V. Special Topics

V.1 Monitoring Cyclical Dynamics in Bank Credits: Evidence from the Turkish Banking Sector

V.1.1 Introduction

Credit growth, an indicator closely monitored by regulatory authorities, plays an important role in macroeconomic dynamics of emerging markets in the context of financial and economic stability. In times of excessive credit squeeze, consumption and investment expenditures decrease in general, economic activity slows down and employment indicators deteriorate. On the other hand, excessive credit growth may cause financial instabilities, irrational asset pricing, worsening in the current account balance and deterioration in macroeconomic indicators with inflation in the lead. Studies in the financial crisis literature suggest that an excessive credit expansion is statistically a significant precursor of crises (Demirguç-Kunt and Detragiache, 1998; Borio and Lowe, 2002; Kaminsky and Reinhart, 1999; Eichengreen and Arteta, 2002). In this context, regulatory authorities monitor the trends in credits closely. Due to expansionary monetary policies implemented by developed countries particularly in the aftermath of the global financial crisis, EMs underwent rapid credit growth, compelling those countries to take macroprudential measures.

For these reasons, economists and policymakers attach particular importance to determining credit movements that deviate from long-term trends and to taking measures through various policy implementations (Buncic and Melecky, 2013; Kiss et al., 2006; Jakubik and Moinescu, 2015; Drehmann et al., 2010). The Bank for International Settlements (BIS) also recommended a calculation method that is based on determination of credit boom and bust periods diverging from the trend for countercyclical capital buffers (BIS, 2010). The literature uses various methods to determine credit boom/bust periods. In addition to filtering methods that rely on obtaining credit gap series by differentiating stand-alone credit indicators from long-term trends[1], econometric methods that examine residual credit series which are not explained by macroeconomic dynamics[2] are the most commonly used. In Turkey, Aydın and Yılmaz (2019) evaluate credit developments for the 1997-2017 period using the credit gap series they obtained through filtering methods, and Çolak et al. (2019) attempted to determine credit growth periods that deviate from their long-run trends over the time period 2005-2019 by using filtering techniques as well as econometric methods. This special topic summarizes the analysis findings of the credit gap indicators obtained using filtering methods in the study of Çolak et al. (2019).   by making use of up-to-date data for the 2005-2019 period

V.1.2 Methodology and Data

This study makes calculations to determine the credit boom/bust periods, in addition to total credit volume for total commercial loans, TL and FX commercial loans, total retail , housing, vehicle and general-purpose loans. Four different credit indicators have been constructed for each loan type. Those credit indicators are logarithm of real credit, annual real credit growth, credit/GDP ratio and the credit impulse developed by Kara and Tiryaki (2013).[3] In the next stage, different credit gap series have been obtained by decomposing the four different credit indicators from their long-term trends using four different filtering methods. In other words, a total of 16 different credit gap series were generated for each credit type.

[1] Drehman et al., 2010; Elekdağ and Wu, 2011; Hosszu et al., 2015.

[2] Barajas et al., 2007; Dell'arcia et al., 2016; Arena et al., 2015.

[3] The credit impulse is calculated as the ratio of the difference between the 12-month change in credits at time t and the same at time t-12 to annual GDP.

The relevant literature comprises various filtering methods commonly used to extract credit series from long-term trends. For instance, for the application of countercyclical capital buffers, the BIS recommended a calculation method to determine credit boom and bust periods deviating from the long-run trend (BIS, 2010). The one-sided HP filter, which is used to prevent end- point bias in the sample, recommended by the BIS as a macroprudential tool. In addition to the HP filter, the Christiano-Fitzgerald (CF) filter, Hamilton filter and Butterworth filter are also used in this study.

