V.1 Effects of Unemployment and Credit Developments on Asset Quality

V.1.1 Introduction

Repayment of loans is significant to the manageability of the cash cycle of the financial sector and healthy functioning of the credit channel. In addition to credit conditions such as amount, maturity and interest, the macroeconomic cycle is also significant to the debtors' capacity to service loan debt. In the firms' side, leading micro indicators such as orders, short term asset and liability amounts and profitability as well as leading macro indicators such as the industrial production index (IPI) and capacity utilization rate facilitate the evaluation of debt repayment performance, while the financial assets, income level and the individual's liability amount are significant factors in terms of debt repayment performance in retail loans. In the context of these factors, indicators regarding the employment market are of great informative value for the course of the credit quality in the retail segment. In the case of income or employment loss, meeting essential needs with current savings is prioritized, while financing expenses becomes secondary. This fact determining the course of NPLs also deteriorates the asset quality of the banking sector, the counterparty of debt service.

This study analyzes the relationship between retail loan NPLs, and the unemployment being among macroeconomic indicators with loan growth, as well as the direction and extent of the effect of these variables on NPL developments. To this end, the direction of the effect of unemployment shocks on NPLs and of the relationship between these factors in the long term is elaborated via econometric methods. Meanwhile, as each new loan extended has a potential to transform into an NPL, the effect of loan growth on asset quality is also included in the analysis. As the ratio of NPL to performing cash loans increases, the bank's asset quality deteriorates and activity capacity narrows (Kapuscinski, 2016). In this respect, NPLs are considered an indicator effective on the monetary transmission mechanism (Escribano, 2013). Retail loans' status as performing through continuing regular payments or their transition to non-performing accounts due to failure in their payments are closely related to the employment status of the users of the loan, observing unemployment is considered an important element in tracking NPL movements. From a macroeconomic perspective, as unemployment increases, the debt repayment capacity of individuals declines, which is likely to have adverse effects on the banks' asset quality. An increase or decrease in loan growth through new loan utilization also stands out as a factor that has direct and indirect effect on NPL movements. As loan growing above its usual trend implies a possible change in the client profile utilizing the loan or an increase in the indebtedness of the people with the same profile, this can be a factor to increase the NPL balance growth in the following period. For these reasons, this study examines banking sector retail loan NPL movements and periodic development, as well as handling NPL movements in subcategories of housing, automobile, general purpose loans and PCC separately. Moreover, periodic analysis of employment and unemployment realizations are made to evaluate breaking points. In the last part of the study, the impact of unemployment and loan growth on NPLs is analyzed. In this context, the direction and dimension of the effects are observed via the Granger causality test, vector autoregressive (VAR) model and autoregressive distributed lag (ARDL) bound test, and similarities derived from the conclusions of the methods are discussed.

There is wide range of literature regarding the determinant factors of NPLs. There are country-based studies as well as those including numerous countries with analyses concerning the course of NPLs. What is more, studies handling the banking sector include panel data analyses, while time series-based methods are mostly preferred in the studies of that literature. As country-specific factors and regulations differ in NPL movements and bear great significance, time series-based analyses are more prevalent. Analyses are mostly oriented towards determining macroeconomic factors that influence NPLs, but there are also studies handling bank-specific factors. In fact, in the study by Louzis et. al. (2011), effects of both macroeconomic and bank-based factors on NPL movements are analyzed. Messai and Jouini (2013) discuss macro and microeconomic determinants of NPLs, and list GDP growth and the bank's return on asset as factors that stand out. Although it depends on the type of loans for which the NPL is analyzed, in general, macroeconomic indicators such as GDP growth, unemployment rate, interest rates, exchange rate, industrial production, inflation and loan growth proved to be effective factors. In the study of Ahmad and Bashir (2013), an analysis of the direction and extent of the impact of nine macroeconomic factors including these indicators on NPL movements were examined. In another study concerning Turkey, Vatansever and Hepsen (2013) concluded that factors such as the unemployment rate, return on equity, CAR, IPI and BIST 100 index were factors that explain NPL movement.

V.1.2 Banking Sector NPL Ratios

In the Turkish banking sector, NPLs are classified according to the provisions of the "Regulation on the Classification of Loans and Provisions to be Set Aside" issued by the BRSA. Accordingly, loans are deemed as non-performing and the required provisions for them set aside when a delay occurs in the installment payment of a loan classified as a performing loan more than 90 days, when an opinion arises that collection of the loan will be delayed for more than 90 days due to macroeconomic conditions or adverse developments peculiar to the debtor, when there is deterioration in the debtor's credit worthiness, or when the loan is subject to lifetime expected credit loss provisioning due to the debtor's default according to the Turkish Financial Reporting Standard (TFRS) 9. Receivables classified as non-performing loans can be re-classified as performing loan as per the provisions stated in the regulation if they are collected without realizing the collateral or they are restructured, whereas they may be deregistered if they are not collectible or sold to an AMC.[1]

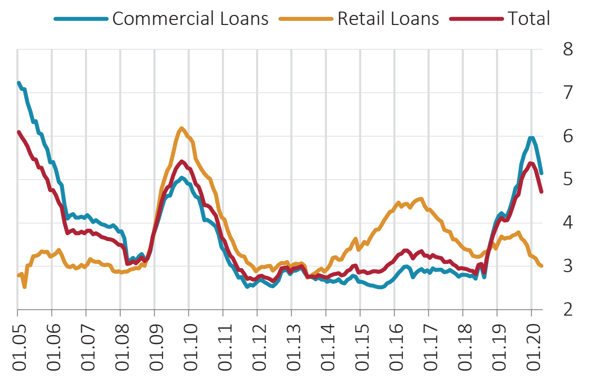
NPL ratios in commercial and retail loans are shaped within macro financial conditions and mostly move in the same directions, yet there have been some periods marked with different directions. Depending on their high share within total credits, NPL developments in commercial loans play a determining role in the total NPL ratio of the banking sector (Chart V.1.1). Cyclical developments, loan supply-demand conditions and economic developments affecting individuals' payment performance affect the development of NPL ratios, while macroprudential policies enforced in view of the period-specific needs can have short- and long-term consequences for NPL ratios.

Due to the structural differences in loan characteristics, collateral, maturity or interest rate, NPL ratios in retail loans record great divergence across subcategories (Chart V.1.2). In housing loans having high collaterals, the NPL ratio stands mostly at low levels, usually below 1%. The NPL ratio follows a relatively stable course in automobile loans as well, and hovered around 3% in the last decade. The NPL ratio in general purpose loans and PCC, which are affected by cyclical developments faster and harder and have shorter maturities than collateralized loans on average, developed a more fluctuating structure, and reached higher values than other retail loan types in the last five years. Since 2005, the NPL ratio in PCC has proved to have the highest values and the most fluctuating structure among retail loan types excluding the global crisis period. The general purpose loan NPL ratio has not been as high and fluctuating as PCC, yet moved in a similar path. In 2009, the global financial crisis resulted in peak levels in NPL ratios across all retail loan types. Since 2013, macroprudential policies such as maximum maturity and installment arrangements applied gradually to PCC and general purpose loans led to increases in NPL in the short and medium term, yet these NPL ratios trended downwards in the following period as payment

[1] Restructuring of non-performing receivables is always possible as per the provisions of the legislation, yet restructuring in certain periods can be facilitated by comprehensive regulations with provisions such as framework contract facility, temporary exemptions from tax or duty or omission of receivables from embezzlement. Regulations in the 2002 "İstanbul Approach", the 2006 "Anatolian Approach" and in 2018 and 2019 can be included within this context. Meanwhile, these regulations are practices for non-performing receivables stemming from commercial loans rather than our study's scope of retail loans. Additionally, with the Board Decision No. 8948 of the BRSA on 17 March 2020, the minimum delay for banks' non-performing receivables, which had been 90 days, was extended to 180 days to be effective until 31 December 2020 (Box I.1.I). As the coverage of the data used in the analysis is until January 2020, they do not include the effect of this decision.

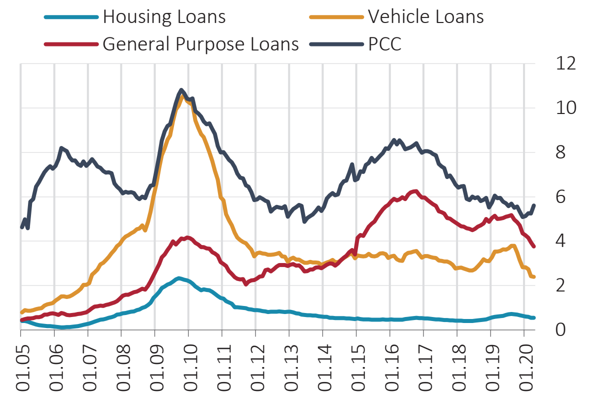
habits of individuals harmonized with the new practices and there was some easing in policies.[2] As macroprudential policies have been implemented gradually towards easing since the third quarter of 2018, retail loan NPL ratios trended downwards, unlike commercial loan NPL ratios.

Chart V.1.1: NPL Ratios by Loan Types (%)



Source: BRSA Latest Observation: 04.20

Chart V.1.2: NPL Ratios by Retail Loan Types (%)



Source: BRSA Latest Observation: 04.20

V.1.3 Employment and Unemployment Rates

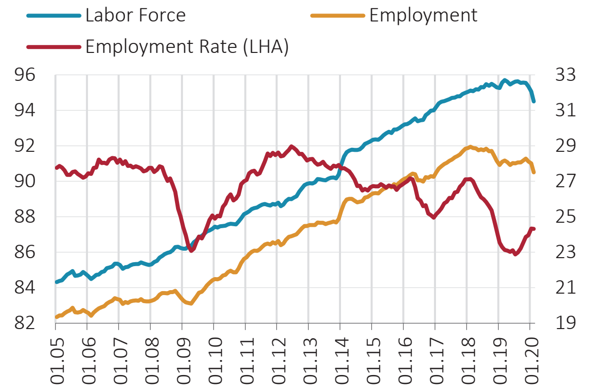
In Turkey, the labor force registers a regular increase in tandem with population, and stood at 32.5 million people at the end of 2019. Meanwhile, the number people employed receded in 2008, the onset of the global financial crisis and in the second half of 2018 as well as the first half of 2019, but increased more slowly than the labor force in the 2012-2016 period, which reflected into the employment rate as a limited yet continuous decline (Chart V.1.3). The most notable trend of recovery in the employment rate was seen in the period from mid-2009 to end-2011. Seasonally-adjusted data suggest that at the end of 2019, the number of people employed was 28.2 million, and the employment rate, which has been on a trend of recovery since the second half of 2019, was 86.9%.

