V. Special Topics

V.1 Financial Inclusion in the World and in Turkey

Financial development, as suggested by different academic studies, has a significant contribution to increasing social welfare, improving income inequalities, and ensuring an inclusive and sustainable development.[1] The concept of financial development is debated based on three different definitions as financial access, financial deepening and financial inclusion. While the first two of these definitions mainly concentrate on secondary needs such as access to the required sources of finance and diversification of financial markets, the latter focuses on the individuals' ability to meet basic financial needs such as opening a bank account. In other words, financial inclusion is defined as a process in which access to financial services is provided for individuals or groups who are excluded from the financial system for any reason. Enhancement of financial inclusion can be summarized as a first step towards financial development.

This special topic presents a comparative overview of the development of financial inclusion in the world and in Turkey over the past decade and analyzes the main determinants of financial inclusion in Turkey by using microdata. First, the trend of financial inclusion in economies in different income groups and Turkey is summarized based on indicators accepted by the literature. The second part analyzes the development of financial inclusion in Turkey as well as its relationship with different factors such as education and labor force participation.

Analysis findings reveal that although there has been notable progress in the field of financial inclusion across the world over the past decade, there is a significant difference between high-income economies and emerging market economies. One major finding is that performance of financial inclusion in Turkey, classified among the upper-middle income economies by the World Bank, is considerably well compared to the average of the countries in the same income group. However, there is still room for improvement in labor force participation, level of education and diversity of products, as suggested by the findings.

V.1.1 Financial Inclusion and Measurement

Financial inclusion aims to increase individuals' and businesses' opportunities to access basic financial products and services such as the use of financial services, benefiting from job opportunities, hedging against risks, investing in education and saving for retirement. Inclusion of individuals or groups that remain outside of the financial system for any reason in the financial system will make a significant contribution to the growth and development of the real economy.[2]

Financial inclusion, generally, is measured by the broadness of the most basic financial institution and service network. Concentration indicators such as the number of ATMs per person and the number of bank branches per person are among the primary generally-accepted measures. Those measures, calculated as the numbers of ATMs and bank branches per 100,000 adults/1,000 square kilometers, denote geographical and demographical outreach of financial service points within a country. Most of these data are provided by the International Monetary Fund (IMF) and the World Bank on a country basis. Meanwhile, the numbers of deposit accounts, POS devices and loan beneficiaries are also used by the World Bank and academia as an indicator of the prevalence of the usage of financial services. Higher scores indicate a broader financial inclusion.

These measures are generally criticized for referring only to banking activities and services, which is somewhat acceptable. However, provision of in-depth and varied as well as comparable data on other financial institutions such as investment banks, insurance corporations, microcredit institutions, pension

[1] See Beck and Levine (2000), Beck et al. (2007), Demirgüç-Kunt et al. (2008), Seven and Yetkiner (2016).

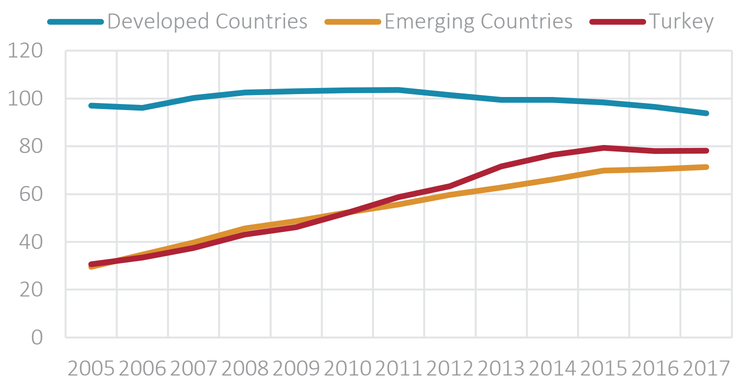
[2] See Goldsmith (1969), McKinnon (1973), Beck et al. (2007).

companies is still out of the question. Therefore, indicators that enable international comparisons have been used in this study.

V.1.2 Financial Inclusion in the World

According to the data compiled from the IMF's Financial Access Survey, while the number of ATMs per 100,000 adults over the past decade has been flat in developed countries, it has increased more than twofold in developing countries (Chart V.1.1).[3] Although this increase in Turkey has been higher than that in the developing countries group, of which Turkey is a part, its differentiation from developing countries after 2010 is noteworthy. This increase is attributed not only to the primary effects such as the growth of the banking sector on the back of the significantly increased capital inflows following the global financial crisis, but also to the secondary effects such as the spread of financial development across the population through the corporate sector, strengthening of regional infrastructure and dissemination of technology.