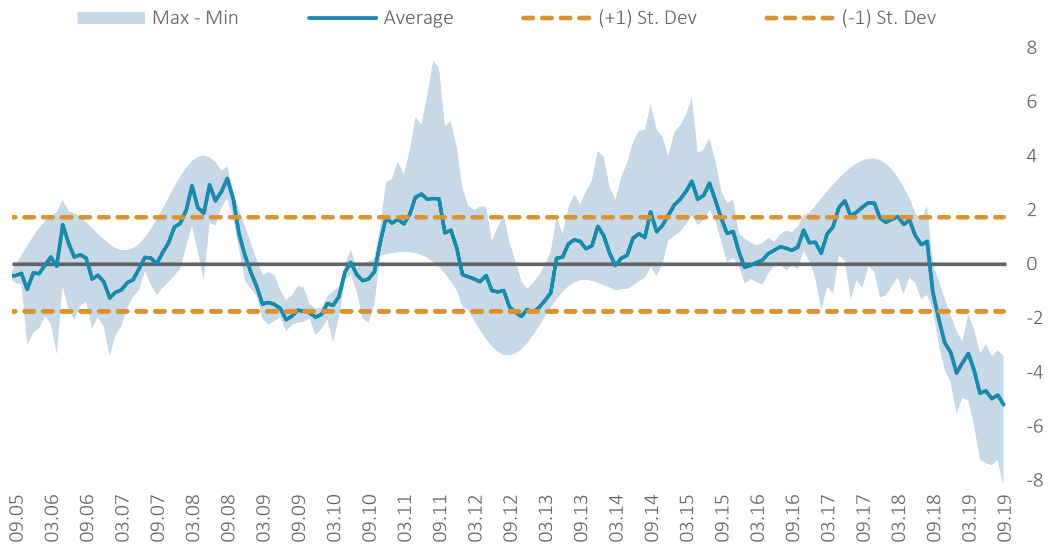
The HP filter is based on minimizing the variance of original series around trend variable and adding to the model the difference from the previous credit value as a smoothing parameter (Hodrick and Prescott, 1997). In the Hamilton filter, credit series are regressed on its lagged values and the residuals are used as credit gap series (Hamilton, 2018). The CF and Butterworth filters, on the other hand, aim to derive optimal credit gap series from stochastic series that are among time series assumed to be infinite in the frequency domain(Christiano and Fitzgerald, 2003; Pollock, 2000).[4] These methods have some limitations. The main conviction is that the cycle results may change depending on the starting periods of the series used in trend estimates. While the HP filter results, in particular, are quite sensitive to the value of the smoothing parameter, the Hamilton filter might give results with relatively higher variation for some periods as it uses past values of the series. Meanwhile, the CF filter's assumptions related to the analyzed time series might be restrictive. In this this special topic, in order to support the coherency and robustness of findings, various methods are utilized rather than sticking to a single method for filtering.

As prescribed by the literature, if the credit gap indicators obtained via filtering techniques are above/below a specific threshold value relative to the trend, that period is called "credit boom"/"credit bust". In the literature, this threshold value is calculated by multiplying the credit gap series by a particular standard deviation ratio. While Mendoza and Terrones (2008) propose a standard deviation ratio of 1.75, Elekdağ and Wu (2011) use 1.55 as a threshold value. The IMF study (2004) defines a 1 standard deviation rule to compute the extent of the credit deviation from the trend. This study opted for a more cautious approach and used threshold values as the standard deviation multiplied by (+1) and (-1) of the gap series obtained by different filtering methods.

To illustrate methodology, Chart V.I.1 shows average values of credit gap series obtained applying four different filtering methods to the ratio of total loans to GDP, as well as the band between minimum and maximum values. Values below zero indicate a credit gap below the trend, and those above zero indicate a credit gap above the trend. Episodes of credit gap series exceeding the (+1) standard deviation value are called “credit boom" and those falling below the (-1) standard deviation are called "credit bust". Accordingly, the average value of credit gap series for the gross loan/GDP indicator found by using four filtering methods suggest a credit boom for pre-crisis 2007, the first half of 2011, the first half of 2015 and for 2017. Likewise, below-trend periods are those marked by a credit bust: the 2009 crisis period, the second half of 2012 and the period since August 2018. Besides this exhibit is based on the average credit gap series, each filtering method might give results differing from other filtering methods in some periods. For instance, while we observe a credit/GDP gap within reasonable limits on average in the first half of 2012, the credit gap series with the minimum value suggest a credit bust. Again, in 2014, maximum value of credit gap series implies a credit boom, while the credit gap remains within reasonable limits on average

[4] Çolak et al. (2019) give technical details of filtering methods.

