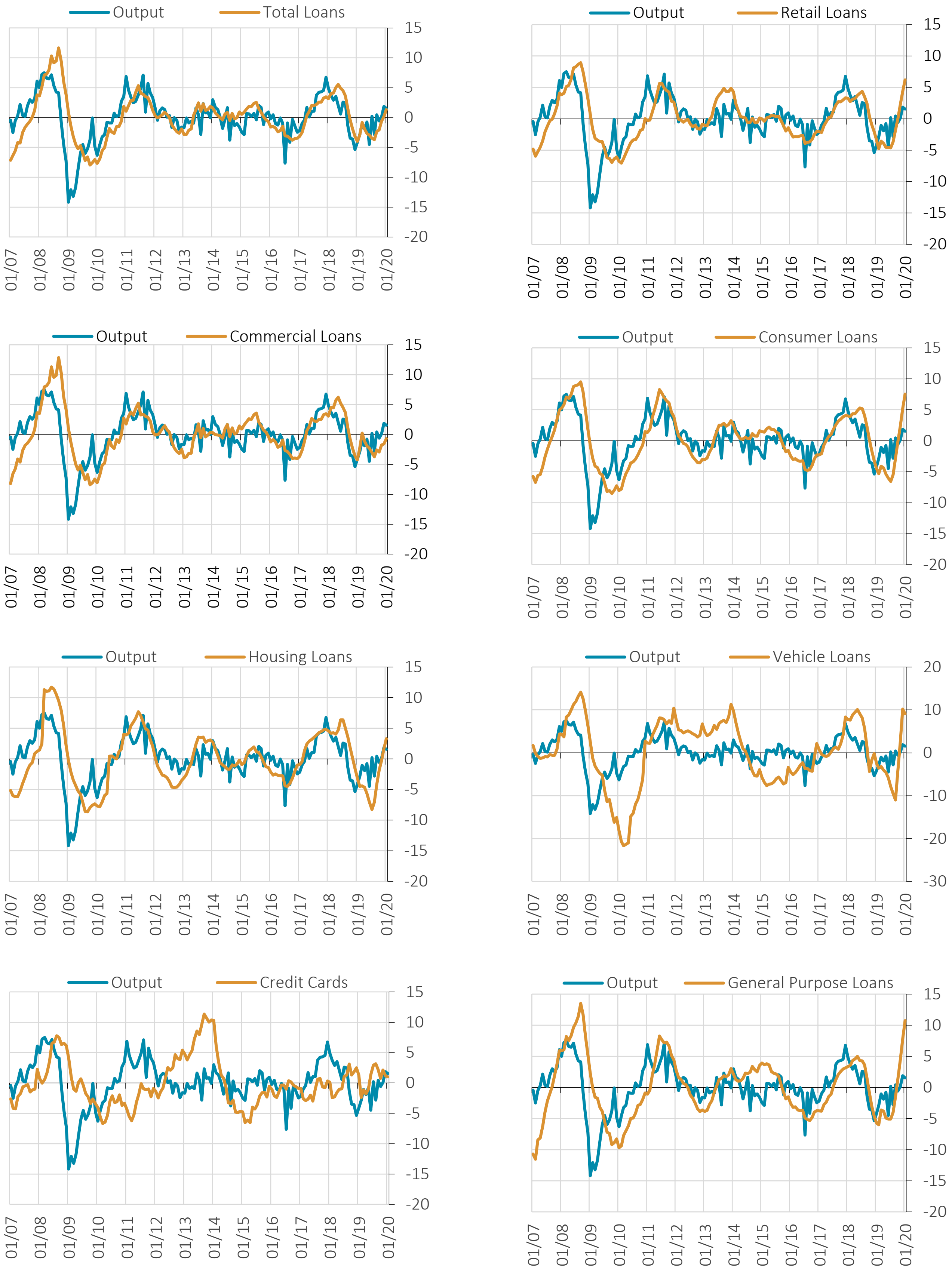
Note: ***, **, * denote the statistical significance at 1%, 5% and 10% significance levels, respectively.

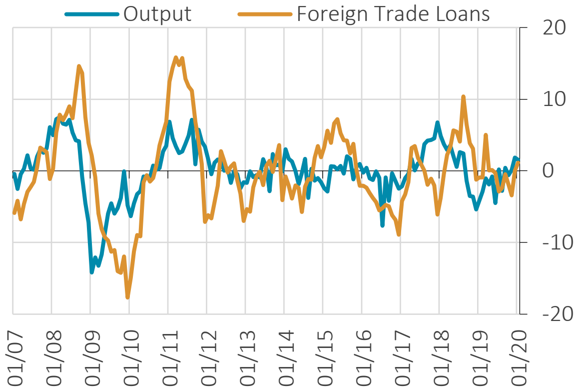
Table 2: Diagnostics of PCA

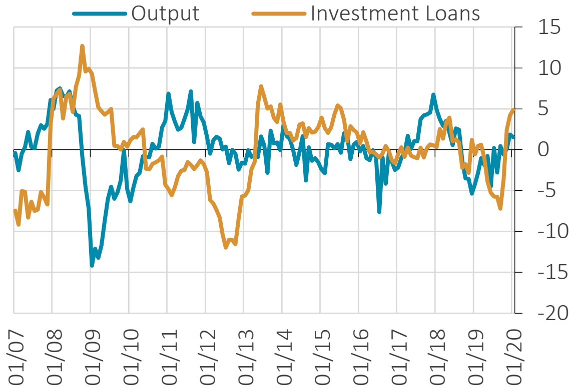
Variable	Bartlett's Test of Sphericity (Chi-Square Test Statistic)	Kaiser-Meyer-Olkin (KMO) Measure	Percentage of the Total Variance Explained by the First PC	Eigenvalue of the First PC
Local Financial	2519.9***	0.859	%72	7.37
Global Financial	1770.9***	0.746	%55	5.51

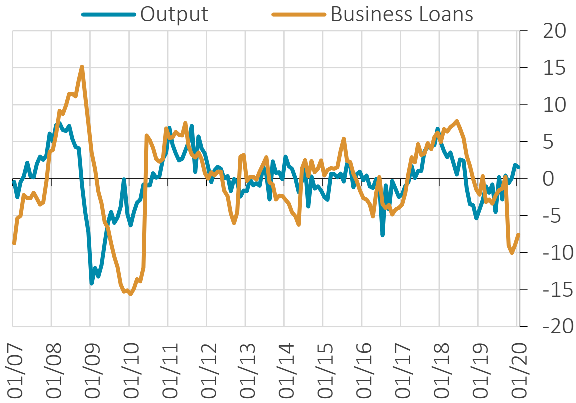
Note: ***, **, * denote the statistical significance at 1%, 5% and 10% significance levels, respectively.