In Turkey, the unemployment rate posted increases up to 5 percentage points from the second quarter of 2008 to the second half of 2009 due to the global financial crisis; from the second quarter of 2016 to the start of 2017 due to the domestic and geopolitical developments and from 2018 following the fluctuations in the exchange rate markets to mid-2019 (Chart V.1.4). Excluding these periods, the unemployment rate mostly fluctuated in a relatively narrow band between 8% and 10%. Meanwhile, the unemployment rate, which was on a downward trend in the start of the reporting period, may have increased again as of mid-March, the period marked by the impacts of the coronavirus pandemic.

In the agricultural sector providing around 17.5% of employment, the unemployment rate hovers at historically low levels due also to the widespread small family businesses, and remains broadly unaffected by cyclical developments. Fluctuations in total unemployment rates mostly stem from the non-agricultural unemployment rate which is affected directly by cyclical developments. Accordingly, both data fluctuate from time to time, yet non-agricultural unemployment rate stands 2-2.5 points above the total unemployment rate and moves in tandem with the headline rate.

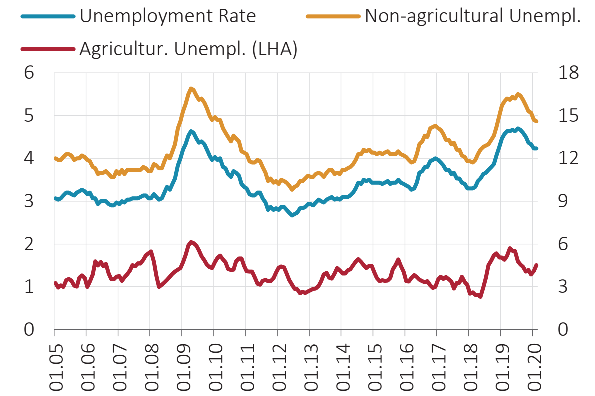
[2] Gaudencio et al. (2019) showed in a study covering eight European countries that extension of maturity in retail loans increases the probability of loans transforming into NPL's.

Chart V.1.3: Labor Force, Employment Levels and Employment Rate (Seasonally Adjusted, Million People, %)



Source: TURKSTAT Latest Observation: 02.20

Chart V.1.4: Unemployment Rates (Seasonally Adjusted, %)



Source: TURKSTAT Latest Observation: 02.20

Note: Agricultural unemployment data employs 3-month average.

V.1.4 Data and Method

Fundamental econometric methods are employed in this section to see the impact of the unemployed population and loan growth on NPLs and the dimensions of this impact. In this context, the effect of employment movements on NPLs, the direction of the effect of the shocks in unemployment on the NPL movement and the relationship between these factors in the long term are analyzed. In addition, the effect of loan growth at this stage is analyzed. Monthly data pertaining to the January 2006-January 2020 period (169 observations) were used in analyses. In the VAR model used in the analysis, a structure was formed as illustrated below:

$$Z_t = \beta_0 + \sum_{i=1}^{k} \beta_i Z_{t-i} + \varepsilon_t$$

Where Z_t: is a 3 variable vector formed by NPL, U and KR series and the observation value at the t time. β_0: is the fixed term, β_i: i. is the lag coefficient matrix, ε_t: is the vector of error terms. Definitions of NPL, U and KR series in the model are as follows:

NPL: symbolizes the annual percentage change in the proportion of the non-performing receivables balance deflated by CPI in retail loans extended by the banking sector.

U: is the annual percentage change in the number of unemployed in the main labor statistics announced by TURKSTAT.

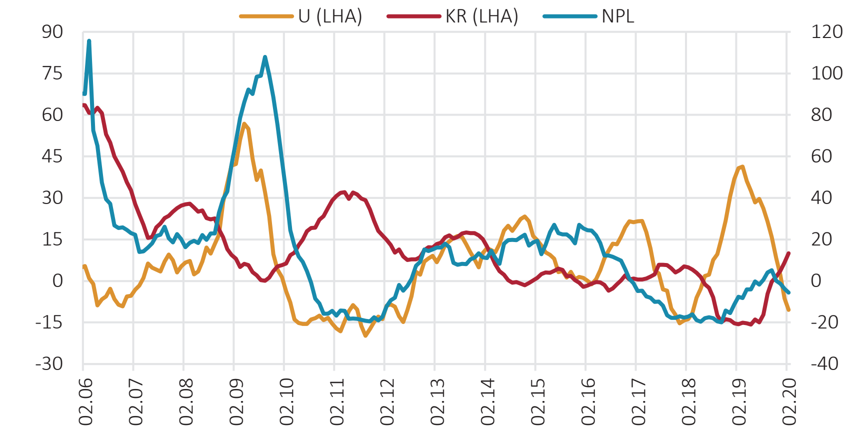
KR: is the annual percentage change of the retail performing loan stock balance deflated by CPI. The historical evolution of these series suggests that the highest volatilities coincide with times of global financial crisis (Chart V.1.5).

As the loan and NPL data are taken as annual percentage changes in balances, to ensure uniformity in the compilation format of the data and put forward the effects of explanatory variables more clearly, the annual percentage change series in the number of unemployed as an indicator of unemployment was preferred over the unemployment rate. The strong relationship between U and NPL stands out, it is observed that movements in U precedes NPL. In fact, the highest correlation with NPL was found between 3 and 4 lagged values of U with a 55% correlation coefficient. Accordingly, it can be asserted that shocks in unemployment spill over into NPL movements after 3-4 months.

Stationarity of the series was tested through the Augmented Dickey Fuller (ADF) test and the Phillips-Perron (PP) stationarity test and the relationship between series was tested with the Granger causality test, and the direction and degree of the relationship between variables was tested through VAR analysis.

With the help of the VAR model, impulse-response analysis and variance decomposition was made, and lastly the results of ARDL bound test were included in the analysis.

Chart V.1.5: Historical Evolution of Series in the Model (%)



Source: BRSA, TURKSTAT Latest Observation: 02.20

According to the results of both the ADF and PP unit root tests, all series are stationary at 10% level.[3] Moreover, according to Zivot and Andrews (ZA) and Perron unit root test results with structural breaks, the fact that the series are stationary despite structural break supports the results of the ADF and PP unit root tests.[4]

Table V.1.1: Granger Causality Test Results

Null hypotheses	F-Statistics	Probability
U is not the Granger cause of KR	2.93	0.06
KR is not the Granger cause of U	4.07	0.02
NPL is not the Granger cause of KR	1.15	0.32
KR is not the Granger cause of NPL	3.67	0.03
NPL is not the Granger cause of U	5.27	0.01
U is not the Granger cause of NPL	14.95	0.00

Note: Significance of 1%, 5% and 10% are symbolized as ***, ** and * respectively. SIC is used for appropriate lag.

The Granger causality test measures whether the NPL, U and KR variables have the power to explain each other. The direction of causality obtained from the causality analysis determines the direction of the relationship between variables employed in the model (Yılmaz, 2005). U and KR variables, the effects of which on NPL are analyzed with this test, are expected to be the Granger cause of NPL. According to Schwarz and Akaike information criteria (SIC and AIC), the number of lags are 2 and 12, respectively, and as the number of observations in the analysis is few, SIC is taken as the base here. Test statistics results and the corresponding probability values reveal that all variables found to be "Granger cause" prove to

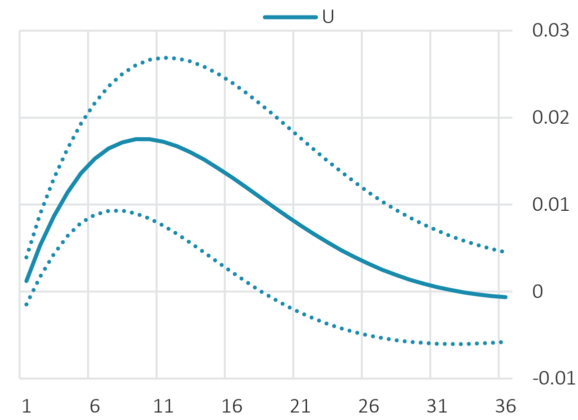
[3] When any time series model is developed, if the quality of the stochastic process obtained changes in time, as the series is not stationary, it is not possible to represent the past and future structure of the series with a simple algebraic model. To determine the stationarity of series, ADF and PP unit root tests were made. After appropriate lags are determined for variables using Schwarz and Akaike information criteria (SIC and AIC), stationarity of series was tested in with constant, with constant-trend and without constant-trend models.

[4] In cases of structural breaks in time series, the accountability of tests such as ADF and PP can be questioned, and they may suggest that the test results are not stationary for a series which is in fact stationary. The null hypothesis of structural break unit root tests of ZA (1992) and Perron (1997) suggest unit root when the series has structural breaks. According to ZA and Perron test results, structural breaks emerged as of the last quarter of 2009. This implies that structural breaks are a result of the global financial crisis.

have statistical significance (Table V.1.1). Both U and KR being a Granger cause for NPL supports the idea that these variables have the power to precede NPL.

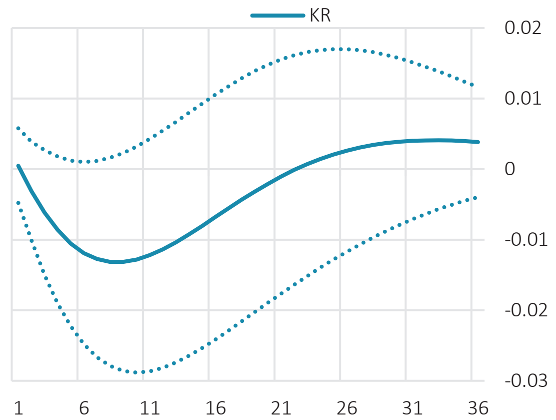
After the Granger causality status is determined, impulse-response functions and variance decomposition are analyzed with the VAR model constructed by 2 lag according to SIC. In the Granger causality analysis, KR and U were found to be the “Granger cause” of NPL. Meanwhile, NPL and U, which were found to be the “Granger cause” of each other makes us think that the ordering here should be U and NPL with an economic approach. As a result, while establishing the VAR model, ordering of variables was carried accordingly, i.e. from external to internal (KR U NPL).

Chart V.1.6: Responses of NPL to shocks in U (%)



Source: BRSA, TURKSTAT, Author’s estimates Latest Observation: 01.20
Note: X axis in the NPL’s response function represents months following the shock. Dashed lines denote confidence intervals.

Chart V.1.7: Responses of NPL to shocks in KR (%)



Source: BRSA, TURKSTAT, Author’s estimates Latest Observation: 01.20
Note: X axis in the NPL’s response function represents months following the shock. Dashed lines denote confidence intervals.