Chart V.1.1: Credit Gap Series Calculated for Loan/GDP Ratio (HP Filter)



Sources: BRSA, CBRT Calculations Last Observation: 09.19

Note: Dashed lines show the (+1) and (-1) standard deviation values of the average credit gap series during the respective period.

How many out of the 16 credit gap series indicate a credit boom/bust for the respective period will be a measure for cyclical credit dynamics in this study. The total credit data that we have examined separately according to credit type and currency are at monthly frequency in the period between 2005 and 2019.[5] Our analysis comprises vehicle, housing and general purpose loans in addition to the total banking sector loans and total commercial loans (with a TL-FX breakdown for commercial loans).

V.1.3 Boom and Bust Periods by Credit Type

Chart V.1.2 shows the number of indicators signaling boom and bust stages for total loans adjusted for exchange rate effects. If the number of indicators is high, there is strong evidence that the respective period witnessed a credit episode above or below the trend. In the sample, approximately 14 of the 16 indicators point to a credit boom before 2006 due to the ongoing financial deepening and a rapid recovery in Turkey's credit markets. During the global financial crisis, the external liquidity drain , the increase in funding costs and the declines in the international trade volume led to a deterioration in credit conditions and domestic economic activity. Almost all the indicators suggest that the credit volume contracted during the respective period. However, implementation of nonconventional monetary policies by advanced economy monetary policy authorities after the crisis caused a heavy liquidity flow towards EME financial systems. As a result, while the number of indicators suggesting a credit boom in this period, led by easing credit supply conditions and recovering demand for bank loans, reached 10; the positive tendencies in credit cycle dynamics remained in place until the end of 2011.

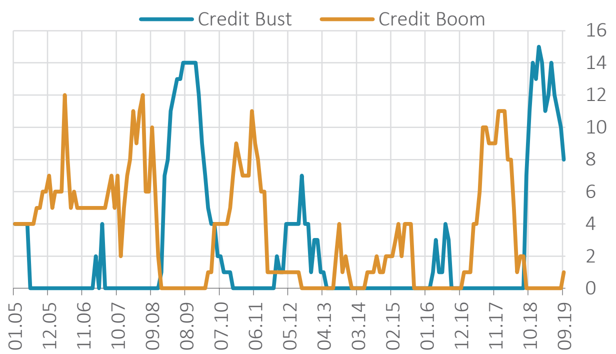
Following this episode, marked by a widening current account deficit and a noticeable expansion in credit allocations, significant macroprudential measures were taken to safeguard financial stability. Accordingly, implementation of policies such as reserve options mechanism, loan/value ratio and instalment restrictions in retail loans curbed the credit growth pace and the number of indicators signaling a bust in this period increased. From 2013 to 2016, credit markets regained stability and only a limited number of indicators signaled a credit crunch. From early 2017 to the second half of 2018, new credit guarantees were introduced in coordination with the Credit Guarantee Fund (KGF) to support the credit channel and economic activity. Through these facilities, the banking system extended approximately TRY 300 billion worth of loans to non-financial corporations. Easier access to credit with KGF collaterals led to a sizeable

[5] To calculate the loan/GDP ratio, the GDP data provided by TURKSTAT are collected quarterly and converted to monthly frequency by using the interpolation method developed by Fernandez (1981).

growth in commercial loans and approximately 10 out of 18 indicators captured the credit expansion in this period. Finally, heightened volatility in local financial markets by mid-2018 led to a worsening in credit conditions and 15 of the indicators suggested a credit bust in the last quarter of 2018. Credit markets have recovered slightly and the number of indicators implying a bust has trended down since the third quarter of 2019.