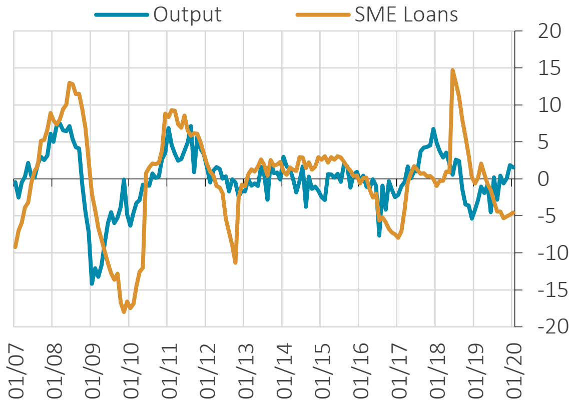
Figure 3: Business and Credit Cycles

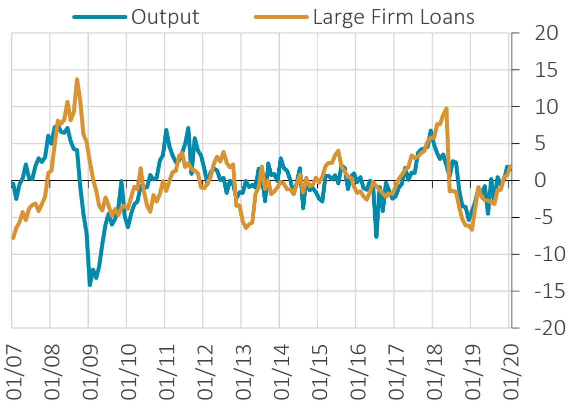












Source: BRSA, TurkStat, Authors' Calculations.