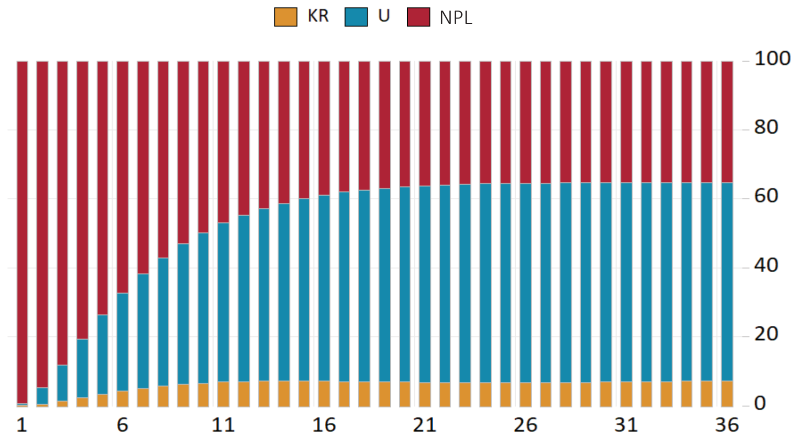
Impulse-response functions show the responses of other variables to a 1-percent shock in a variable within the system. The response of the NPL variable to the impulse stemming from shocks in the U variable proved positive (Chart V.1.6). These results imply that shocks that increase U also increased NPL. The response of NPL to the impulse stemming from a shock in U proves statistically insignificant after 18 months.[5] It was found that a 1-percent increase in U pushed NPL by 0.24% at the end of 18 months.[6] On the other hand, the change in the KR variable does not lead to a significant effect on NPL in the short term (Chart V.1.7).

Results of the variance decomposition method show the sources of the change in NPL for 36 terms. This method indicates the percentage of the changes in NPL in terms of sources, whether in the NPL itself or shocks in U and KR. As expected, almost all of the change in the initial terms was accounted for by the dependent variable, while the explanatory power of the NPL decreased until the end of the term and was replaced by the U variable. According to the VAR model with 2 term lags, the U variable accounts for 48% of the change in NPL; while NPL accounts for 45% of the change and KR accounts for 7% of the change at the end of 12 months (Chart V.1.8). With flattening at the end of 20 months, U, NPL and KR account for 57%, 36% and 7% of the change. On the other hand, results of the VAR analysis made for retail loan sub-items reveal a stronger effect of U on NPL in PCC, whereas in sub-items of consumer loans do not suggest any statistically significant result.

[5] Evaluation of responses to impulses within confidence intervals with ± 2 standard errors suggest the statistical insignificance of the response following the response of NPL to U around 18 months, and to its own shock after about 12 months.

[6] Analysis on PCC yielded the same results as that on retail loans.

Chart V.1.8: Variance Decomposition for NPL (%)



Source: BRSA, TURKSTAT, Authors' estimates Latest Observation: 01.20

Note: x axis in variance decomposition denotes months.

In the ARDL method, variables in the model are not required to be stationary in level. For the determination of the long-term equilibrium relationship, an appropriate lag ARDL model is established, and it is analyzed whether there is a long-term equilibrium relationship, i.e. co-integration and long-term coefficients are obtained. Finally, ARDL-based error correction model (ECM) is established to analyze the short-term relationship.

Table V.1.2: ARDL Bound Test and Long-Term Equilibrium Model

	Model	F-Statistics	Coefficient Value
F-Statistics		11.8***	
F Table (Bottom-Top) Value (10%)		2.71 - 3.45	
F Table (Bottom-Top) Value (5%)		3.24 - 4.05	
F Table (Bottom-Top) Value (1%)		4.36 - 5.39	
Long-term Equilibrium Model	NPL = -15.27 + 2.27xU + 0.79xKR [0.4]*** [0.3]**		
Error Correction Coefficient			-0.096***

Note: Significance of 1%, 5% and 10% are symbolized as ***, ** and * respectively. Values in square brackets in the long-term equilibrium model give standard errors of coefficients.

The number of lags determined according to SIC were used while establishing the ARDL model, and accordingly the appropriate model for NPL, U and KR variables, ARDL was determined as (1,0,0). Accordingly, with the bound test, the null hypothesis, which is no long-term equilibrium or co-integration, was checked. As the F-statistics calculated according to test results proved even higher than the upper bound of 1 statistical significance level, the null hypothesis was rejected, and it was concluded that there was long-term equilibrium or co-integration among variables (Table V.1.2).

According to the resulting long-term equilibrium model, both the U and the KR variables prove to have a positive effect on NPL. The effect of U is statistically significant and larger than KR. A co-analysis of it with the result of the impulse-response analysis suggests that the effect of an increase in retail loan growth on the growth rate of non-performing receivables balance in the short term is statistically insignificant, while partial default in repayment of some of the loans utilized in the long term increased this rate in real terms. Retail loan repayment performance of the household gets weaker due to the impaired debt repayment power as a result of the decline in employment.

Following the long-term equilibrium model analysis, the short-term relationship was examined with the ECM established based on the ARDL model. The ECM coefficient showing the time that shocks need to reach long-term equilibrium due to the changes in the short term is -0.096, which is statistically significant. Thus, it reveals that about 9.6% of the shocks will be corrected in a term. Accordingly, correction of the shock and realization of the long-term equilibrium takes about 12-18 months. This is consistent with the results obtained from the variance decomposition and impulse-response functions.

V.1.5 Conclusion

As a regular income is a significant factor for individuals to repay their credit debts in time, the rise in the annual percentage change in the number of unemployed is expected to increase the annual growth in non-performing loans. The analyses undertaken also support this. Meanwhile, since all new loans extended bear the potential to have delays in collection, increases in annual growth in retail loans are believed to increase the annual growth in these non-performing loans, and analyses pointed out that this is the long-term effect. Increased indebtedness reduces the individuals' debt service capacities, which weighs on the probability of loans being transformed into NPL in the long term. As a result of the methods used, the course of NPLs in the term proved to move in tandem with the annual percentage change in the number of unemployed and retail loan balance, which are the explanatory variables. Results regarding unemployment imply that employment developments are quite influential in the course of retail loan NPL both in short, medium, and long terms. The rise to be recorded in unemployment led by the adverse impact of the recent coronavirus pandemic on the employment market is expected to spill over into NPL in the upcoming period. Timely policy actions such as the extension of transition to NPL to 180 days, banks' delay of payment of the debt, and enforcement of short-term employment allowance are projected to slow down transitions in this period.

References

Ahmad, F. and Bashir T. (2013). Explanatory Power of Macroeconomic Variables as Determinants of Non-Performing Loans: Evidence from Pakistan.

Escribano, M.G. (2013). Monetary Transmission in Brazil: Has the Credit Channel Changed? IMF Working Paper No. 13/251.

Gaudêncio, J., Mazany A. and Schwarz C. (2019). The Impact of Lending Standards on Default Rates of Residential Real Estate Loans. ECB Occasional Paper Series, No 220.

Göktaş Yılmaz, Ö. (2005). Türkiye ekonomisinde büyüme ile işsizlik oranları arasındaki nedensellik ilişkisi. İstanbul Üniversitesi İktisat Fakültesi Ekonometri ve İstatistik Dergisi 2, 11-29 (in Turkish).

Kapuscinski, M. (2016). The Role of Bank Balance Sheets in Monetary Policy Transmission. Evidence from Poland. NBP Working Paper No. 245

Louzis D. P., Vouldis A. T. and Metaxas V. L. (2011). Macroeconomic and Bank-Specific Determinants of Non-Performing Loans in Greece: A Comparative Study of Mortgage, Business and Consumer Loan Portfolios.

Messai A. S. and Jouini F. (2013). Micro and Macro Determinants of Non-performing Loans.

Perron, P. (1997). Further evidence on breaking trend functions in macroeconomic variables. Journal of econometrics, 80(2), 355-385.

Sevüktekin M. and Çınar M. (2014). Econometric Time Series Analysis Eviews Applied. (5th edition). Ankara: Dora Yayıncılık.

Vatansever M. and Hepsen A. (2013). Determining Impacts on Non-Performing Loan Ratio in Turkey.

Zivot, E. and Andrews, D. W. K. (1992). Further Evidence on the Great Crash, the Oil- Price Shock, and the Unit-Root Hypothesis. Journal of Business & Economic Statistics, 10(3):251-270.

V.2 The Coherence between Credit and Business Cycles: Evidence from the Turkish Banking Sector

V.2.1 Introduction and Related Literature

Advanced financial markets are among the factors that support economic growth by enabling the distribution of funds and channeling the funds required for investments to the real sector. Besides the effects on the supply side, it is argued that economic growth also increases the demand for financial intermediation activities and plays an important role in the cyclical behavior of loans (Hicks, 1969; Minsky, 1977). Specifically, in the aftermath of the global financial crisis, studies examining the co-movements and interactions of credit and business cycles have gained importance in empirical literature. The fact that global economic meltdowns coexisted with financial market volatility, asset price drops, liquidity squeezes and rapid slowdowns in credit extension has recently increased the importance of the relationship between credit and business cycles in terms of financial stability (Jorda et al., 2011; Jorda et al., 2016).Studies reveal that credit cycles have information value in predicting financial imbalances and economic crises (Schularick and Taylor, 2012; Drehmann et al., 2012). The duration and magnitude of economic stagnations seem to depend on the nature of financial cycles (Claessens et al., 2011). The deviation of financial cycles from the long-term averages generated by loan growth and asset prices in particular, is one of the most successful early warning indicators of crises (Borio and Drehmann, 2009).

A section of the recent empirical literature that is more relevant to this special topic aims to measure the synchronization of direct credit and growth cycles. Claessens et al. (2012) find that growth and credit cycles are synchronized across the sample by 80% while covering a wide period using data from 44 countries. Comparisons between country groups show that cyclical synchronization is higher in advanced economies than in EMEs. Similarly, Kurowski and Rogowicz (2018) conclude that the synchronization between financial cycles and cyclical movements in macroeconomic aggregates is high and becomes more evident in times of crisis. Focusing on Spanish case, Sala-Rios et al. (2016), on the other hand, quantify cyclical synchronization and determine that the business cycle leads credit developments. While credit cycles are found to last longer than business cycles, the phases of credit expansion and credit contraction have similar durations on average in the case of the Spanish banking sector. Across different types of loans, loans extended to the real sector seem to be largely aligned with the direction of economic activity. Among loans extended to households, home loans serve as a leading indicator for the macroeconomic outlook.

In the first stage of this study, we analyze the degree of coherence between credit and business cycles in Turkey for the 2007-2020 period, based on three different indices. The synchronization index used in Mink et al. (2012) and Samarina et al. (2017) reveals itself as the most basic method. This index basically tests whether output and credit gap indicators register the same mark over a given time period. As it is dynamically calculated on a time dimension, this index can monitor the relationship better than the static correlation method. As a second method, we preferred the concordance index introduced by Harding and Pagan (2006). This index shows whether the series representing financial intermediation and economic activity are in co-expansion or co-contraction phases on the cyclical plane. In other words, it helps to capture the co-movement of the momentums of economic and credit cycles. As a third and final indicator, we calculated the similarity index used in Mink et al. (2012) and Samarina et al. (2017). In addition to the position and momentum of the cycles, this index also provides a definitional demonstration of the coherence of their magnitudes. The suitability of total loans as well as various subcategories of loans with the business cycle is analyzed using the same methods. In the second stage of this study, we analyze local and global macro-financial factors that affect different coherence characteristics of credit and business cycles using ordered logistic regression methods.