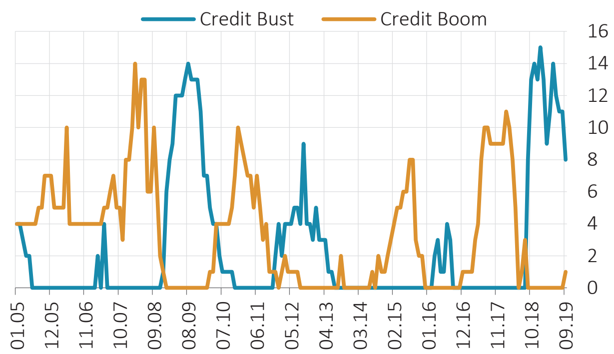
Credit gap indicators calculated for total commercial loans and retail loans can capture historical trends more broadly than total loans (Chart V.1.3). A detailed analysis of the dynamics indicates that in 2017, TL commercial loans moved into the expansion zone due also to the KGF facility. It is understood from the indicators that all credit types expanded largely above the trend throughout this period (Chart V.1.4). On the other hand, considering FX-denominated commercial loans, the results have differed from those of TL commercial loans particularly since end-2016 (Chart V.1.5). During 2017 to 2018, due to the regulation that linked firms' FX loans to their FX incomes and rising awareness of nonfinancial firms' FX risk management because of increased exchange rate volatility, FX loans contracted. The number of indicators signaling a bust in FX loans has been on the rise in recent months. The bust in FX loans began earlier than that in TL loans, in 2016, causing the trend to be downward and therefore, the number of indicators showing a bust remained slightly less for FX loans compared to TL loans.

Chart V.1.2: Number of Indicators Showing Boom and Bust in Total Loans



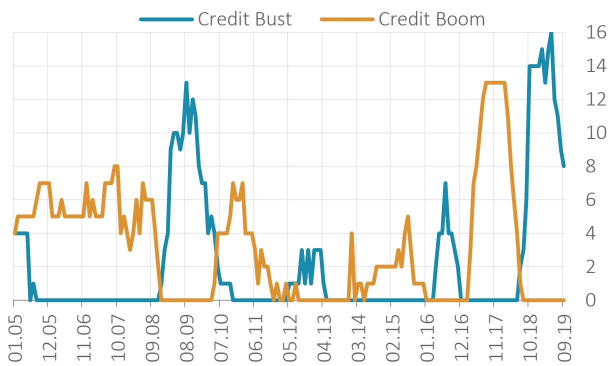
Sources: BRSA, CBRT Calculations Last Observation: 09.19

Chart V.1.3: Number of Indicators Showing Boom and Bust in Total Commercial Loans



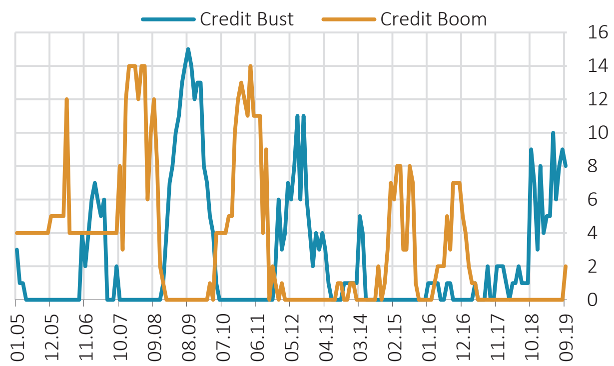
Sources: BRSA, CBRT Calculations Last Observation: 09.19

Chart V.1.4: Number of Indicators Showing Boom and Bust in TL Commercial Loans



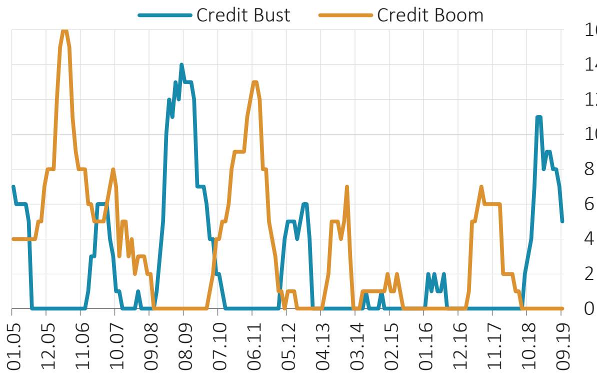
Sources: BRSA, CBRT Calculations Last Observation: 09.19