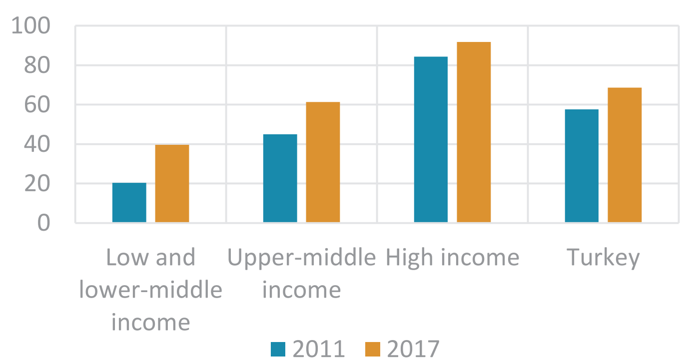
Chart V.1.1: ATM Number/Population Ratio: Turkey and Country Groups Comparison (per 100,000 adults, 15+ Age)



Source: IMF, 2019. Last Observation: 2017

A breakdown by the World Bank country group classification (low and lower-middle, upper-middle and high-income economies) indicates higher financial inclusion for countries with high gross national income between 2011 and 2017 (Chart V.1.2). The ratio of bank account ownership in Turkey is above that of the upper-middle income group economies, in which Turkey is classified. Yet, the growth in the ratio of bank account ownership remained below the average growth rate in the upper-middle income group.

Chart V.1.2: Bank Account Ratio (%, 15+ Age)



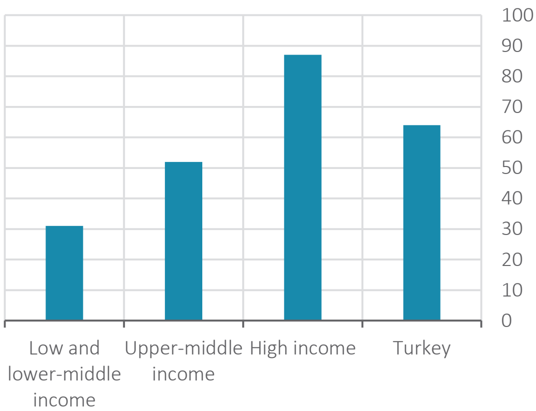
Source: World Bank

[3] Financial Access Survey (2019).

A breakdown of the bank account ownership presents a similar outlook. In high-income economies, there is a narrow gap between females and males, low and high-educated individuals, rural and urban population, and youngsters and adults in terms of holding a bank account. Although differentiation of financial inclusion in terms of educational status is not as noticeable as gender-based differentiation, it is prevalent in all countries of different income groups. This is an indication that countries that are willing to increase financial inclusion have room for improvement in such fields as education, demography and financial product diversity.

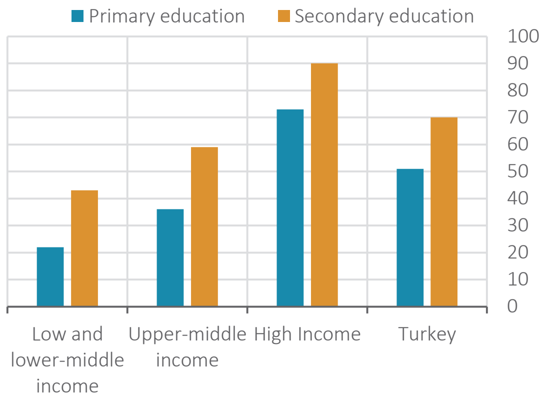
Online and digital banking that have progressed very fast all over the world thanks to advances in technology are expected to contribute to financial inclusion positively[4]. Chart V.1.3 and Chart V.1.4 show the use of online and digital banking in different income economies as a part of financial inclusion in 2017. According to the World Bank 2017 data, the ratio of the age group of 15 and above, who made or received a digital payment the year before, increases proportionately with the country income level. A breakdown of the same measure by educational status indicates that the ratio of the usage of financial services increases with educational level. A breakdown by educational status states that although there is a gap between low and high-educated people in Turkey, it is smaller than the gap between lower-middle and upper-middle income groups. It is considered that the rising young population, increasing educational level and technological advancements are likely to increase financial inclusion in Turkey and close the gap between Turkey and high-income economies.