V.2.2 Credit Market Outlook during Growth Shocks

In the sample period, the Turkish banking sector provides an adequate framework to examine the time-varying synchronization of business and financial cycles. As shown in Charts V.2.1 and V.2.2, three time frames of worsened economic outlook can be identified over the examined period. Shocks in these periods have high heterogeneity in terms of source, quality, duration and subsequent policy measures. January 2009 is a period when the global financial crisis affected domestic macroeconomic developments, external demand shrunk, capital outflows occurred, and investments weakened. Looking at the level of loans and monthly rates of change across a 24-month window over the pre- and post-crisis period, it is observed that the recovery in total loans took relatively longer and the recovery in commercial loans was weaker compared to retail loans. Weak investment and export appetite and stagnant commercial activity were likely to blame for the belated recovery in commercial loans.

In July 2016 when global and local geopolitical risks prevailed, credit growth remained partially intact as the growth shock had a relatively lower impact and policy measures were in place to help economic agents access financing in the period thereafter. Specifically, as CGF-guaranteed loans eliminated credit constraints and supported the recovery in economic activity, commercial loans registered a faster and larger growth than retail loans over the study period. More recently, financial market volatilities and tight financial conditions caused economic activity to be particularly weaker at the end of 2018. In this period, thanks to improved expectations and macroprudential policy measures taken to ensure the smooth functioning of the credit channel, the credit market saw a rapid recovery led by retail loans.

Chart V.2.1: Credit Market Outlook during Growth Shocks (Level, BLTS, t_0=100)

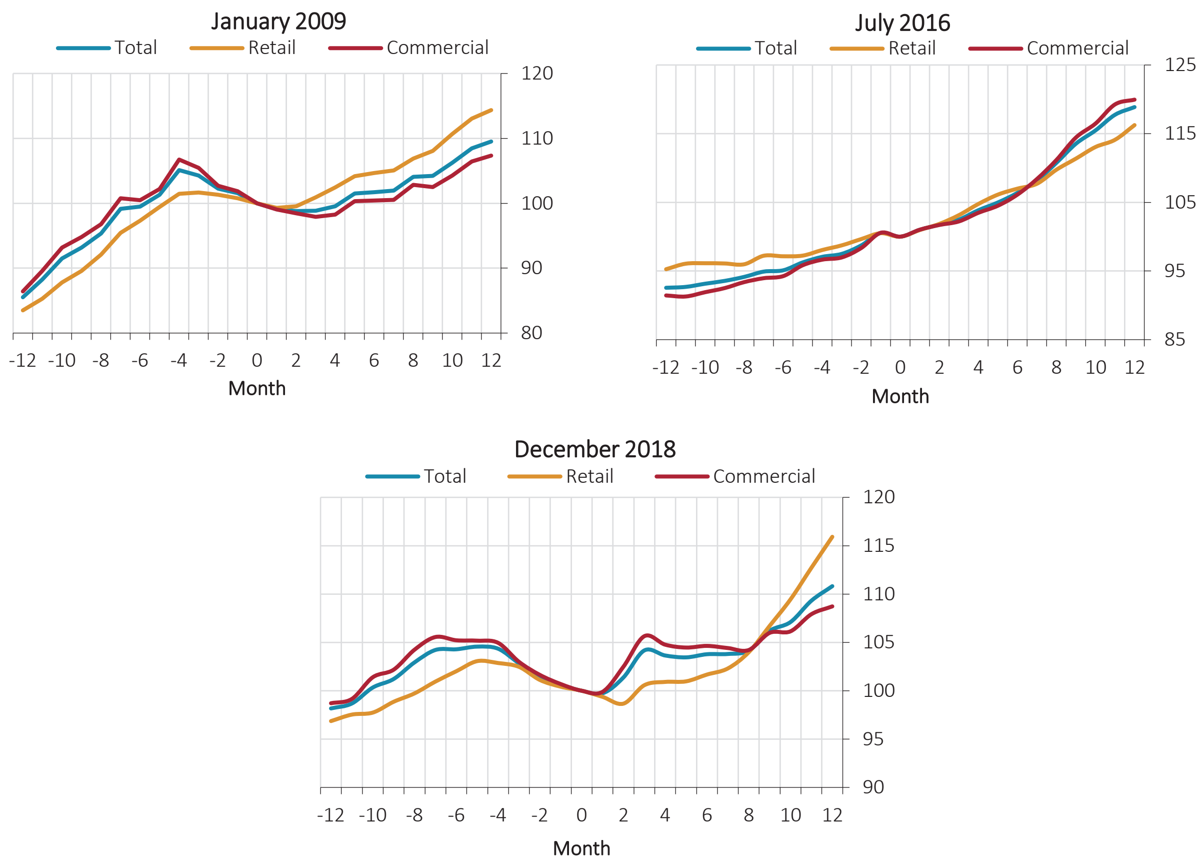
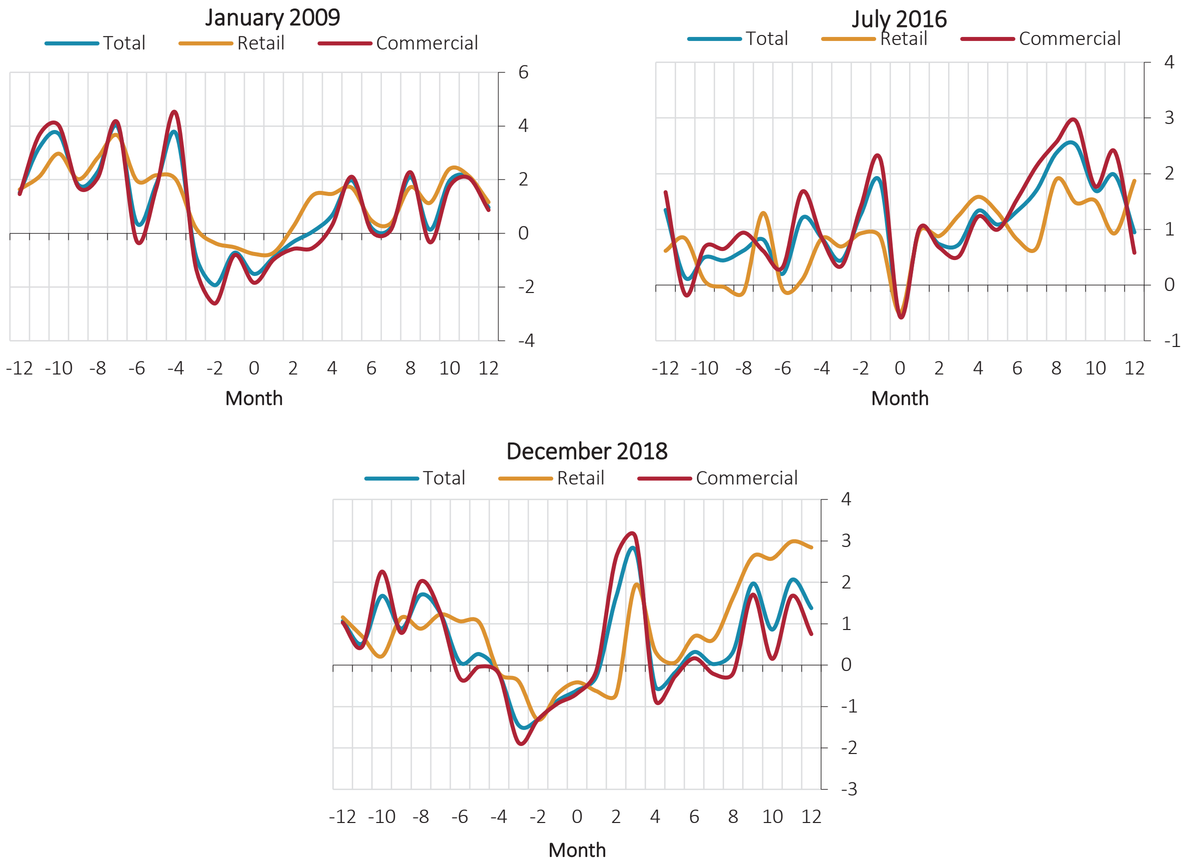


Chart V.2.2: Credit Market Outlook during Growth Shocks (Monthly percentage change, BLTS)



V.2.3 Methodology and Data

The sample period is January 2007 to January 2020. In the first stage, business and credit cycles were obtained using a one-sided Hodrick-Prescott (HP) filter.[1] This method allowed us to build output and credit gap indicators, which signify the deviation of economic activity and credit series from their long-term trend. We used a seasonal and calendar adjusted IPI as it is more representative of economic activity at high frequency. Credit gap series, on the other hand, were obtained using both total loans and subcategories of loans, comprising retail loans, commercial loans, consumer loans, credit cards, housing loans, vehicle loans, SME loans, large firm loans, foreign trade loans, investment loans and business loans.[2]

The synchronization index is the first indicator used to measure the coherence of credit and business cycles. The index value for a certain period was estimated as in Mink et al. (2012) and Samarina et al. (2017):

$$Sycnhronization_t = \frac{Output\ Gap_t * Credit\ Gap_t}{|Output\ Gap_t * Credit\ Gap_t|} \quad (1)$$

In periods when the synchronization index takes the value of 1, the output gap and the credit gap are of the same sign, whereas a difference in the sign of these two indicators causes the index to take the value -1. This index aims to measure the synchronization of positions between credit and growth dynamics on the cyclical plane in a simple structure. The second coherence indicator, i.e. the concordance index, is

---

[1] The lambda parameter was set to 14,400, the commonly accepted value for monthly data. The one-sided version of the filter reduces the effect of future observations on previous estimates.

[2] Loans are adjusted for exchange rate effects. Series used in the analysis are retrieved from the TURKSTAT, CBRT and Bloomberg databases.

calculated by the method suggested in Harding and Pagan (2006), Meller and Metiu (2017) and Oman (2019):

$$Concordance_t^{BC} = (B_t * C_t) + (1 - B_t) * (1 - C_t) \tag{2}$$

$$B_t = \begin{cases} 1 & if\ output\ gap\ is\ in\ upturn\ phase \\ 0 & if\ output\ gap\ is\ in\ downturn\ phase \end{cases}$$

$$C_t = \begin{cases} 1 & if\ credit\ gap\ is\ in\ unpturn\ phase \\ 0 & if\ credit\ gap\ is\ in\ dowturn\ phase \end{cases}$$

In this model, B_t and C_t are dummy variables that indicate whether the output gap and the credit gap are in an increasing or decreasing phase. In periods when economic activity and credit series move from "trough-to-peak", they take the value of 1, and when they move from "peak-to-trough", they take the value of 0. The index itself is set to take the value of 1 if the cycles are in the same phase and 0 if not.