Figure 4: Composite Distance Indicators

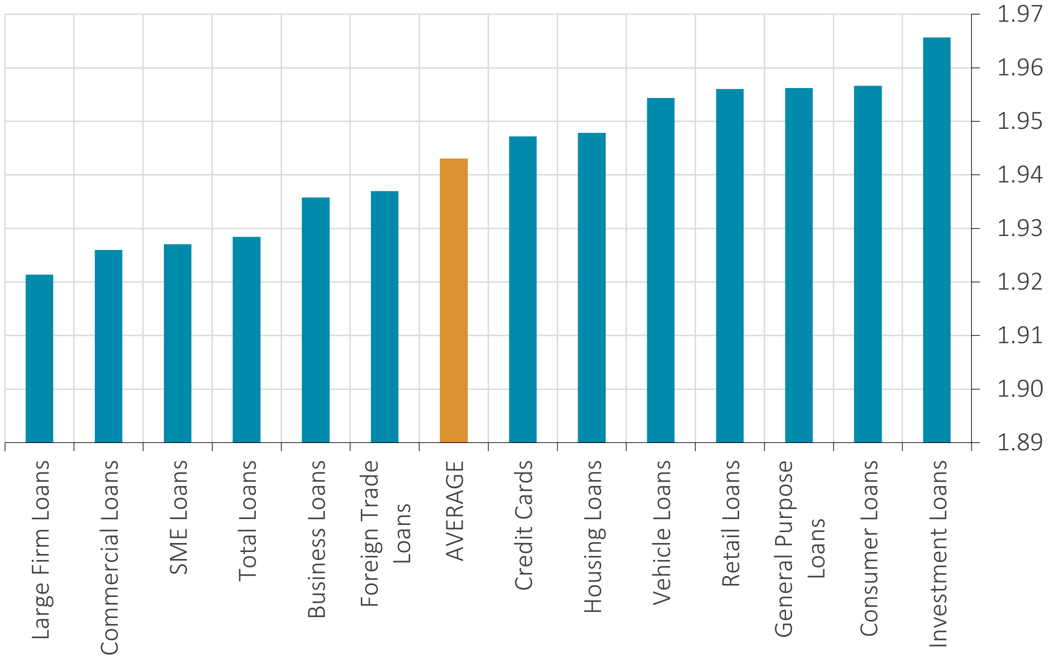


Table 3: Correlation of Output Gap with Lag Values of Credit Gap

Lag Values	Correlation	Lag Values	Correlation	Lag Values	Correlation
$\boldsymbol{Total\ Loans_t}$	**0.617***	$\boldsymbol{Retail\ Loans_t}$	**0.589***	$\boldsymbol{Commercial\ Loans_t}$	**0.602***
$Total\ Loans_{t-1}$	0.484*	$Retail\ Loans_{t-1}$	0.480*	$Commercial\ Loans_{t-1}$	0.466*
$Total\ Loans_{t-2}$	0.347*	$Retail\ Loans_{t-2}$	0.343*	$Commercial\ Loans_{t-2}$	0.335*
$Total\ Loans_{t-3}$	0.188*	$Retail\ Loans_{t-3}$	0.201*	$Commercial\ Loans_{t-3}$	0.175*
$Total\ Loans_{t-4}$	0.043	$Retail\ Loans_{t-4}$	0.067	$Commercial\ Loans_{t-4}$	0.031
$Total\ Loans_{t-5}$	-0.081	$Retail\ Loans_{t-5}$	-0.058	$Commercial\ Loans_{t-5}$	-0.089
$Total\ Loans_{t-6}$	-0.199*	$Retail\ Loans_{t-6}$	-0.173*	$Commercial\ Loans_{t-6}$	-0.204*
$\boldsymbol{Consumer\ Loans_t}$	**0.658***	$\boldsymbol{Housing\ Loans_t}$	**0.626***	$\boldsymbol{General\ Purpose\ Loans_t}$	**0.511***
$Consumer\ Loans_{t-1}$	0.563*	$Housing\ Loans_{t-1}$	0.529*	$General\ Purpose\ Loans_{t-1}$	0.406*
$Consumer\ Loans_{t-2}$	0.439*	$Housing\ Loans_{t-2}$	0.409*	$General\ Purpose\ Loans_{t-2}$	0.276*
$Consumer\ Loans_{t-3}$	0.302*	$Housing\ Loans_{t-3}$	0.281*	$General\ Purpose\ Loans_{t-3}$	0.133
$Consumer\ Loans_{t-4}$	0.168*	$Housing\ Loans_{t-4}$	0.154	$General\ Purpose\ Loans_{t-4}$	-0.001
$Consumer\ Loans_{t-5}$	0.045	$Housing\ Loans_{t-5}$	0.034	$General\ Purpose\ Loans_{t-5}$	-0.116
$Consumer\ Loans_{t-6}$	-0.074	$Housing\ Loans_{t-6}$	-0.089	$General\ Purpose\ Loans_{t-6}$	-0.229*
$Credit\ Cards_t$	0.045	$Vehicle\ Loans_t$	0.463*	$\boldsymbol{Foreign\ Trade\ Loans_t}$	0.488*
$Credit\ Cards_{t-1}$	-0.038	$Vehicle\ Loans_{t-1}$	0.354*	$Foreign\ Trade\ Loans_{t-1}$	0.392*
$Credit\ Cards_{t-2}$	-0.131	$Vehicle\ Loans_{t-2}$	0.238*	$Foreign\ Trade\ Loans_{t-2}$	0.303*
$Credit\ Cards_{t-3}$	-0.196*	$Vehicle\ Loans_{t-3}$	0.109	$Foreign\ Trade\ Loans_{t-3}$	0.206*
$Credit\ Cards_{t-4}$	-0.254*	$Vehicle\ Loans_{t-4}$	-0.002	$Foreign\ Trade\ Loans_{t-4}$	0.124
$Credit\ Cards_{t-5}$	-0.312*	$Vehicle\ Loans_{t-5}$	-0.102	$Foreign\ Trade\ Loans_{t-5}$	0.056
$Credit\ Cards_{t-6}$	-0.345*	$Vehicle\ Loans_{t-6}$	-0.191*	$Foreign\ Trade\ Loans_{t-6}$	-0.003
$Investment\ Loans_t$	-0.096	$\boldsymbol{Business\ Loans_t}$	**0.470***	$\boldsymbol{SME\ Loans_t}$	**0.578***
$Investment\ Loans_{t-1}$	-0.164*	$Business\ Loans_{t-1}$	0.366*	$SME\ Loans_{t-1}$	0.497*
$Investment\ Loans_{t-2}$	-0.235*	$Business\ Loans_{t-2}$	0.265*	$SME\ Loans_{t-2}$	0.395*
$Investment\ Loans_{t-3}$	-0.326	$Business\ Loans_{t-3}$	0.161*	$SME\ Loans_{t-3}$	0.271*
$Investment\ Loans_{t-4}$	-0.349*	$Business\ Loans_{t-4}$	0.057	$SME\ Loans_{t-4}$	0.166*
$Investment\ Loans_{t-5}$	-0.403*	$Business\ Loans_{t-5}$	-0.018	$SME\ Loans_{t-5}$	0.080
$Investment\ Loans_{t-6}$	-0.433*	$Business\ Loans_{t-6}$	-0.111	$SME\ Loans_{t-6}$	-0.009
$\boldsymbol{Large\ Firm\ Loans_t}$	**0.459***				
$Large\ Firm\ Loans_{t-1}$	0.321*				
$Large\ Firm\ Loans_{t-2}$	0.209*				
$Large\ Firm\ Loans_{t-3}$	0.071				
$Large\ Firm\ Loans_{t-4}$	-0.063				
$Large\ Firm\ Loans_{t-5}$	-0.178*				
$Large\ Firm\ Loans_{t-6}$	-0.284*				

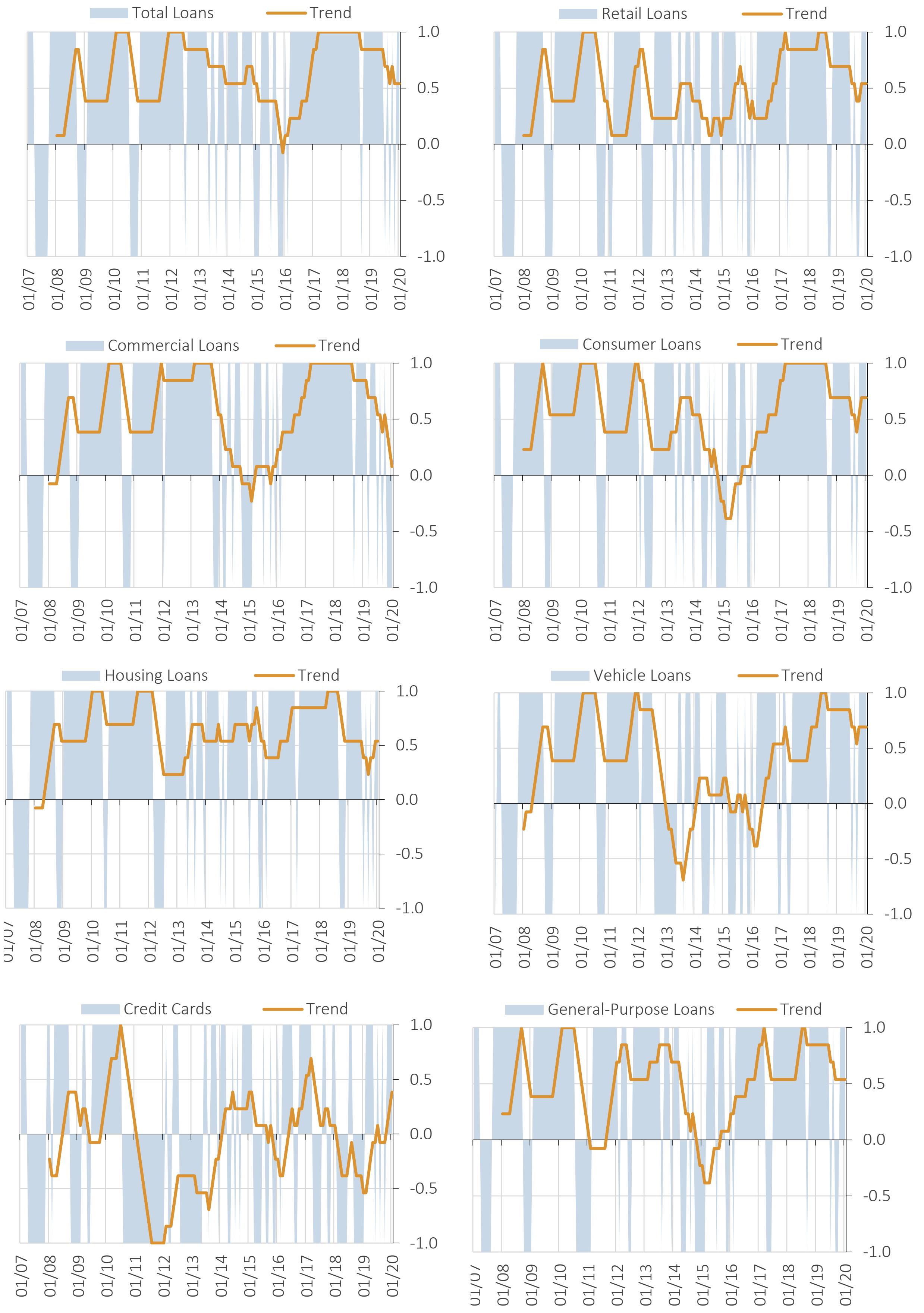
Note: * denotes the statistical significance at 5% significance level.