Chart V.1.5: Number of Indicators Showing Boom and Bust in FX Commercial Loans



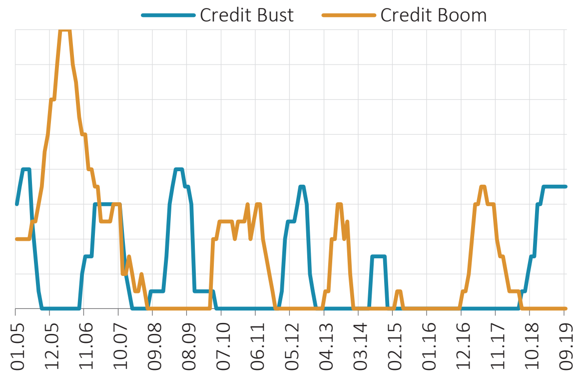
Sources: BRSA, CBRT Calculations Last Observation: 09.19

Chart V.1.6: Number of Indicators Showing Boom and Bust in Total Consumer Loans



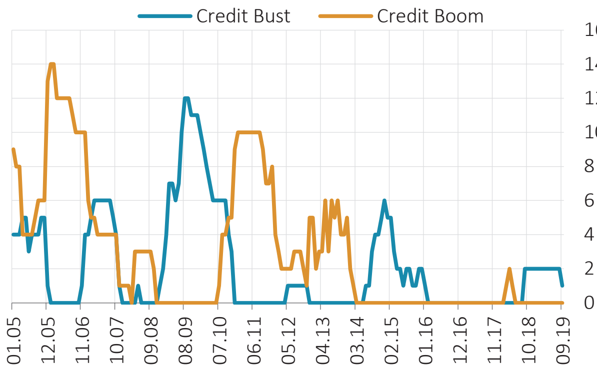
Sources: BRSA, CBRT Calculations Last Observation: 09.19

Chart V.1.7: Number of Indicators Showing Boom and Bust in Housing Loans



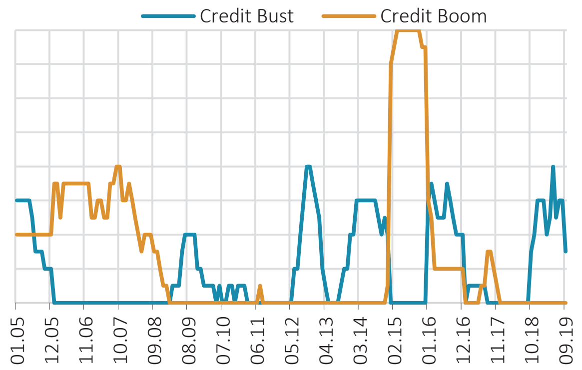
Sources: BRSA, CBRT Calculations Last Observation: 09.19

Chart V.1.8: Number of Indicators Showing Boom and Bust in Vehicle Loans



Sources: BRSA, CBRT Calculations Last Observation: 09.19

Chart V.1.9: Number of Indicators Showing Boom and Bust in General Purpose Loans



Sources: BRSA, CBRT Calculations Last Observation: 09.19

The number of indicators that showed a bust in total retail loans during the global crisis reached quite high levels as in the case with commercial loans (Chart V.1.6). During the 2012-13 period in which macroprudential measures intensified, the number of indicators showing a credit bust increased, followed by a stable course in retail loans until 2017. In 2017, the number of indicators implying an above-the-trend expansion across retail loans rose, followed by a bust period after the last quarter of 2018. There has been a slowdown in the credit crunch trend since the third quarter of 2019. With the incentives provided for mortgaged house sales towards the end of 2016, the number of indicators of a credit boom reached eight (Chart V.1.7). In 2018, a dramatic decline was observed in mortgage-financed house sales due to the hike in housing loan rates and approximately eight indicators suggested a below-the-trend slowdown in housing loans. On the vehicle loans front, a more moderate outlook was seen owing to the considerable decline in the banking sector's share in financing vehicles and the active role of consumer financing companies in that regard (Chart V.1.8). Vehicle loans that have been extended by the banking sector in particular since 2016 have not depicted extreme movements.