As the last indicator, we estimated a similarity index using the methodology suggested by Mink et al. (2012) and Samarina et al. (2017). This index summarizes how coherent the magnitudes of business and credit cycles are:

$$Similarity_t = 1 - \frac{|Output\ Gap_t - Credit\ Gap_t|}{0.5 * (|Output\ Gap| + |Credit\ Gap_t|)} \tag{3}$$

Unlike the first two indices, this index, which is a continuous variable, takes values in the range of [-1,1]. High index values indicate better synchronization between the magnitudes of cyclical movements while low values denote impaired synchronization.

In the next stage of the study, using the ordered logistic regression method, we explored how indices measuring the coherence of cycle positions, momentums and magnitudes interact with global and local macro-financial variables. We preferred this method as all indices are limited to certain values and feature ordinal ranking.

$$Index_t = \alpha + \beta(Local\ Financial)_t + \gamma(Macro\ Volatility)_t + \delta(Capital\ Flows)_t + \theta(Global\ Financial)_t + \varepsilon_t \tag{4}$$

This regression was estimated separately for cases where synchronization, concordance and similarity indices were dependent variables. In addition to the coherence of economic activity and total credit cycles, estimates were repeated with indices obtained for subcategories of loans. Large data sets were used to create explanatory variables. In this context, the factor that denotes local financial conditions was established by applying the principal component analysis (PCA) to nine series, which have information value on foreign exchange, bonds, stock markets and risk premium. As a representation of macroeconomic volatilities, the volatility estimations of a GARCH (1.1) model for ten series on inflation, economic activity, external trade and public finance were aggregated by the PCA analysis.[3] Portfolio movements by non-residents through stocks, government bonds and corporate bonds were used as a variable for capital flows. Lastly, we built an explanatory variable representative of global financial risks by conducting a static factor analysis on 11 series that consist of indicators for bond returns, oil prices, the foreign exchange market and implied volatility.

[3] Conversions such as annual difference, annual percentage change and annualized percentage change were applied to the series covered by the analysis.

V.2.4 Results

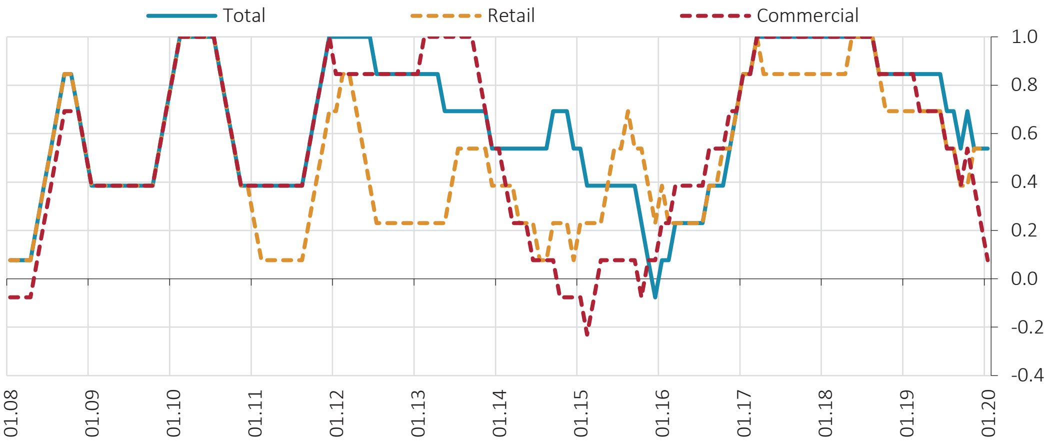
Chart V.2.3 shows the results from the synchronization index that measure the coherence of relative positions on the cyclical plane.[4] The fact that the index from the coherence of loan and output gaps is in positive territory indicates a high synchronization between economic activity and the credit outlook throughout the sample period. It is noteworthy that this synchronization was maintained to a great extent across all loan categories, including during crisis periods, but was largely lost from the second half of 2014 to 2016. A more detailed analysis shows that this discrepancy was caused by the credit gap being in positive territory versus the output gap being in negative territory cyclically. An important finding regarding subcategories of loans is that the synchronization between personal loans and economic activity was lower, especially in the post-2011 period, when macroprudential policies were heavily in place. In fact, installment limitations and factors, the CCF in particular, affecting the use of retail loans reduced the coherence with the position of economic activity, as intended. Vehicle loans, credit cards and general-purpose loans, to which these policies were applied, played a role in the reduced synchronization. With CGF-backed loans in 2017, the synchronization of the position between commercial loans and economic activity improved. As of mid-2019, there has been a synchronized increase in economic activity and credit growth amid improved expectations and easing financial conditions. Looking at sub-details, it seems that even though retail loans remained highly synchronous, the synchronization of commercial loans and business cycles decreased in this period due to developments in the risk premium and a sluggish investment appetite.

The results from the concordance index monitoring co-movements of expansion and contraction are shown in Chart V.2.4. The convergence of the index to 1 indicates that credit and economic cycles are more inclined to share the same phase, whereas a convergence to 0 indicates a stronger tendency to be in a different phase. Across the sample, business cycles precede credit cycles by 3 to 6 months, based on the type of loan. In line with this, the lagged relationship also strengthened during the global financial crisis, when the magnitude and duration of economic shocks were high, and co-existence in the same phase (expansion / contraction) weakened. In fact, when economic activity was back on a recovery track (in an upward phase) in this period, the credit cycle continued to narrow (in a downward phase) and displayed a delayed “trough-to-peak” movement. The level of concordance has been lower in recent shocks but is relatively high for total and commercial loans. However, there has been a decline across all subcategories of retail loans (housing, vehicle, credit cards, general-purpose).

Finally, we are presenting the results from the similarity index that monitors the coherence between cycle magnitudes (Chart V.2.5). Having been volatile at the beginning of the sampling period, the magnitudes of economic activity and credit cycles varied significantly, especially between 2012 and 2015. This period was marked by massive credit movements in the face of relatively low-volume business cycles. The CGF practices of 2017 supported the magnitude suitability of business cycles, particularly for commercial loans. The divergence in cycle magnitudes of commercial loans and economic activity has recently been more pronounced for SME and business loans.

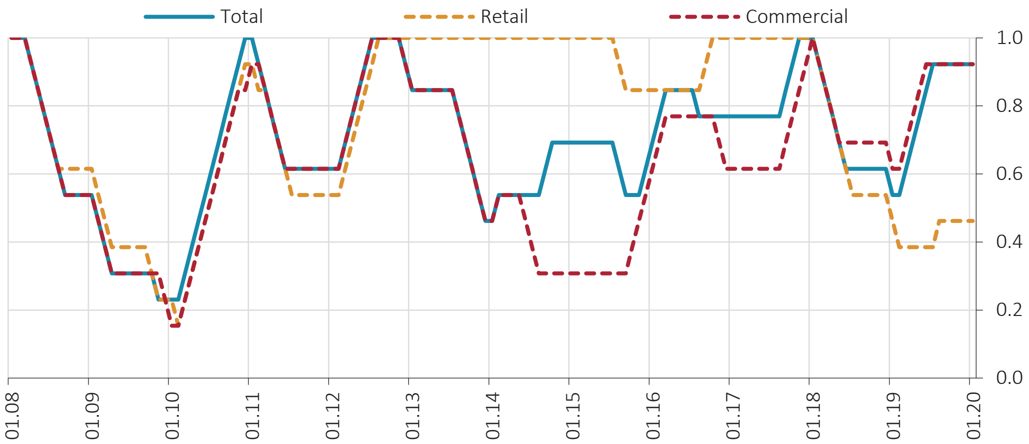
[4] Indices are presented in the form of 12-month moving averages to keep track of overall trends.

Chart V.2.3: Synchronization Index (Coherence in Cyclical between Loans and Economic Activity, 12-Month MA)



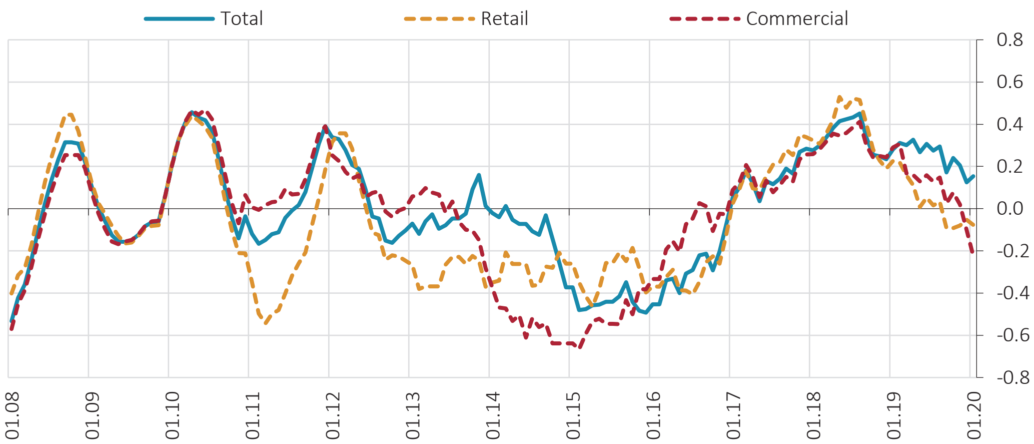
Source: Author's calculations. Last Observation: 01.20

Chart V.2.4: Concordance Index (Coherence in Cyclical Phases between Loans and Economic Activity, 12-Month MA)



Source: Author's calculations Last Observation: 01.20

Chart V.2.5: Similarity Index (Coherence in Cyclical Magnitudes between Loans and Economic Activity, 12-Month MA)



Source: Author's calculations Last Observation: 01.20

Findings from the second stage of the analysis provide information on the factors affecting the coherence of cycle positions, momentums and magnitudes (Tables V.2.1 and V.2.3). Results of the synchronization index provide evidence that local financial conditions increase the synchronization of loans with economic activity. Periods of tight local financial conditions can also be defined as periods with a closer positioning to the business cycle, especially for housing, foreign trade, business and SME loans. The fact that bank loans account for a significant share of household and corporate liabilities and financing through loans is at a historically high level is one of the structural factors supporting the role of local financial conditions. On the other hand, the highly volatile macroeconomic outlook increases the synchronization for vehicle loans, credit cards, business loans and SME loans. Meanwhile, capital flows are found to have a major impact on the subcategories of loans. As shown in Table V.2.1, stronger capital inflows support the synchronization of credit and business cycles. It is known that when capital flows are stronger, banks borrow more from abroad, loan supply strengthens and asset prices increase. Thus, firms' access to low-cost liquidity and finance amid strong capital flows increases cyclical synchronization by supporting investment activity.