Chart V.1.3: Ratio of Digital Remittance or Receipts in the Past Year (2017) (%, 15+ Age)



Source: World Bank

Chart V.1.4: Ratio of Digital Remittance or Receipts in the Past Year (by Education, 2017) (%, 15+ Age)

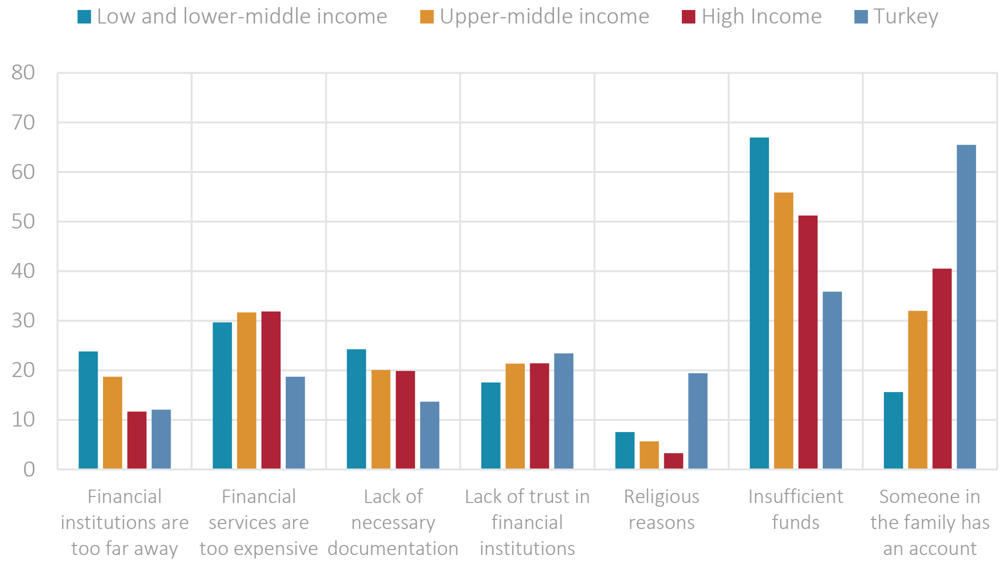


Source: World Bank

There still exist some challenges to financial inclusion. Compiled from the World Bank data, Chart V.1.5 shows the barriers to opening a bank account for those who do not have any financial account. The most common barrier across all income groups is that these individuals do not have enough money. The ratio of those deprived of enough money to open an account is 67% in the low and lower-middle income economies while this ratio is 51% in high-income economies and 36% in Turkey. Other major barriers to becoming banked are religious reasons and ownership of an account by other family members. These two barriers are the primary reasons for which Turkey diverges from other country groups. High costs of financial services, distant location of banks, lack of necessary documentation, and distrust in financial corporations can be cited among other barriers in a descending order.

[4]See United Nations (2016), P. Gomber et al. (2017), USA (2016).

Chart V.1.5: Reasons for Being Unbanked
(Adults without a financial institution account, 2017) (%, 15+ Age)



Source: World Bank.

V.1.3 Determinants of Financial Inclusion in Turkey

This part focuses on the main indicators that distinguish Turkey from other economies. Related analyses are based on the data of the Banks Association of Turkey (BAT) and BRSA, along with the household labor force survey of the Turkish Statistical Institute. As BAT data for the surveyed regions (26 regions from NUTS-2 level) cover a yearly period starting from 2010, the analysis is based on the 2010-2017 period. The analyses aimed to reveal regional divergences in terms of financial inclusion, along with the related driving factors without any attempt to debate causality. To ensure comparability with the above analyses, the numbers of bank accounts and ATMs were surveyed to measure financial inclusion in Turkey. The number of accounts denotes the number of deposit accounts per person, and the number of ATMs denotes the number of ATMs per 100,000 people.

Chart V.1.6: Female Labor Participation Rate - Number of Bank Accounts per Person

Source: BAT, BRSA, TURKSTAT Last Observation: 2017

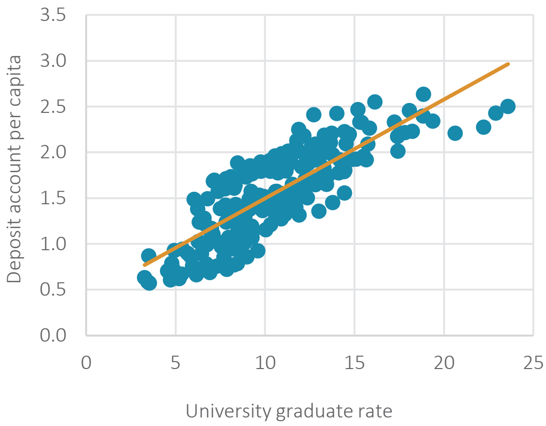
Chart V.1.7: Female Labor Participation Rate - Number of ATMs per Person

Source: BAT, BRSA, TURKSTAT Last Observation: 2017

The data suggest that in regions where female labor participation is high, the number of deposit accounts per person (Chart V.1.6) and the number of ATMs per person (Chart V.1.7) are higher. In other words, there is a positive relationship between female employment and financial inclusion.[5] Employed women join the financial system and increase the possibilities of opening a bank account by both raising their earnings and making savings.[6] Besides, with the inclusion of women in the financial system, banking services are expected to become more widespread. The first step of this is to increase the number of ATMs as they are more handy and economic for banks.