Cyclical movements of general-purpose loans differ from other consumer loan types (Chart V.1.9). The contraction seen in general-purpose loans during the periods of economic slowdown is not as discernible as the trends seen in other loan types. For instance, credit bust indicators during the 2009 global financial crisis remained limited to four and reached eight at maximum in 2019. This can be attributed to households' rising inclination to use general-purpose loans to finance their expenditures or debts due to increased unemployment and decreased real disposable income driven by sluggish economic activity. On account of historically low household NPL ratio and credit risk, banks tightened general-purpose loans less compared to other loan types in times of economic stagnation. Credit boom indicators that surged in 2015 are explained by intensive use of general-purpose loans by households due to the restrictions on credit card installments introduced during that period.

V.1.4 Evaluation

This special topic aimed to develop a measure to monitor credit boom and bust periods that deviate from long-term trends for the Turkish banking sector loans. The methodological and data-related framework of the analysis has several contributions to the existing literature related to credit developments in Turkey. Above all, this study composes de-trended credit indicators in monthly frequency so that the credit market can be monitored in higher frequency. Besides, rather than relying on a single filtering technique, it extracts credit cycle realizations with the help of multiple time series filters including the HP, CF, Butterworth and Hamilton filters. Finally, through inclusion of various credit types and breakdowns, in addition to the total credit volume, in the analysis, credit developments can also be monitored for retail and commercial loans. Findings obtained from the indicators constructed by different filtering methods and credit ratios in the study present consistency with the credit market cycles in the sampling period.

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V.2 Asset Management Companies and NPL Sales by Banks

Banks can collect loans that they classify as NPLs by their own means, sell them to asset management companies (AMCs) depending on market conditions when collection is limited, write them off under certain conditions, or re-classify them as performing loans when the debtor's repayment performance improves and such NPLs comply with the conditions specified in the regulation.[1] Banks primarily try to collect their NPLs. However, limited debt collectability, the lengthy legal follow-up process and cost factors urge financial institutions to write off NPLs through sales. Therefore, AMCs play an important role in the resolution of NPLs in our country.

Asset Management Companies

AMCs are established to purchase, collect, restructure and sell the receivables of banks and other financial institutions. In Turkey, the foundational and operational principles of AMCs were first identified in the regulation published in 2002. The legal framework for the liquidation of NPLs was strengthened by the Banking Law No. 5411 in 2005 and the regulation updated on 1 November 2006.[2]

AMCs can offer new solutions for issues that debtors and banks cannot reconcile. When the debt is taken over, a new legal and commercial relationship starts between the debtor and the AMC, and the debt is restructured based on the debtor's solvency. Thus, in order to collect a debt, AMCs can partially or completely give up interest on the debt, make a deduction from the principal, extend the maturity of the debt and provide additional financing to the borrowers if necessary.

NPL sales to AMCs first started with NPL sales of SDIF banks in 2004-2005 to resolve troubled loans after the 2001 crisis. In the following period, private banks also started to sell NPLs, thus increasing the number of NPL selling banks over the years. The amendment made in 2017 enabled sales of receivables from state banks to AMCs. Albeit fluctuating, the number of banks selling NPLs and the average amount of sales increased over the years due to new AMCs entering the system (Charts V.2.1 and V.2.2).