Table 4: Correlation of Output Gap with Lead values of Credit Gap

Lead Values	Correlation	Lead Values	Correlation	Lead Values	Correlation
$Total\ Loans_{t}$	0.617*	$Retail\ Loans_{t}$	0.589*	$Commercial\ Loans_{t}$	0.602*
$Total\ Loans_{t+1}$	0.692*	$Retail\ Loans_{t+1}$	0.655*	$Commercial\ Loans_{t+1}$	0.678*
$Total\ Loans_{t+2}$	0.742*	$Retail\ Loans_{t+2}$	0.696*	$Commercial\ Loans_{t+2}$	0.727*
$\boldsymbol{Total\ Loans_{t+3}}$	**0.770***	$\boldsymbol{Retail\ Loans_{t+3}}$	**0.712***	$\boldsymbol{Commercial\ Loans_{t+3}}$	**0.759***
$Total\ Loans_{t+4}$	0.760*	$Retail\ Loans_{t+4}$	0.708*	$Commercial\ Loans_{t+4}$	0.747*
$Total\ Loans_{t+5}$	0.728*	$Retail\ Loans_{t+5}$	0.680*	$Commercial\ Loans_{t+5}$	0.714*
$Total\ Loans_{t+6}$	0.693*	$Retail\ Loans_{t+6}$	0.647*	$Commercial\ Loans_{t+6}$	0.680*
$Consumer\ Loans_{t}$	0.658*	$Housing\ Loans_{t}$	0.626*	$General\ Purpose\ Loans_{t}$	0.511*
$Consumer\ Loans_{t+1}$	0.715*	$Housing\ Loans_{t+1}$	0.686*	$General\ Purpose\ Loans_{t+1}$	0.587*
$Consumer\ Loans_{t+2}$	0.742*	$Housing\ Loans_{t+2}$	0.709*	$General\ Purpose\ Loans_{t+2}$	0.637*
$\boldsymbol{Consumer\ Loans_{t+3}}$	**0.745***	$\boldsymbol{Housing\ Loans_{t+3}}$	**0.710***	$General\ Purpose\ Loans_{t+3}$	0.669*
$Consumer\ Loans_{t+4}$	0.729*	$Housing\ Loans_{t+4}$	0.685*	$\boldsymbol{General\ Purpose\ Loans_{t+4}}$	**0.682***
$Consumer\ Loans_{t+5}$	0.692*	$Housing\ Loans_{t+5}$	0.641*	$General\ Purpose\ Loans_{t+5}$	0.671*
$Consumer\ Loans_{t+6}$	0.647*	$Housing\ Loans_{t+6}$	0.589*	$General\ Purpose\ Loans_{t+6}$	0.655*
$Credit\ Cards_{t}$	0.045	$Vehicle\ Loans_{t}$	0.460*	$Foreign\ Trade\ Loans_{t}$	0.488*
$Credit\ Cards_{t+1}$	0.096	$Vehicle\ Loans_{t+1}$	0.541*	$Foreign\ Trade\ Loans_{t+1}$	0.550*
$Credit\ Cards_{t+2}$	0.157	$Vehicle\ Loans_{t+2}$	0.593*	$Foreign\ Trade\ Loans_{t+2}$	0.574*
$Credit\ Cards_{t+3}$	0.196*	$Vehicle\ Loans_{t+3}$	0.637*	$Foreign\ Trade\ Loans_{t+3}$	0.586*
$Credit\ Cards_{t+4}$	0.231*	$\boldsymbol{Vehicle\ Loans_{t+4}}$	**0.656***	$\boldsymbol{Foreign\ Trade\ Loans_{t+4}}$	**0.589***
$Credit\ Cards_{t+5}$	0.245*	$Vehicle\ Loans_{t+5}$	0.655*	$Foreign\ Trade\ Loans_{t+5}$	0.571*
$\boldsymbol{Credit\ Cards_{t+6}}$	**0.260***	$Vehicle\ Loans_{t+6}$	0.654*	$Foreign\ Trade\ Loans_{t+6}$	0.545*
$Investment\ Loans_{t}$	-0.096	$Business\ Loans_{t}$	0.470*	$SME\ Loans_{t}$	0.578*
$Investment\ Loans_{t+1}$	-0.065	$Business\ Loans_{t+1}$	0.542*	$SME\ Loans_{t+1}$	0.637*
$Investment\ Loans_{t+2}$	-0.029	$Business\ Loans_{t+2}$	0.602*	$SME\ Loans_{t+2}$	0.677*
$Investment\ Loans_{t+3}$	0.022	$Business\ Loans_{t+3}$	0.640*	$\boldsymbol{SME\ Loans_{t+3}}$	**0.683***
$Investment\ Loans_{t+4}$	0.054	$\boldsymbol{Business\ Loans_{t+4}}$	**0.655***	$SME\ Loans_{t+4}$	0.673*
$Investment\ Loans_{t+5}$	0.080	$Business\ Loans_{t+5}$	0.647*	$SME\ Loans_{t+5}$	0.651*
$\boldsymbol{Investment\ Loans_{t+6}}$	**0.095**	$Business\ Loans_{t+6}$	0.628*	$SME\ Loans_{t+6}$	0.629*
$Large\ Firm\ Loans_{t}$	0.459*				
$Large\ Firm\ Loans_{t+1}$	0.519*				
$Large\ Firm\ Loans_{t+2}$	0.554*				
$\boldsymbol{Large\ Firm\ Loans_{t+3}}$	**0.594***				
$Large\ Firm\ Loans_{t+4}$	0.580*				
$Large\ Firm\ Loans_{t+5}$	0.542*				
$Large\ Firm\ Loans_{t+6}$	0.503*				

Note: * denotes the statistical significance at 5% significance level.