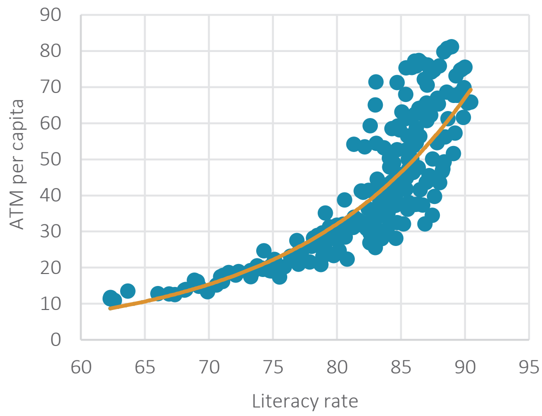
Meanwhile, as having a higher education level will bring about not only a higher probability of participating in the labor force, but also increased financial literacy, financial inclusion is expected to grow accordingly.[7] Chart V.1.8 shows the relationship between the share of university graduates in the total regional population and the average number of deposit accounts per person in respective regions. The chart reveals a strong relationship between the two variables. Additionally, Chart V.1.9 demonstrates the positive relationship between the ratio of literates within a region in the total population of that region and the number of ATMs per person. Likewise, in regions where the ratio of university graduates in the population above the age of 15 is high, the ratio of the number of online banking clients to the population is high, too (Chart V.1.10).

Chart V.1.8: Ratio of University Graduates - Number of Bank Accounts per Person



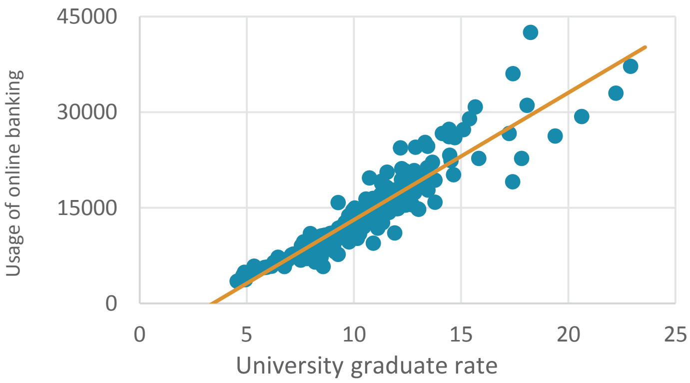
Source: BAT, BRSA, TURKSAT Last Observation: 2017

Chart V.1.9: Literacy Rate - Number of ATMs per Person



Source: BAT, BRSA, TURKSAT Last Observation: 2017

Chart V.1.10: Ratio of University Graduates - Usage of Online Banking



Source: BAT, BRSA, TURKSAT Last Observation: 2017

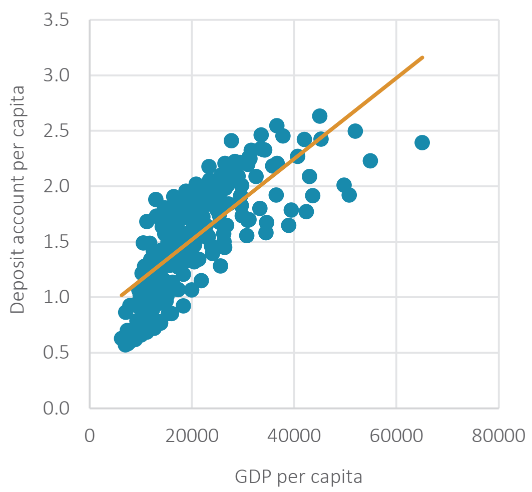
[5] The analyses give the same result for the number of bank branches per person and the number of POS devices per person.

[6] Academic studies conducted suggest that due to gender inequalities in labor participation and earnings, female earnings remain low, which decreases the possibility of opening an account in official financial institutions (Chen et al., 2005; Fletschner and Kenney, 2011).

[7] See Atkinson and Messy (2013).