According to results from the logistic regression analysis, where the concordance index is a dependent variable, tight local financial conditions help increase the concordance of economic activity with consumer, housing, business and SME loans. Unlike the synchronization index, macroeconomic fluctuations have a negative effect on phase concordance. This effect is statistically significant for consumer, vehicle, general-purpose and investment loans. As in position synchronization, stronger capital flows support phase concordance as well, which is evident for all subcategories of loans. Lastly, we analyzed the determinants of the similarity index, which provides information on the coherence of magnitudes between the cycles. As shown in Table V.2.3, unlike positioning and momentum coherence, local financial conditions have less impact on this index. On the other hand, high volatility heightens the similarity index across all subcategories of loans. Meanwhile, capital flows seem to support the similarity of magnitudes between commercial loans and the growth cycle.

The results of these three indices show that local financial conditions are an important factor in the cyclical co-movements between business loans and economic activity. The fact that business loans are of shorter term and more of a revolving nature than investment loans affects the sensitivity to financial conditions. Capital flows, on the other hand, affect the coherence with economic activity across all subcategories of commercial loans. As they determine the amount, maturity and cost of financing, capital flows fuel cyclical movements in economic activity through investment trends. In addition, global financial indicators appear to have less explanatory power for the coherence between loans and economic activity.

The coronavirus pandemic poses downside risks to industrial production and external trade on a global scale, and to consumer and investment spending on a domestic scale through mobility constraints and mounting uncertainties. Moreover, the sharp weakening of capital flows and the decreased investment appetite for risky financial assets may affect loan supply negatively, which will potentially cause a rapid deterioration in the coherence of commercial and retail loans with macroeconomic cycles. On the other hand, the measures taken by public authorities and the CBRT to support market liquidity and sustain a functioning credit channel will ease loan supply and demand conditions, and maintain the synchronization of credit and business cycles as economic activity recovers in the upcoming period.

Table V.2.1: Ordered Logistic Regression Results

Dependent Variable: Synchronization Index (Trend)	Total	Retail	Commercial	Consumer	Hpousing	Vehicle	Credit Cards
Local Financial	0.120* (0.066)	0.057 (0.068)	0.166** (0.066)	0.079 (0.065)	0.143** (0.068)	0.025 (0.072)	-0.089 (0.064)
Macro Volatility	0.020 (0.099)	0.167 (0.102)	0.146 (0.101)	0.094 (0.099)	0.015 (0.102)	0.220** (0.101)	0.210** (0.099)
Capital Flows	0.522*** (0.176)	0.064 (0.172)	0.150*** (0.055)	0.585*** (0.178)	-0.019 (0.185)	0.242 (0.178)	-0.208 (0.177)
Global Financial	0.026 (0.067)	-0.013 (0.071)	-0.001 (0.069)	-0.040 (0.067)	-0.041 (0.069)	0.046 (0.069)	0.092 (0.074)
Number of Observations	145	145	145	145	145	145	145
Dependent Variable: Synchronization Index (Trend)	**General-Purpose**	**Foreign Trade**	**Investment**	**Business**	**SME**	**Large Firm**	
Local Financial	0.054 (0.070)	0.139** (0.070)	-0.003 (0.072)	0.135** (0.068)	0.165** (0.072)	0.008 (0.061)	
Macro Volatility	0.150 (0.101)	0.202** (0.101)	0.035 (0.104)	0.177* (0.100)	0.254** (0.0993)	0.025 (0.101)	
Capital Flows	0.140 (0.171)	0.513*** (0.177)	0.555*** (0.173)	0.497*** (0.174)	0.607*** (0.185)	0.377*** (0.177)	
Global Financial	0.054 (0.079)	0.001 (0.077)	0.006 (0.076)	0.008 (0.069)	0.038 (0.081)	0.013 (0.065)	
Number of Observations	145	145	145	145	145	145	

Robust standard deviations are presented in parentheses. Constant term is added to logistic regressions. ***, **, * denote a statistical significance of 1%, 5% and 10%, respectively.

Table V.2.2: Ordered Logistic Regression Results

Dependent Variable: Concordance Index (Trend)	Total	Retail	Commercial	Consumer	Housing	Vehicle	Credit Cards
Local Financial	0.037 (0.065)	0.081 (0.069)	0.060 (0.062)	0.130** (0.066)	0.173** (0.069)	0.073 (0.065)	-0.022 (0.060)
Macro Volatility	-0.364*** (0.109)	-0.342*** (0.117)	-0.187* (0.100)	-0.225** (0.106)	-0.095 (0.109)	-0.255** (0.109)	-0.122 (0.101)
Capital Flows	0.467*** (0.178)	0.150 (0.172)	0.474*** (0.177)	0.619*** (0.181)	0.607*** (0.177)	0.0325 (0.172)	-0.623*** (0.183)
Global Financial	0.002 (0.068)	-0.023 (0.066)	-0.032 (0.067)	0.010 (0.066)	-0.023 (0.066)	0.011 (0.068)	0.026 (0.066)
Number of Observations	145	145	145	145	145	145	145
Dependent Variable: Concordance Index (Trend)	**General-Purpose**	**Foreign Trade**	**Investment**	**Business**	**SME**	**Large Firm**	
Local Financial	0.054 (0.0604)	0.116 (0.075)	0.092 (0.063)	0.175*** (0.068)	0.138** (0.066)	-0.006 (0.062)	
Macro Volatility	-0.168* (0.099)	-0.173 (0.105)	-0.194* (0.103)	-0.113 (0.099)	-0.018 (0.104)	-0.017 (0.096)	
Capital Flows	0.430** (0.172)	0.344** (0.170)	0.101 (0.176)	0.742*** (0.180)	0.533*** (0.178)	0.211*** (0.065)	
Global Financial	-0.013 (0.065)	-0.004 (0.069)	-0.023 (0.068)	-0.023 (0.066)	-0.010 (0.069)	0.026 (0.064)	
Number of Observations	145	145	145	145	145	145	

Robust standard deviations are presented in parentheses. Constant term is added to logistic regressions. ***, **, * denote a statistical significance of 1%, 5% and 10%, respectively.

Table V.2.3: Ordered Logistic Regression Results

Dependent Variable: Similarity Index (Trend)	Total	Retail	Commercial	Consumer	Housing	BVehicle	Credit Cards
Local Financial	0.082 (0.073)	0.039 (0.073)	0.141** (0.069)	0.107 (0.072)	0.106 (0.072)	0.027 (0.071)	-0.122* (0.066)
Macro Volatility	0.229** (0.098)	0.316*** (0.099)	0.296*** (0.100)	0.340*** (0.098)	0.040 (0.097)	0.385*** (0.101)	0.315*** (0.099)
Capital Flows	0.149 (0.168)	0.029 (0.171)	0.427** (0.168)	0.101 (0.168)	0.069 (0.175)	-0.033 (0.173)	-0.219 (0.173)
Global Financial	0.063 (0.071)	0.066 (0.072)	0.046 (0.072)	0.053 (0.077)	0.001 (0.068)	0.124* (0.073)	0.136* (0.075)
Number of Observations	145	145	145	145	145	145	145
Dependent Variable: Similarity Index (Trend)	**General-Purpose**	**Foreign Trade**	**Investment**	**Business**	**SME**	**Large Firm**	
Local Financial	0.053 (0.076)	0.168** (0.071)	-0.063 (0.072)	0.133* (0.073)	0.093 (0.079)	-0.041 (0.068)	
Macro Volatility	0.301*** (0.101)	0.511*** (0.106)	0.483*** (0.122)	0.351*** (0.099)	0.350*** (0.098)	0.191** (0.096)	
Capital Flows	0.149 (0.175)	0.457*** (0.177)	0.624*** (0.176)	0.398** (0.169)	0.396** (0.178)	0.141 (0.168)	
Global Financial	0.119 (0.082)	0.012 (0.085)	0.126 (0.084)	0.039 (0.073)	0.046 (0.087)	0.066 (0.065)	
Number of Observations	145	145	145	145	145	145	

Robust standard deviations are presented in parentheses. Constant term is added to logistic regressions. ***, **, * denote a statistical significance of 1%, 5% and 10%, respectively.

V.2.5 Conclusion

In this study, we produced indices that digitize the coherence of economic activity and credit cycles. Inspired by the methodologies of recent studies in the literature, we used a synchronization index that monitors whether the output gap and the credit gap have the same directional bias (position coherence), a concordance index that monitors whether they are in the same phases of contraction/expansion (phase-momentum coherence), and a similarity index that monitors whether they have the same cyclical magnitude (magnitude coherence). The results of the analysis show that the synchronization of credit and business cycles has recently declined, particularly for commercial loans. This was mostly due to a commercial loan stimulus package as well as macroprudential measures. In addition, the upsurge in retail loans has reduced the phase co-movements. Likewise, magnitude coherence seems to have decreased in all subcategories of loans recently. Factors affecting magnitude synchronization include stimulus packages, exchange rate-driven changes in FX commercial loan balances and the conversion to TL in loans. Among findings from the subsequent analysis, the results of a ordered logistic regression indicate that the coherence of credit and business cycles strengthened in periods of accelerated capital flows and elevated macroeconomic volatility. In fact, capital flows are an important determinant of domestic financial conditions in EMEs with high external debt, such as Turkey. With the waning effect of the coronavirus pandemic and reduced downward pressures on economic activity in the upcoming period, improvements in loan supply and demand conditions will impel greater cyclical harmony.

References

Borio, C. E., & Drehmann, M. (2009). Assessing the risk of banking crises–revisited. BIS Quarterly Review.

Claessens, S., Kose, M. A., & Terrones, M. E. (2011). Financial cycles: What? How? When? In International Seminar on Macroeconomics (Vol. 7, No. 1, pp. 303-344). Chicago, IL: University of Chicago Press.

Claessens, S., Kose, M. A., & Terrones, M. E. (2012). How do business and financial cycles interact? Journal of International economics, 87(1), 178-190.

Drehmann, M., Borio, C. E., & Tsatsaronis, K. (2012). Characterising the financial cycle: don't lose sight of the medium term!

Harding, D., & Pagan, A. (2006). Synchronization of cycles. Journal of Econometrics, 132(1), 59-79.

Hicks, J. (1969). A theory of economic history (Vol. 9). Oxford: Oxford University Press.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2011). Financial crises, credit booms, and external imbalances: 140 years of lessons. IMF Economic Review, 59(2), 340-378.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2016). Sovereigns versus banks: credit, crises, and consequences. Journal of the European Economic Association, 14(1), 45-79.

Kurowski, Ł., & Rogowicz, K. (2018). Are business and credit cycles synchronised internally or externally? Economic Modelling, 74, 124-141.

Meller, B., & Metiu, N. (2017). The synchronization of credit cycles. Journal of Banking & Finance, 82, 98-111.

Mink, M., Jacobs, J. P., & de Haan, J. (2012). Measuring coherence of output gaps with an application to the euro area. Oxford Economic Papers, 64(2), 217-236.