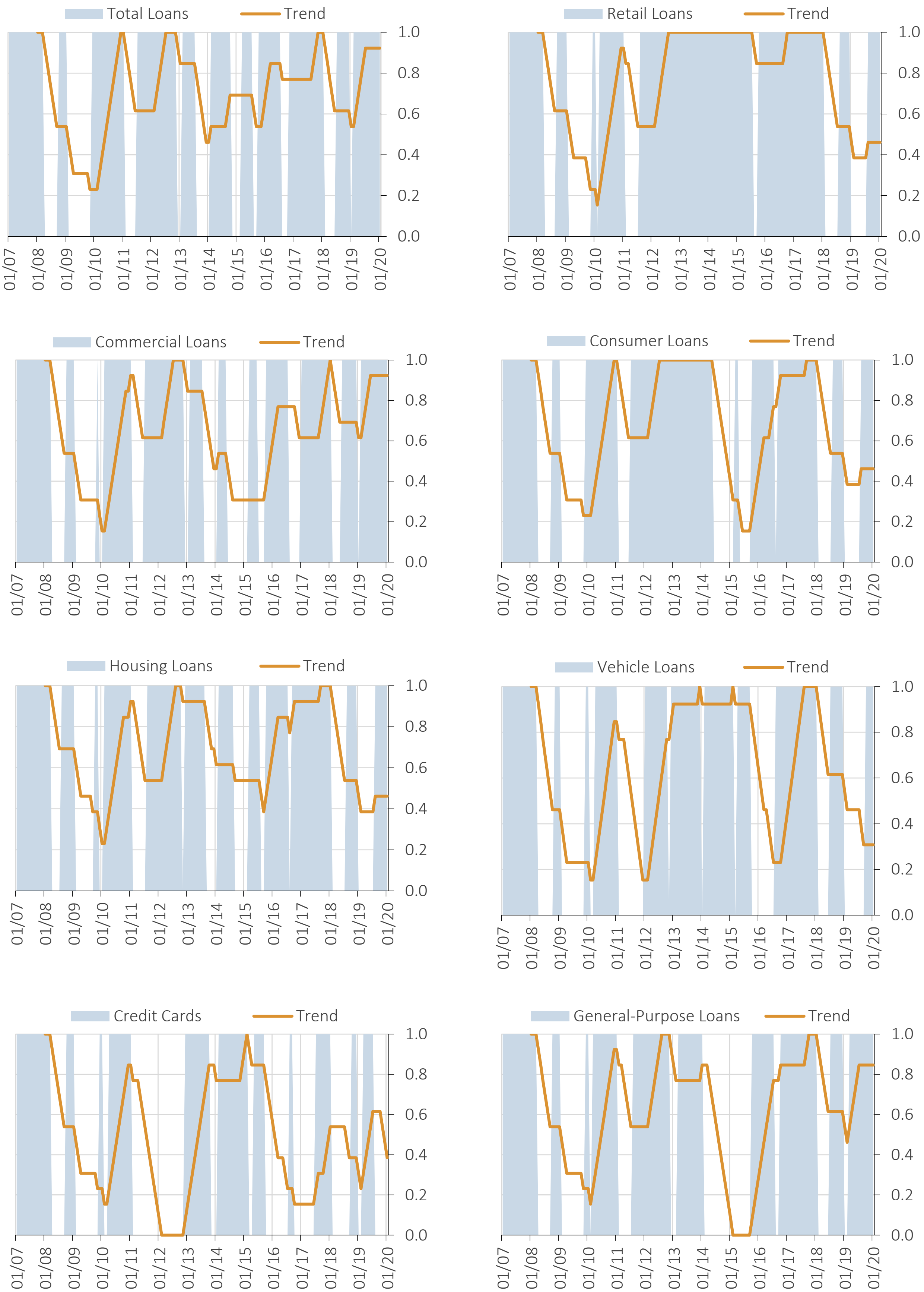
Figure 5: Synchronization Index of Credit Cycles in Relation with Business Cycle

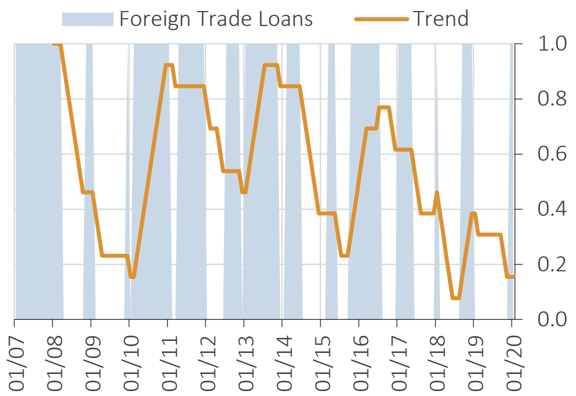


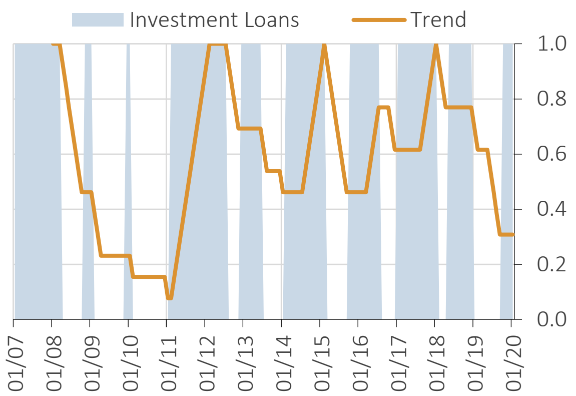
Note: 12-month moving average of monthly synchronization index values are depicted in the graphs. The last graph shows the number of months where synchronization index takes the value of 1 as a percentage of total number of months in the sample for each loan category.

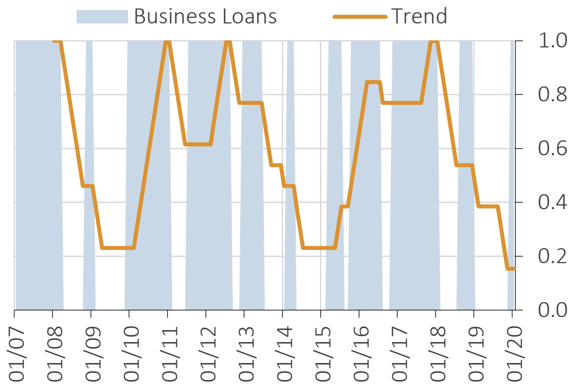
Source: Authors' Calculations.