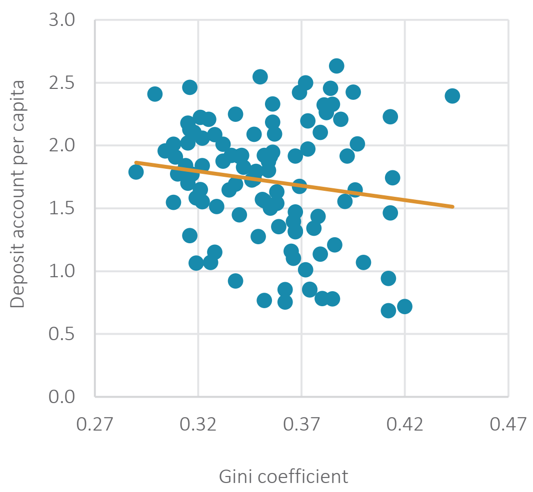
The analyses given in Chapter V.1.2 conclude that high-income economies have higher a level of financial inclusion. In order to test the regional prevalence of this relationship in Turkey, the relationship between the GDP per person and the number of bank accounts per person is shown in Chart V.1.11. According to the chart, there is a positive relationship between the GDP per person and the number of accounts per person. In other words, higher the income of a region, higher the financial inclusion. On the other hand, the negative relationship between income inequality (calculated by Gini coefficient), which is an important socioeconomic issue, and financial inclusion is presented in Chart V.1.12. Although the results do not provide a causality analysis, they reveal that in regions with high-income inequalities, the number of bank accounts per person is low.

Chart V.1.11: GDP per Person-Number of Bank Account per Person



Source: BAT, TURKSTAT Last Observation: 2017

Chat V.1.12: Gini Coefficient-Number of Bank Account per Person



Source: BAT, TURKSTAT Last Observation: 2017

In sum, according to the results of the analysis made based on 2010-2017 data of Turkey's 26 regions:

(i) Measures of financial inclusion take high values in regions where female labor force participation rate is high.

(ii) Higher educational level brings about higher financial inclusion and narrows the gap between educated and low-educated groups.

(iii) There is a positive relationship between the ratio of university graduates and the number of online banking clients.

(iv) Increased GDP per person and improved income distribution support financial inclusion.

V.1.4 Conclusion and Assessment

This study primarily summarizes the trend of financial inclusion in different income economies and in Turkey in a comparative way. The second part examines the aspects that distinguish Turkey from similar country groups, using regional microdata.

According to the analysis results, financial inclusion has increased significantly all over the world over the past decade. Although Turkey ranks above similar economies in terms of several indicators peculiar to itself, it displays inequalities in the gender and education-based distribution of financial inclusion.

Results derived from this study suggest that it will be of benefit to target the practices that will raise the level of financial education and ensure inclusion of young population in the financial system. Additionally, it is essential that the policies to be implemented do offer products diverse enough to meet sociocultural needs.

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V.2 Transition Matrices for Corporate Loans

The Basel Committee on Banking Supervision and other regulatory authorities have introduced new regulations and practices for a more effective measurement and management of the credit risk to which banks are exposed as well as for determination of capital requirements to counter those risks. Transition matrices for bank loans and probabilities derived from these matrices are among the modern credit risk measurement and management methods. This study explores the probabilities of default and produces transition matrices for the corporate loan portfolio of the Turkish banking sector by using loan-level data. The study focuses on banks' rating migrations among loan classes over the past decade, along with the potential resulting implications on NPL movements.

V.2.1 Probabilities of Default in Credit Risk Measurement and Transition Matrices

Within the framework of measuring and reporting banking sector credit risk, two different loss definitions prevail: expected loss and unexpected loss. Expected loss is calculated considering the average loss realizations of a credit portfolio in the past and calls for provisions to be set aside. Whereas, unexpected loss denotes the values in the tails of regarding banks' past credit loss distributions, and calls for capital requirements. Credit default probability is used as an important input in the calculation of expected and unexpected losses. Therefore, calculation of default probability is critical in terms of monitoring risks.

In line with Basel regulations, the BRSA has published regulations on calculation of credit risk weighted assets using an internal rating. These regulations include the details of calculating default probability. Basel regulations define probability of default as the ratio of the number of debtors defaulting in the course of one year to total number of debtors in the same rating grade. According to the BRSA's regulation, it denotes a debtor's probability of defaulting in the course of one year.

Credit risk (default probability) is quantified by calculating the probability of loans' migration from one class/rating grade to another class/rating grade historically, using transition matrices. Transition matrices calculate credit migration probabilities mostly on one-year time horizons. Under the assumption that a loan's probability of migrating from one class/rating grade to another depends on its current state only, and that the initial state of the loans does not count for determination of migration probabilities, a Markov chain model is widely used. In this sense, standard models, in which credit rating migration probabilities are determined for one time period, are called first-order Markov models. Under the assumption that migration probabilities do not change over time, longer-term migration probabilities can be drawn based on the first-order Markov matrix.