Minsky, H. P. (1977). The financial instability hypothesis: An interpretation of Keynes and an alternative to “standard” theory. Challenge, 20(1), 20-27.

Oman, W. (2019). The synchronization of business cycles and financial cycles in the euro area. International Journal of Central Banking, 15(1), 327-362.

Sala-Ríos, M., Farré-Perdiguer, M., & Torres-Solé, T. (2018). How do Housing Prices and Business Cycles Interact in Spain? An Empirical Analysis. Estudios de Economía Aplicada, 36(3).

Samarina, A., Zhang, L., & Bezemer, D. (2017). Credit cycle coherence in the eurozone: Was there a euro effect? Journal of International Money and Finance, 77, 77-98.

Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. American Economic Review, 102(2), 1029-61.

V.3 Factors Impacting CDS Premium in EM Economies: A Case Study for Turkey

V.3.1 Introduction

A credit default swap (CDS) is an insurance protecting bond investors against the debtor's default risk. The CDS seller makes a commitment to pay the whole or a pre-determined portion of the receivables to the party holding the bond and the CDS contract in the case of a setback in the repayment of the bond's principal or coupon. CDS premium as an indicator of the debtor's likelihood of default is monitored closely by markets.

In the CDS markets, investors can take naked or over-insured positions against the default of the debtor.[1] Investors' ability to implement such diverse investment strategies in the CDS market facilitates speculation over the default of institutions/countries issuing bonds. Therefore, premiums on the instruments issued by corporates are affected by firm-specific factors such as profitability, mergers-acquisitions and new job opportunities, while country CDS premiums can be influenced by many country-specific factors such as reserves, the current account balance, economic growth, global risk appetite, public contingent liabilities that may change the FX cash flow of the public sector as well as global uncertainty and risk sentiment. In the case of Turkey, providing hedging against the default of issues of FX-denominated bonds (Eurobond) by the Ministry of Treasury and Finance, the CDS instruments can also be used by investors to take a position against the TL owing to its high correlation with the FX market. Especially when there is limited access to derivative products to which the FX risk can be transferred such as the FX currency swap, exchange rate volatility may increase the use of CDS as well as the its premium. Finally, the usually limited number of CDS sellers in the CDS market may cause upside movements in CDS premiums due to supply constraints/liquidity conditions in times of sudden demand increases for CDS.

In this study, the relationship between fundamental macro-financial indicators and CDS premiums is analyzed. After the identification of the factors, the degree of coherence between CDS premium realizations and what is implied by macro-financial outlook is investigated. Accordingly, a wide set of variables that may be related to CDS premiums were formed primarily for the EME group. Then, these variables were eliminated according to explanatory powers on CDS premiums using machine learning methods. Selected variables were used in a linear regression model for countries excluding Turkey and parameter values of the model were found. Lastly, CDS premiums projected by these parameters for Turkey were formed using the realizations of macro-financial variables in the Turkish economy. Through this method, the extent of the compatibility of the relationship between CDS premiums of countries other than Turkey and fundamental macroeconomic and financial variables was analyzed. Obtained results show that CDS premiums of EMEs are affected by variables such as the exchange rate level and volatility, the VIX index, indebtedness ratios of public sector, households and financial institutions, loan interest rate, inflation, short-term rate spread, current account balance and the FX reserve level. Moreover, results indicate that for Turkey, CDS premiums' realizations hover above the levels implied by EME dynamics in terms of macro-financial forces.

Studies in empirical literature show that variables such as indebtedness, current account balance, financial markets, economic activity, inflation, budget deficit, FX reserves and global risk appetite have an impact on CDS premiums. Aizenman et al. (2011) found that in countries affected adversely by the Eurozone crisis inflationary pressures, the increased external indebtedness and deterioration in indicators of the fiscal space pushed CDS premiums upwards. In an analysis of the data on EMEs, Ho (2015) showed that contraction in the current account deficit had significant effects on CDS premiums. The focal finding

[1] Naked position denotes purchasing CDS in the absence of bond ownership, while an over-insured position represents hedging above the value of the nominal value of the bonds possessed.

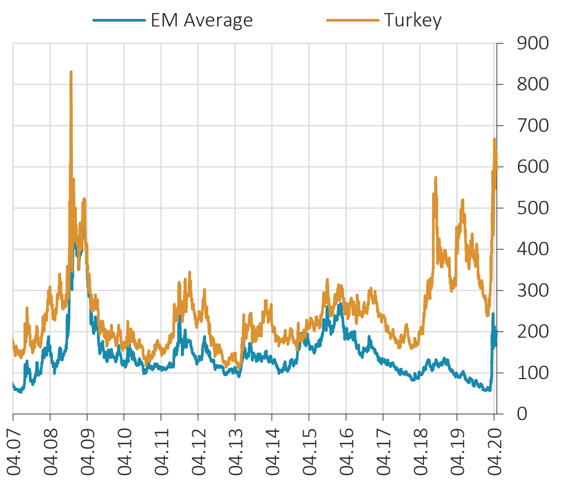
of Longstaff et al. (2011) suggested that international reserves were related to CDS premiums. Setting out with a wide range of country samples, Küçüksaraç and Duran (2016) expressed the informative value of variables such as growth, inflation, public debt and net international investment position on the CDS premium. Employing the methodological framework of Amstad et al. (2016), Çepni et al. (2017) suggested that EME CDS premiums moved jointly in a global scale, while the public debt and reserve level increase the sensitivity to global movements. Akçelik and Fendoğlu (2019) conducted research on the role of macro-financial factors such as the budget balance, private sector debt, current account balance and reserve adequacy in EME risk premiums in view of the asymmetries in global risk appetite.

V.3.2 Risk Premium Developments in Turkey and Other Emerging Economies

Sovereign CDS premiums in Turkey have moved historically close to the EME average, but slightly above the average tendencies (Chart V.3.1).[2] The Global Financial Crisis period saw decreases in financial asset prices in EMEs, volatilities in financial market indicators and deterioration in global investor risk sentiment. These developments affected the risk outlook specific to these countries and caused notable hikes in CDS premiums. In fact, CDS premiums in Turkey and the EME average hit all-time high levels in this period. The European debt crisis led to new increases in CDS premiums in this period. Other historical periods causing upward movements in CDS premiums were the 'taper tantrum' period in 2013 marked by the Fed's announcement of a possible tightening in monetary policy and the US presidential elections of 2016. Amid the coronavirus pandemic, the deterioration in expectations for global growth and foreign trade outlook, tightening in local financial conditions and the decline in the risk appetite, risk premiums have recently increased across the EME group.

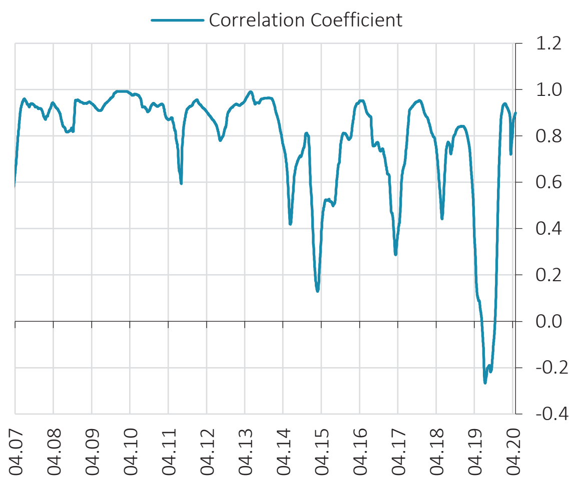
In Turkey, risk premiums have diverged from the EME group since 2016. The depreciation in exchange rates, financial market volatilities, growing downside risks in economic activity, increases in inflation, risks regarding FX indebtedness of the non-financial sector and geopolitical tensions shaped CDS premiums in 2018 in particular. In this period, CDS premiums of Turkey diverged notably and negatively from the average of peer countries. In fact, the correlation coefficient between Turkey and the EME average had been quite high until that time but has declined since the second half of 2018 and turned even negative, albeit for a short time (Chart V.3.2).

Chart V.3.1: CDS Developments (Basis Points)



Source: Bloomberg Last Observation: 28.04.20

Chart V.3.2: Correlation between Turkey and EM CDS Premium (264-day Moving Window)

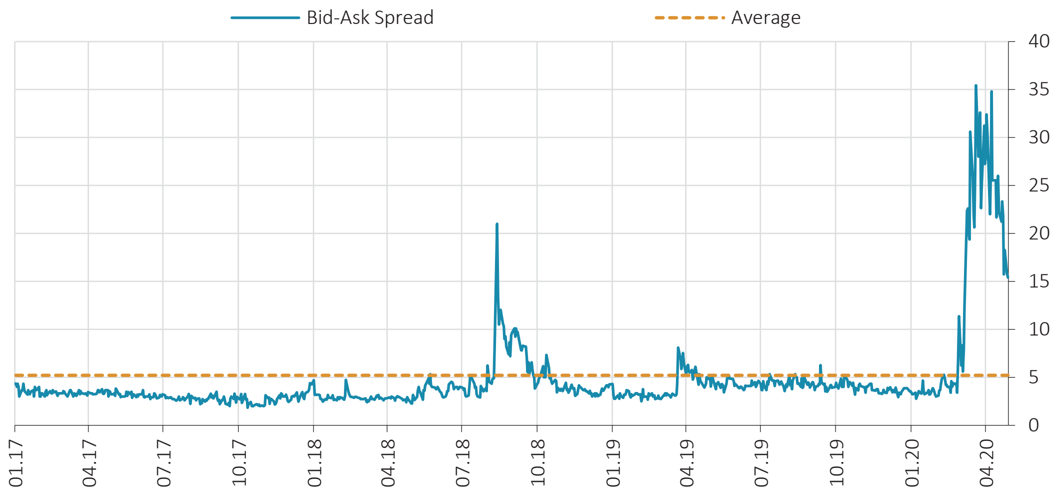


Source: Authors' Calculations Last Observation: 28.04.20

[2] In view of data constraints, Brazil, Chile, China, Colombia, Indonesia, S. Korea, Malaysia, Mexico, Russia, S. Africa and Thailand were included in the sample. The data were obtained from the databases of Bloomberg, IMF, the World Bank and IIF.

In addition to the risk premium, market liquidity is one of the significant variables in the determination of CDS premiums. The bid-ask spread of 5-year CDS contracts' premiums was analyzed as an indicator of liquidity developments. In August 2018, the bid-asked spread recorded an upsurge, the CDS liquidity declined, the number of transactions got higher, and in the ensuing period that difference re-approached the long-term average amid the normalization in the market (Chart V.3.3). Meanwhile, following the coronavirus pandemic, financial volatilities aggravated, which led to spikes in spreads.