Chart V.2.1: Number of Banks Selling to AMCs
(Flow, Unit)

Source: BRSA

Chart V.2.2: Average Sale per Bank
(Flow, TRY million)

Source: BRSA

As of October 2019, there are 22 AMCs actively operating in the market and subject to the BRSA's approval and supervision. Currently, there are also AMCs that have operating permits but are not active. Activities of AMCs include mostly purchases of bad debts of banks and a small number of asset purchases from factoring, leasing and finance companies. Sometimes, AMCs also trade assets among each other.

[1] Regulation On Procedures And Principles For Classification Of Loans And Provisions To Be Set Aside.
[2] Regulation on the Foundational and Operational Principles of Asset Management Companies - 1 November 2006.

Table V.2.1: Balance Sheet of AMCs (September 2019, TRY million)

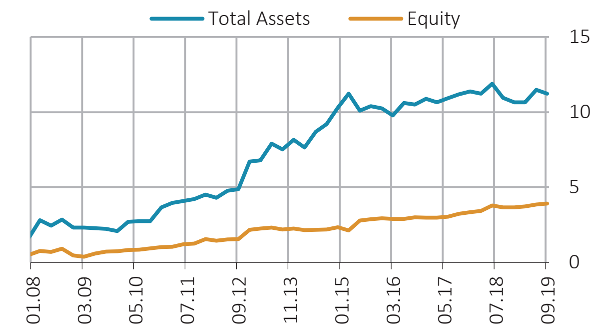
Assets		Liabilities	
Receivables from financial institutions	274	Loans received	2,047
Loans	388	Issued securities	360
Non-Performing Loans	6,120	Other	561
Provisions for expected losses (-)	2,867	Equity	1,672
Non-current assets held for sale	223		
Other	660		
Total assets	4,798	Total liabilities	4,798
Equity/Total asset (%)	34.8		
Coverage ratio (%)	46.9		

Source: BRSA, CBRT

As of September 2019, the asset size of AMCs is TRY 4.8 billion. Non-performing loans account for a large share in the asset composition of AMCs. The coverage ratio that AMCs put aside for expected losses of NPLs is around 47%. The non-equity funding of AMCs consists mainly of loans obtained from domestic banks and other institutions. Some AMCs also issue securities to finance their assets. AMCs finance more than one third of their assets with their equity. The balance sheets of AMCs are dominated by TL assets and liabilities.

Equities and assets of AMCs continue to increase in real terms. Both profitability and capital growth contribute to the upward trend of their equity (Chart V.2.3). The profitability ratios of AMCs show significant volatility from time to time depending on the number of active AMCs in the system (Chart V.2.4).

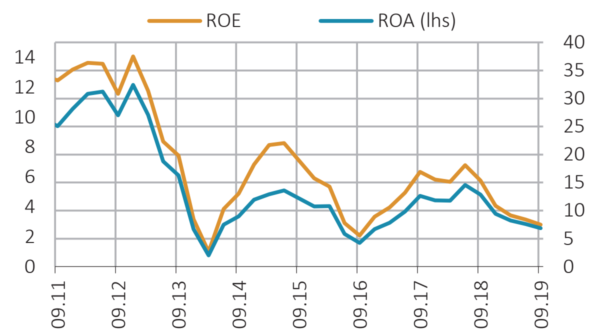
Chart V.2.3: Asset and Equity Development of AMCs (In real terms, TRY billion)



Source: BRSA

Last Observation: 09.19

Chart V.2.4: Asset and Equity Profitability of AMCs (%)