In a representative transition matrix, it is assumed that N (number) credits are monitored during T (time) and that N (number) credit ratings are reported in each period. At the beginning of the transition period$(t-1)$, the number of credits with i rating is expressed as $n_i(t-1)$. The number of credits that have migrated to j credit rating in the current period (t) despite having been rated i at the beginning of the transition period $(t-1)$ is shown as $n_{ij}(t)$. Under the assumption that credit ratings vary up to S, which is a finite number, the probability of migration from i credit rating to j credit rating can be calculated by the following equation.

$$p_{ij}(t) = \frac{n_{ij}(t)}{n_i(t-1)}, \qquad i, j \in S \tag{1}$$

By using Equation 1, a transition matrix for a credit portfolio including five rating grades can be found (Figure 1). For loans that were in the first rating grade at the beginning of the transition period, the probability of transition to the fifth grade during the analysis period is represented by (p_{15}). Total probabilities in each row add up to 1. Diagonal elements of the matrix denote probabilities of staying in the same rating grade in the following period. In the event that the loan is repaid at maturity or removed from the portfolio via derecognition from the balance sheet, is shown in the exit column.

Figure V.2.1. Transition Matrix

$$\boldsymbol{Transition\ Matrix} = \begin{array}{c} \\ \mathbf{1} \\ \mathbf{2} \\ \mathbf{3} \\ \mathbf{4} \\ \mathbf{5} \end{array} \begin{array}{cccccc} \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} & \mathbf{5} & \boldsymbol{Exit} \\ p_{11} & p_{12} & p_{13} & p_{14} & p_{15} & p_{1E} \\ p_{21} & p_{22} & p_{23} & p_{24} & p_{25} & p_{2E} \\ p_{31} & p_{32} & p_{33} & p_{34} & p_{35} & p_{3E} \\ p_{41} & p_{42} & p_{43} & p_{44} & p_{45} & p_{4E} \\ p_{51} & p_{52} & p_{53} & p_{54} & p_{55} & p_{5E} \end{array}$$

V.2.2 Transition Matrices in the Turkish Banking Sector

Banks have been classifying their loans in five groups since 2009 according to the “Regulation on Procedures and Principles for Classification of Loans and Provisions to be Set Aside”: Performing loans in the first group (loans of a standard nature) and in the second group (loans under close monitoring), group three (loans with limited collectability), group four (doubtful loans) and group five (loans classified as loss). There are plenty of studies in advanced economies regarding credit risk analyses made based on corporates’ credit ratings. However, only a limited number of corporates in Turkey, having been credit rated, provide enough information to enable transition matrices.

This study presents transition matrices for the Turkish banking sector calculated in a way largely compliant with the Basel and the BRSA regulatory framework using banking reports based on clients and credit groups. Inter-grade transition rates are established by proportioning the number of migrated loans to the total number of loans included in the respective credit grade a year ago. For instance, the ratio of the total number of corporate loans, which, despite being classified as performing loan a year ago, were classified as NPL in the course of one year, to the number of corporate performing loans a year ago gives the probability of default. The same method has been repeated for all periods by using the sliding window protocol, which gave us a transition rate as time series.

The loan portfolio transition matrix for the Turkish banking sector calculated for the March 2019 period indicates that in the March 2018 period, of the loans classified as standard, approximately 65 percent were standard loans, 6.5 percent were loans under close monitoring (second group), and 1.8 percent (the total of group 3, 4 and 5 loans) were classified as NPL (Table V.2.1). Loans under close monitoring that are of lower quality are more susceptible to migrate into the NPLs, as expected. Approximately 19 percent of the loans that were under close monitoring a year ago migrated to NPL grades. Loans that were classified as NPLs the year before are not likely to be reclassified as performing loans, as suggested by the 0.6 percent migration probability. The transition matrix reveals that a significant portion of last year’s loans has not been reported this year. This can be interpreted differently for performing loans and loans classified in the NPL grade. The majority of performing loans implying an exit are considered to have been closed as they matured. Banks may extend revolving credits in order to meet short-term liquidity needs of the real sector. The non-usage/non-renewal of loans in the current reporting period increases the exit rate in the transition matrix. NPL collections, sales and write-offs from assets are considered to play a role in exits from the balance sheet. In this framework, banks removed from balance sheets approximately 35 percent of the NPL portfolio through collection, sale and write-offs.