Chart V.3.3: CDS Liquidity Conditions (Bid-Ask Spread, Basis Points)



Source: Bloomberg, Authors' Calculations Last Observation: 28.04.20

V.3.3 Data and Methodology

In addition to financial market developments such as the exchange rate level and volatility, risk premiums are affected by macroeconomic indicators like growth, current account balance and public finance. In this context, the relationship between macroeconomic and financial indicators that entail information about riskiness and CDS premiums for the EME group was analyzed. The relationship between CDS premiums and macro-financial variables was assessed in this study using the data of 11 countries in the EME group and Turkey.

In the first phase, a broad list of variables was formed for the 2005Q4-2019Q4 period regarding global risk appetite, local exchange rate and stock market, exchange rates, growth and inflation dynamics, public finance, interest rates, indebtedness of the household as well as financial and non-financial firms, foreign trade, current account balance and reserves. In cases of numerous candidate explanatory variables and limited number of observations, the out-of-sample prediction capacity of linear multivariate regression models diminishes. Moreover, in such cases, hypothesis tests on coefficients cannot bring about effective results.

In this context, the Lasso method put forth by Tibshirani (1996) is another alternative tool to be used. In the model by which coefficient estimations are obtained through the Lasso method, variables with relatively low contribution in terms of objective function are excluded:

$$min_{\beta} \quad \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i'\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j| \tag{1}$$

$$\hat{\beta}_{Lasso} = argmin\sum_{i=1}^{n}(y_i - x_i'\beta)^2 \tag{2}$$

$$s.t. \quad \sum_{j=1}^{p}|\beta_j| < \tau \tag{3}$$

In this illustration, n represents the number of observations, and p is the number of variables. The λ parameter defined as penalty term in the objective function was determined according to Extended Bayesian Information Criterion based on Chen and Chen (2008). Macroeconomic and financial factors that are believed to affect CDS risk premium were used in the linear regression model using the Lasso method. A Lasso model estimating EME CDS premiums through quarterly variables was constructed and variables with low contributions to in-sample explanatory power of the model were removed. According to the results of the analysis, variables such as the US dollar exchange rate index, implied exchange rate volatility, GDP growth rate, VIX index, household and financial institutions indebtedness ratio, inflation, loan interest rate, FX reserves, current account balance and US dollar local currency rate spread proved to have an explanatory power on CDS premiums. In this phase, observations belonging to the EME group were used to train the model, while observations regarding Turkey were used to test the model performance. In this context, out-of-sample estimations defined over the values that the model implied for Turkey were compared to realizations.

In the second phase, the estimation power of the direction of the short-term changes in CDS premiums in the variables determined by the Lasso method was analyzed. In this context, univariate logistic regression models investigating periods of increases and decreases in risk premiums based on CDS changes were constructed and individual explanatory power of macro-financial factors was analyzed. In this model, in which the dependent variable is 1 in the case of a year-on-year increase in CDS premium, and 0 in other cases, the explanatory power was shown using non-parametric receiver operating characteristic (ROC) curves.

ROC curves are another measure of performance used frequently in model selection and variable classification in many areas in addition to economic studies and show the explanatory power in econometric models such as logistic regression in which the dependent variable takes the value of 0 or 1 (Pepe et al., 2006). The increase in the area remaining below the ROC curves, based on the graphical representation accommodating true (false) prediction of binary outcome variable in vertical (horizontal) axis, implies better in-sample predictive power. Area values above 0.50 represented by a 45-degree line, the critical threshold value, show that the explanatory power of the examined covariate outperforms the random guessing, while area values below this level show that the explanatory power of this variable is limited.

V.3.4 Econometric Results

According to Lasso model results, variables such as the US dollar exchange rate index, implied exchange rate volatility, GDP growth rate, VIX index, indebtedness ratio of the household and financial institutions, inflation, loan interest rate, FX reserves, current account balance and foreign currency-local currency rate spread proved to have an explanatory power on CDS premiums of EMEs. Moreover, the dummy variable showing the relationship between the change of direction in CDS premiums and explanatory variables is shown using the areas below the non-parametric ROC curve (Table V.3.1).

In the EME group, the VIX index denoting global risk appetite is the variable with the highest explanatory power, while exchange rate volatility, loan interest rate, inflation, private sector FX debt ratio, foreign trade volume and change in reserves stand out as significant variables singularly. Meanwhile, the same analysis for Turkey suggests that the exchange rate index, exchange rate volatility, short-term rate spread, loan interest rate and reserve variables proved to have higher informative value, and going above 0.50, private sector debt-burden indicators turn out to be influential.

After that, a linear regression model was estimated to analyze the relationship between the variables with high explanatory power and the CDS premiums using the data for EME excluding Turkey and model parameters.[3] Through this approach, average CDS premiums that macroeconomic and financial dynamics imply for Turkey in in EME were compared to CDS premium realizations (Chart V.3.4).

---

[3] Due to macroeconomic data constraints on different countries, analyses end at 2019Q4.

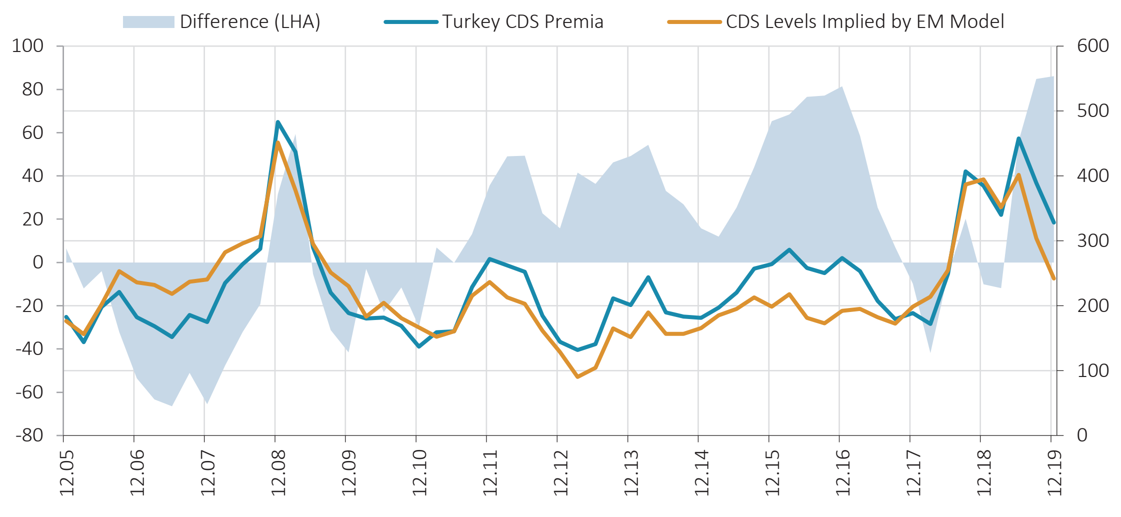
Table V.3.1: ROC Analysis Results

EME Group	Area Under the ROC Curve	Turkey	Area Under the ROC Curve
Spot Exchange Rate Index	0.50	Spot Exchange Rate Index	0.57
Exchange Rate Volatility	0.62	Exchange Rate Volatility	0.72
VIX Index	0.75	VIX Index	0.62
Short-term Rate Spread	0.58	Short-term Rate Spread	0.75
Local Currency Loan Interest Rate	0.56	Local Currency Loan Interest Rate	0.70
Inflation	0.63	Inflation	0.60
GDP Growth Rate	0.46	GDP Growth Rate	0.34
Public Debt / GDP	0.46	Public Debt / GDP	0.43
Household Debt / GDP	0.48	Household Debt / GDP	0.52
Financial Institutions' Debt / GDP	0.49	Financial Institutions' Debt / GDP	0.56
Change in Current Account Balance / GDP	0.46	Change in Current Account Balance / GDP	0.39
Gross Reserves excl.Gold / GDP	0.52	Gross Reserves excl.Gold / GDP	0.58

Source: Authors' Calculations

Results suggest that CDS premiums in Turkey diverge from the levels implied by the levels of the model constructed by the EME dynamics. The difference between implied and realized CDS premiums may get wider in periods of increased volatility in local financial markets. Especially amid the economic recovery and improved expectations that started in the second half of 2019, these values for Turkey remain above the levels implied by the EME parameters despite the decline in CDS premiums. For example, the CDS premium took the average value of 327 bps for the last quarter of 2019, yet the premium implied by the model is 241 bps.

Chart V.3.4: CDS Levels Implied by EME Model and Turkey CDS Premium (Basis Points)



Source: Authors' Calculations

Last Observation: 12.19

V.3.5 Conclusion

Historically, the CDS Premium in Turkey hovers above the level projected by EME dynamics in terms of main economic aggregates such as the exchange rate level and volatility, VIX index, indebtedness rate of household and financial institutions, loan interest rate, inflation, short-term rate spread and foreign exchange reserve level, and this divergence has grown more pronounced since the second half of 2019. The recent divergence between CDS premiums of EME and Turkey is attributed to the use of CDS as a tool in preserving long positions taken in TL assets. Meanwhile, when the high course of CDS premiums is compared to EMEs, it may also reflect factors such as geopolitical risks and investor risk appetite discussed in literature in addition to the current macroeconomic developments. Moreover, the course of liquidity conditions excluded from the model stands out as one of the factors acting in this divergence.

References

Akçelik, F., & Fendoğlu, S. (2019). Country risk premium and domestic macroeconomic fundamentals when global risk appetite slides. CBRT Research Notes in Economics, No. 19/04.

Aizenman, J., Hutchison, M., & Jinjarak, Y. (2013). What is the risk of European sovereign debt defaults? Fiscal space, CDS spreads and market pricing of risk. Journal of International Money and Finance, 34(April): 37-59.

Amstad, M., Remolona, E., & Shek, J. (2016). How do global investors differentiate between sovereign risks? The new normal versus the old. Journal of International Money and Finance, 66(September): 32-48.

Chen, J., & Chen, Z. (2008). Extended Bayesian information criteria for model selection with large model spaces. Biometrika, 95(3), 759-771.

Çepni, O., Küçüksaraç, D., & Yılmaz, M. H. (2017). The sensitivity of CDS premium to the global risk factor: Evidence from emerging markets. CBRT Research Notes in Economics, No. 17/04.

Ho, S.H. (2016). Long and short-runs determinants of the sovereign CDS spread in emerging countries. Research in International Business and Finance, 36(January), 579-590.

Küçüksaraç, D., & Duran, M. (2016). How different are the factors affecting the credit ratings of developed and emerging countries?. CBRT Research Notes in Economics, No. 16/09.

Longstaff, F.A., Pan, J., Pedersen, L.H., & Singleton, K.J. (2011). How sovereign is sovereign credit risk?. American Economic Journal: Macroeconomics, 3(2): 75-103.

Pepe, M. S., Cai, T., & Longton, G. (2006). Combining predictors for classification using the area under the receiver operating characteristic curve. Biometrics, 62(1), 221-229.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society: Series B (Methodological), 58(1), 267-288.