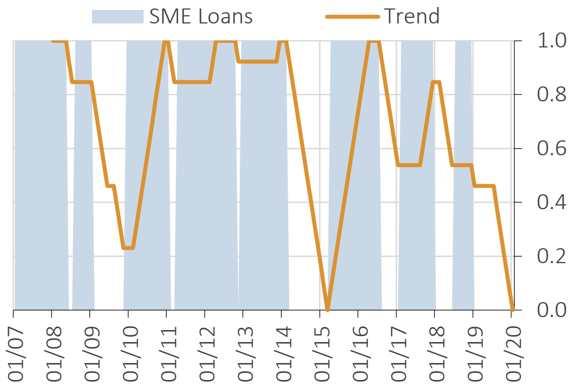
Figure 6: Concordance Index of Credit Cycles in Relation with Business Cycle

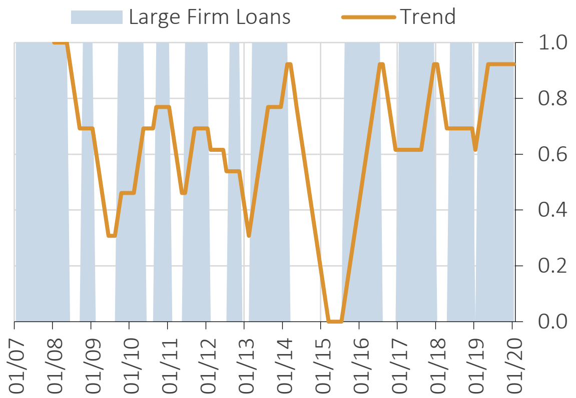


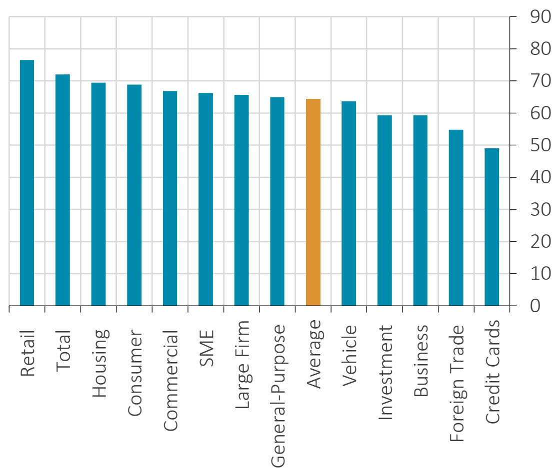








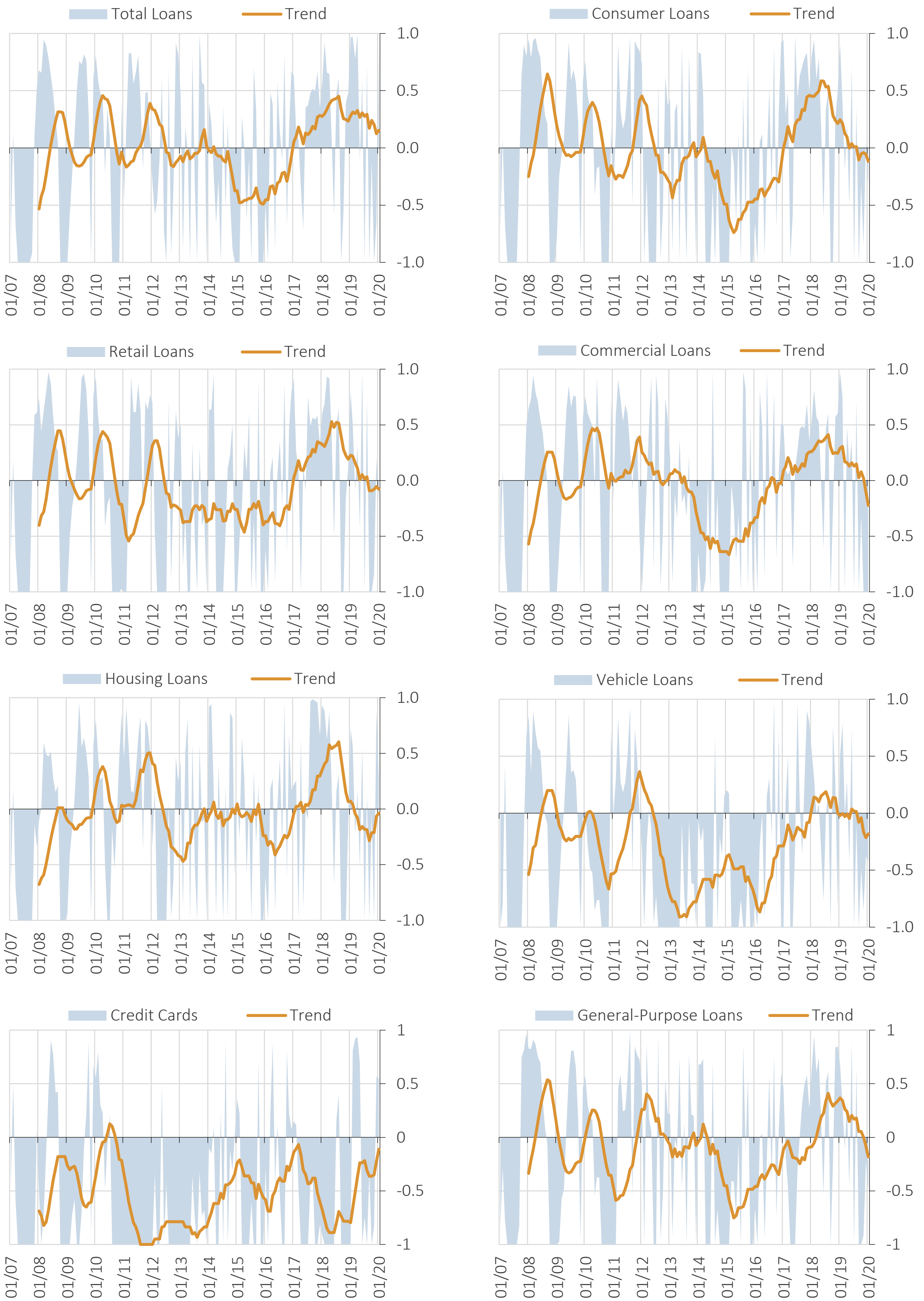


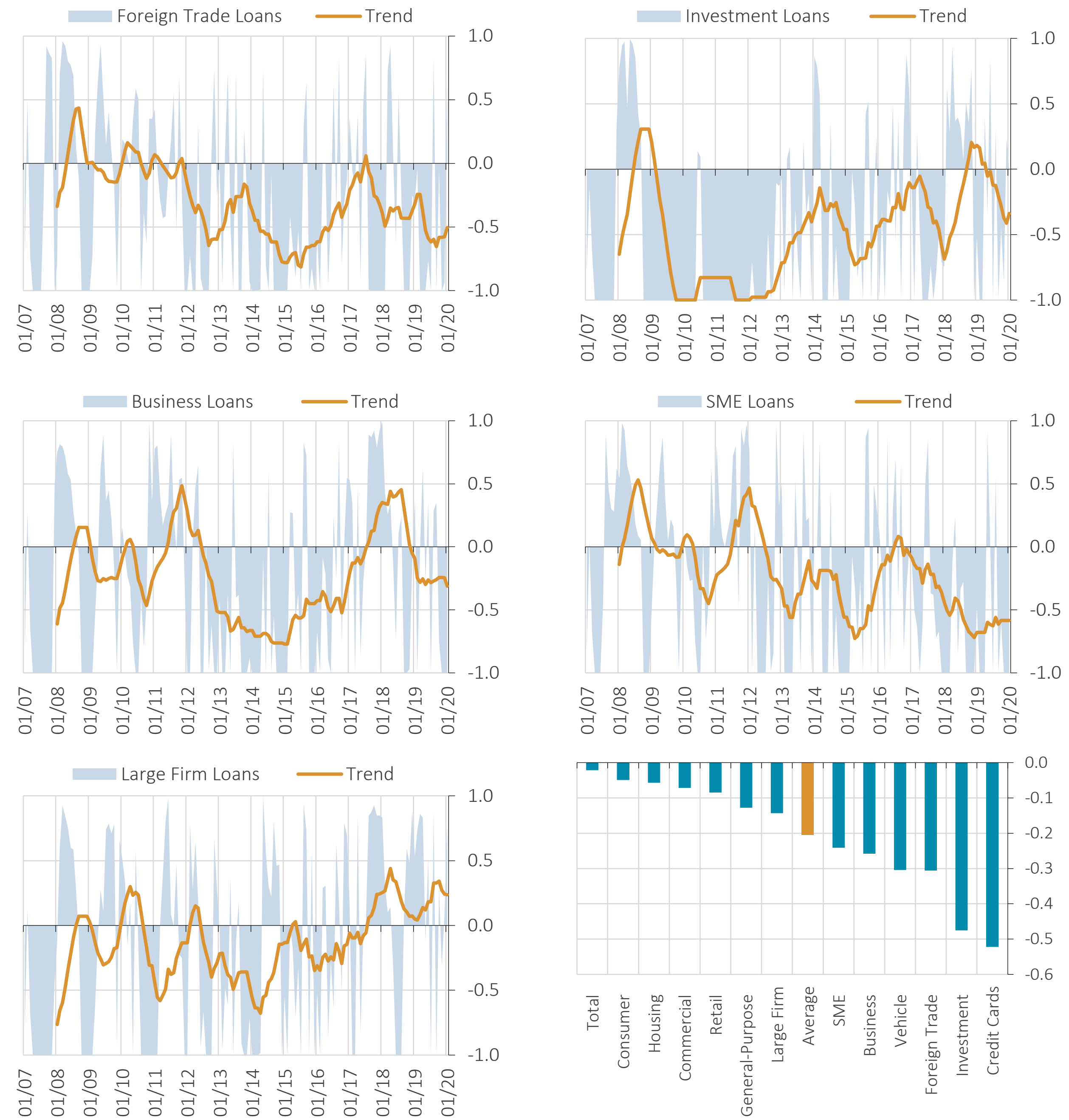


Note: 12-month moving average of monthly concordance index values are depicted in the graphs. The last graph shows the number of months where perfect concordance (index equals 1) occurred as a percentage of total number of months in the sample for each loan category

Source: Authors' Calculations.

Figure 7: Similarity Index of Credit Cycles in Relation with Business Cycle





Note: 12-month moving average of monthly similarity index values are depicted in the graphs. The last graph shows the average similarity index values covering the whole sample period for each loan cycles

Source: Authors' Calculations.

Table 5: Tobit Estimation Results

Dependent Variable: Synchronizaton Index (Trend)	Total Loans	Retail Loans	Commercial Loans	Consumer Loans	Housing Loans	Vehicle Loans	Credit Cards
LF	0.011 (0.009) [0.008]	0.007 (0.010) [0.006]	0.023** (0.006) [0.013]	0.012 (0.013) [0.009]	0.013 (0.009) [0.010]	-0.001 (0.015) [-0.000]	-0.024 (0.015) [-0.021]
MV	0.125*** (0.031) [0.093]	0.029 (0.032) [0.025]	0.102** (0.022) [0.055]	0.003 (0.040) [0.002]	0.025 (0.028) [0.020]	0.062 (0.048) [0.048]	0.031 (0.049) [0.027]