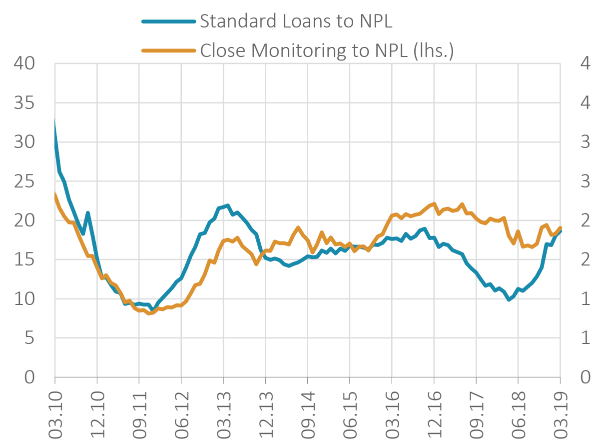
Table V.2.1: Turkish Banking Sector Transition Matrix (March 2019 Period)

2018 March \ 2019 March		Performing Loans		NPLs			Exit
		Group 1	Group 2	Group 3	Group 4	Group 5	
Performing Loans	Group 1	64.5	6.5	0.8	0.9	0.1	27.1
	Group 2	8.9	37.7	4.5	7.9	6.6	34.3
NPLs	Group 3	0.0	0.3	1.8	0.3	61.9	35.7
	Group 4	0.0	0.2	0.1	0.2	58.6	40.9
	Group 5	0.0	0.1	0.0	0.0	68.6	31.2

Source: CBRT

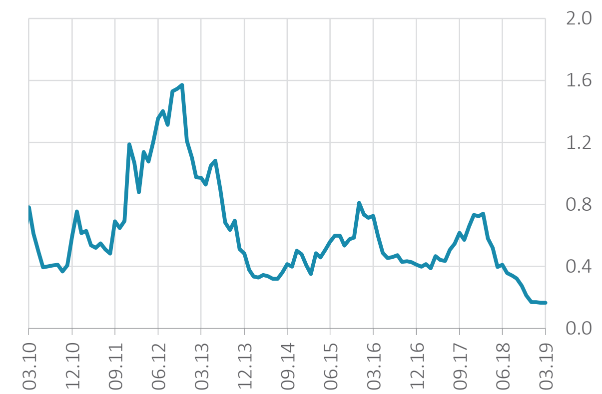
Transition to NPLs and transition from NPLs to performing loans have been examined for a period covering from 2010 to 2019. The highest transition rates for migration to NPLs were seen in 2010, the post-global financial crisis period. The rate of transition from loans under close monitoring into NPLs rose to 17 percent from 9 percent between 2012 and 2013, followed by a flatter course within a margin of 17-20 percent in general after this period. Transitions from standard loans into NPLs have slightly increased to 2 percent in the recent period (Chart V.2.1). Transition from NPLs into performing loans rate declined to 0.3 percent from 1.6 percent between 2012 and 2013. Although this rate rose to 0.8 percent at 2015 and 2017 year-ends, it has trended down since 2018 and recorded its lowest level (0.2 percent) of the reporting period (Chart V.2.2).

Chart V.2.1: Rates of Transition to NPLs (percent)



Source: CBRT Last Observation: March 2019

Chart V.2.2: Rates of Transition from NPLs to Performing Loans (percent)



Source: CBRT Last Observation: March 2019

V.2.3 Transition Matrices and Implied NPL Ratio

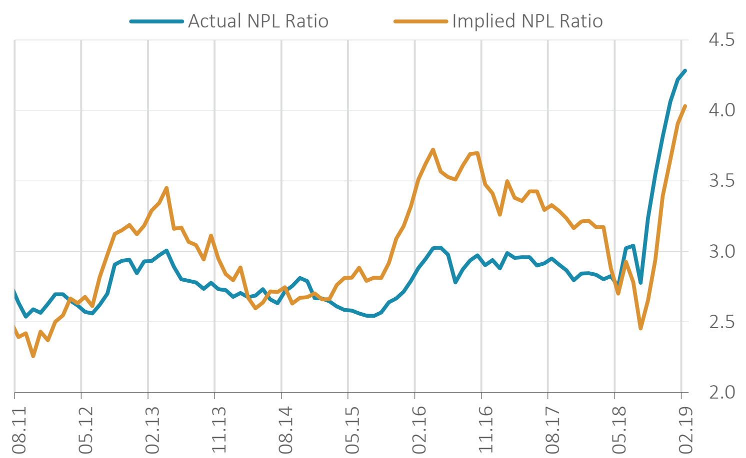
NPL ratio estimations can be made by using the rates of migration to and from NPLs under specific assumptions. Calculation of transition probabilities based on the number rather than the amount of loans is considered to give different results in certain periods. Assuming that transition probabilities, next year, will follow a course similar to that of the past period, the implied NPL ratio for corporate loans for the next year can be calculated based on the following equation.