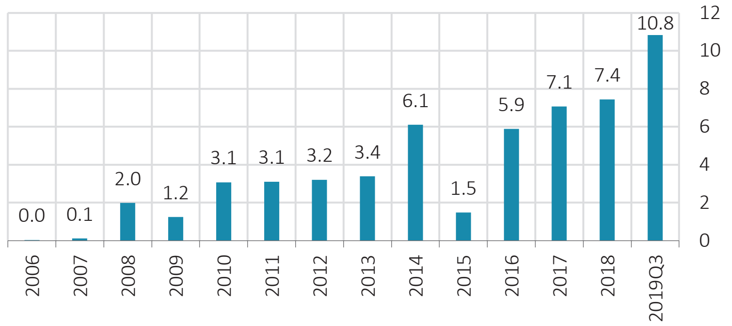
Source: BRSA

Last Observation: 09.19

NPL Sales of Banks

NPL sales made by banks to AMCs have been on the rise since 2008, with total NPL sales made by 31 banks amounting to TRY 55 billion in the 2008-2019Q3 period. In the first nine months of 2019, NPL sales were worth TRY 10.8 billion (Chart V.2.5). Of all NPL sales made by banks between 2006 and 2019, retail loans account for a half and largely consist of typically unsecured general purpose loans and credit cards (Chart V.2.6).

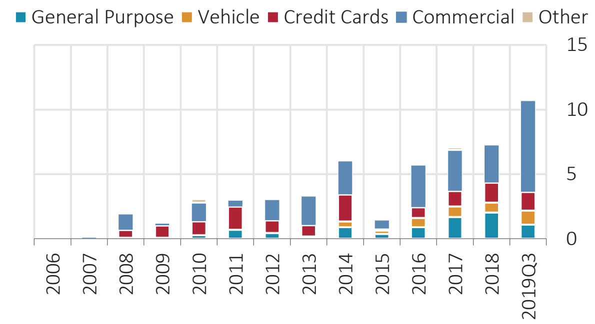
Chart V.2.5: NPL Sales of Banks (Flow, TRY billion)



Source: BRSA

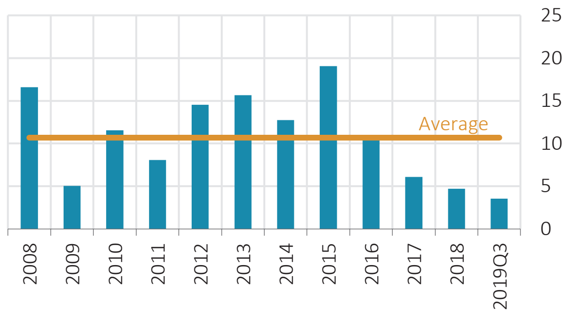
Pricing is an important aspect of NPL sales. Since the date NPL sales started, AMCs paid about 10% of the average asset value for the portfolio they purchased from banks. Among NPLs, housing loan sales recorded the highest price ratio with 34%. The reason housing loans have the highest pricing can be explained by the loan-to-value ratio regulation in Turkey and the fact that housing loans are collateralized. On the other hand, the price ratio barely changes for other types of loans, hovering around 10% on average. Meanwhile, price ratios in sales have been down, particularly since 2016 (Chart V.2.7). This decline was largely driven by the growing share of unsecured retail loans in NPL sales. In addition, these price ratios may see a small drop during episodes of financial fluctuation. In fact, sales price ratios were below the average level during the global crisis in 2009. The interest rate level and the economic slowdown are also assessed to have an impact on the sales price ratio in 2018 and 2019.

Chart V.2.6: NPL Sales of Banks by Type (Flow, TRY billion)



Source: BRSA

Chart V.2.7: NPL Sales Price Ratio (%)



Source: BRSA

When banks make NPL sales, the debt is move off the balance sheet. Loans classified as NPLs are recorded as additional revenue if the total of revenue generated from sales and provisions exceeds the loan amount or as additional expense if this amount is below the total loan. At the same time, when the loan is moved off the balance sheet, the stock NPL balance decreases, which has a positive effect on the asset quality outlook of banks.

Overview

Playing an increasingly prominent role in NPL resolution, AMCs have become an effective means of debt collection over the years. The fact that NPLs are collected by specialized AMCs promotes effective debt management within the financial system by lifting a significant burden from banks. Moreover, whether AMCs have a healthy financial structure is closely monitored in terms of financial stability. AMCs that maintain a strong balance sheet in the face of economic fluctuations since mid-2018 are expected to improve their collection performance with falling interest rates and economic recovery, which will contribute to their profitability over the long term.