CF	0.077*** (0.024) [0.057]	-0.020 (0.026) [-0.017]	0.105*** (0.031) [0.057]	0.023 (0.032) [0.016]	-0.013 (0.023) [-0.010]	0.037 (0.038) [0.029]	-0.044 (0.040) [-0.039]
GF	0.005 (0.010) [0.004]	0.001 (0.011) [0.000]	-0.007 (0.013) [-0.004]	-0.002 (0.013) [-0.001]	-0.004 (0.009) [-0.003]	0.008 (0.016) [0.006]	0.012 (0.016) [0.011]
Observations	145	145	145	145	145	145	145
Pseudo R^2	0.1057	0.0312	0.1587	0.0112	0.0319	0.0193	0.0205
Dependent Variable: Synchronizaton Index (Trend)	**General-Purpose Loans**	**Foreign Trade Loans**	**Investment Loans**	**Business Loans**	**SME Loans**	**Large Firm Loans**	
LF	0.001 (0.012) [0.000]	0.024* (0.013) [0.019]	-0.016 (0.020) [-0.011]	0.026** (0.014) [0.021]	0.031** (0.014) [0.024]	0.007 (0.009) [0.006]	
MV	0.067* (0.039) [0.052]	0.067 (0.042) [0.055]	0.143** (0.064) [0.102]	0.062 (0.045) [0.050]	0.103** (0.046) [0.081]	0.148*** (0.029) [0.136]	
CF	0.019 (0.032) [0.015]	0.097*** (0.034) [0.079]	0.193*** (0.051) [0.138]	0.096*** (0.036) [0.076]	0.106*** (0.036) [0.083]	0.013 (0.024) [0.012]	
GF	0.004 (0.013) [0.003]	0.003 (0.014) [0.002]	0.007 (0.021) [0.005]	0.001 (0.015) [0.000]	0.003 (0.015) [0.002]	0.003 (0.009) [0.002]	
Observations	145	145	145	145	145	145	
Pseudo R^2	0.0655	0.0832	0.0760	0.0842	0.1799	0.0819	

Robust standard errors are presented in the parentheses. Marginal effects are provided in squared brackets. Constant terms are included in the regressions. ***, **, * denote statistical significance at 1%, 5% and 10%, respectively.

Table 6: Tobit Estimation Results

Dependent Variable: Concordance Index (Trend)	Total Loans	Retail Loans	Commercial Loans	Consumer Loans	Housing Loans	Vehicle Loans	Credit Cards
LF	0.007 (0.006) [0.006]	0.013 (0.008) [0.008]	0.009 (0.007) [0.008]	0.021** (0.008) [0.014]	0.018** (0.007) [0.014]	0.017* (0.009) [0.012]	0.004 (0.009) [0.003]
MV	-0.078*** (0.021) [-0.064]	-0.141*** (0.018) [-0.092]	-0.045* (0.026) [-0.036]	-0.124*** (0.027) [-0.090]	-0.060*** (0.022) [-0.049]	-0.044 (0.032) [-0.030]	0.071** (0.030) [0.054]
CF	0.052*** (0.017) [0.043]	0.041** (0.021) [0.027]	0.061*** (0.020) [0.049]	0.101*** (0.023) [0.073]	0.072*** (0.018) [0.059]	0.026 (0.025) [0.018]	-0.073** (0.024) [-0.055]
GF	0.004 (0.007) [0.003]	-0.002 (0.005) [-0.001]	0.002 (0.008) [0.001]	-0.004 (0.009) [-0.003]	-0.003 (0.031) [-0.002]	0.003 (0.011) [0.002]	0.005 (0.010) [0.004]
Observations	145	145	145	145	145	145	145
Pseudo R^2	0.1356	0.1348	0.1527	0.1892	0.1924	0.0439	0.0854
Dependent Variable: Concordance Index (Trend)	General-Purpose Loans	Foreign Trade Loans	Investment Loans	Business Loans	SME Loans	Large Firm Loans	
LF	0.011 (0.009) [0.008]	0.013 (0.009) [0.010]	0.012 (0.008) [0.009]	0.028*** (0.008) [0.023]	0.022** (0.009) [0.014]	0.001 (0.008) [0.000]	
MV	-0.077** (0.031) [-0.054]	-0.049* (0.028) [-0.039]	-0.107*** (0.028) [-0.084]	-0.029 (0.026) [-0.024]	-0.011 (0.030) [0.054]	-0.011 (0.027) [-0.008]	
CF	0.078*** (0.024) [0.055]	0.054** (0.023) [0.043]	0.011 (0.009 [0.009])	0.106*** (0.022) [0.086]	0.081*** (0.024) [0.054]	-0.004 (0.022) [-0.003]	
GF	-0.001 (0.010) [-0.000]	0.002 (0.009) [0.001]	0.001 (0.009) [0.000]	-0.004 (0.009) [-0.003]	-0.001 (0.010) [-0.000]	0.005 (0.009 [0.004]	
Observations	145	145	145	145	145	145	
Pseudo R^2	0.1487	0.1272	0.0754	0.1379	0.1304	0.0402	

Robust standard errors are presented in the parentheses. Marginal effects are provided in squared brackets. Constant terms are included in the regressions. ***, **, * denote statistical significance at 1%, 5% and 10%, respectively.

Table 7: Tobit Estimation Results

Dependent Variable: Similarity Index (Trend)	Total Loans	Retail Loans	Commercial Loans	Consumer Loans	Housing Loans	Vehicle Loans	Credit Cards
LF	0.005 (0.009) [0.004]	0.005 (0.010) [0.004]	0.016 (0.011) [0.012]	0.012 (0.011) [0.007]	0.015* (0.008) [0.013]	0.001 (0.012) [0.000]	-0.020** (0.010) [-0.016]
MV	0.016 (0.031) [0.016]	0.029 (0.033) [0.023]	0.027 (0.033) [0.021]	0.049 (0.037) [0.037]	0.011 (0.029) [0.010]	0.093** (0.037) [0.087]	0.053 (0.032) (0.043)
CF	0.017 (0.024) [0.017]	0.004 (0.026) [0.003]	0.064** (0.027) [0.059]	0.013 (0.012) [0.012]	0.000 (0.024) [0.000]	-0.016 (0.029) [-0.015]	-0.039 (0.026) [-0.032]
GF	0.006 (0.010) [0.006]	0.008 (0.011) [0.008]	0.000 (0.011) [0.000]	0.007 (0.050) [0.006]	-0.003 (0.009) -0.002	0.013 (0.012) [0.012]	0.012 (0.010) [0.010]
Observations	145	145	145	145	145	145	145
Pseudo R^2	0.0784	0.0547	0.0813	0.0506	0.0486	0.0995	0.0956
Dependent Variable: Similarity Index (Trend)	General-Purpose Loans	Foreign Trade Loans	Investment Loans	Business Loans	SME Loans	Large Firm Loans	
LF	0.001 (0.011) [0.000]	0.017* (0.009) [0.016]	-0.019 (0.0112) [-0.015]	0.023* (0.12) [0.021]	0.008 (0.011) [0.007]	-0.010 (0.009) [-0.009]	
MV	0.017 (0.034) [0.016])	0.164*** (0.029) [0.160]	0.042 (0.040) [0.032]	0.095** (0.038) [0.090]	0.049 (0.035) [0.047]	0.027 (0.031) [0.026]	
CF	0.010 (0.027) [0.090]	0.046** (0.023) [0.045]	0.142*** (0.032) [0.112]	0.046 (0.031) [0.044]	0.046 (0.028) [0.045]	0.034 (0.025) [0.033]	
GF	0.016 (0.011) [0.014]	0.006 (0.009) [0.005]	0.015 (0.013) [0.011]	0.004 (0.013) [0.003]	0.010 [0.012] [0.009]	0.009 (0.010) [0.008]	
Observations	145	10.0045	145	145	145	145	
Pseudo R^2	0.0501	0.1075	0.0805	0.1024	0.0369	0.0293	

Robust standard errors are presented in the parentheses. Marginal effects are provided in squared brackets. Constant terms are included in the regressions. ***, **, * denote statistical significance at 1%, 5% and 10%, respectively.

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