$$\text{NPL Amount}\ (t) = \text{NPL Amount}\ (t-1) + \sum_{j=3}^{5} p_{1,j} * \text{Standard Loan}\ (t-1) + \sum_{j=3}^{5} p_{2,j}\ \text{Close Monitoring}\ (t-1)$$
$$- \sum_{i=3}^{5}\sum_{j=1}^{2} p_{i,j} * \text{NPL Amount}\ (t-1)_i - \sum_{i=3}^{5} p_{i,exit} * \text{NPL Amount}\ (t-1)_i \tag{2}$$

The corporate NPL ratio calculated based on transition rates is expected to display a consistent trend with the actual NPL ratio. In fact, it is possible to state that they display a consistent trend in general, except for certain periods (Chart V.2.3). As historical transition rates are based on actual data, they are affected by conjunctural developments in the respective period. Existence of conjunctural developments in the estimation period, which are not consistent with the past, leads to deviations between the estimated and actual NPL ratios.

The distribution of the corporate NPL ratio implied for the following year is obtained by using historical realization of transition rates. Under the assumption that the loan growth would hover at levels close to its recent period course, the NPL ratio is expected to follow a course consistent with historical averages. However, various factors such as the fact that 2018 was a period of transition to TFRS-9 reporting standards for the banking sector, the weak economic activity and developments in financial conditions may have an effect on the asset quality outlook.

Chart V.2.3: Corporate NPL Ratio and Implied Corporate NPL Ratio (percent)



Source: CBRT

Last Observation: March 2019

V.2.4 Assessment

Transition matrices are used in calculating and managing the credit risk effectively. In the study conducted for corporate loans extended by Turkish banks, the non-performing loan portfolio has been estimated using corporate loan transition rates. A comparison of actual historical NPL ratios and the NPL ratios implied by transition probabilities, which show a consistent course with each other, gave positive signals on the NPL estimation ability of transition matrices. In this sense, a dynamic monitoring of transition probabilities will strengthen credit risk analyses of banks and legal authorities.

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V.3 A Close Look at Closely Monitored Loans: Impact of the Turkish Financial Reporting Standards-9 (TFRS-9)

Before 2018, the main criterion for loan classification was whether the repayment by clients was timely or not although expectations for borrower's debt repayment capacity were also taken into account.[1] Loans with arrears between 30 to 90 days were classified as closely monitored loans (second group). Since January 2018, the majority of banks have employed the TFRS-9 in loan classification and in determining the provisions for these loans, and the credit risk levels and credit classification of firms and individuals have been determined by individual internal credit models of banks. This study analyzes the development of closely monitored loans and the impact of the transition to the use of internal credit models under the TFRS-9.

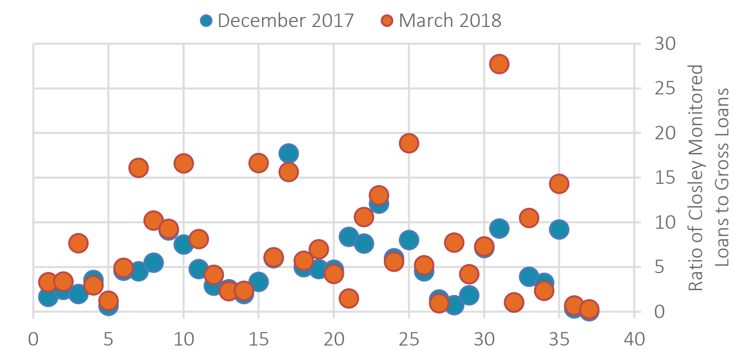
As of March 2019, the share of banks using internal credit modelling in the sector grew to 98%.[2] With the transition to the TFRS-9, in addition to impaired loans, loans that are not impaired but are found to have "a significant increase in credit risk" according to model results also started being classified as closely monitored loans by banks. Accordingly, the amount of closely monitored loans increased in 2018.

Internal models employed by banks under the TFRS-9 include both micro and macroeconomic parameters. The model results are affected not only by figures pertaining to the past periods but also by expectations for the future period. However, variations in bank-based models and macroeconomic variable assumptions make it difficult to decouple the effect of the TFRS-9 and the effect of loan impairment on the increase in the rate of closely monitored loans observed since 2018.

V.3.1 Development of Closely Monitored Loans and Implications of the TFRS-9

With the adoption of the TFRS-9, the amount of closely monitored loans in the banking sector increased in the period between December 2017 and January 2018. This increase was significantly driven by the rise in the TL-equivalent of FX-denominated closely monitored loans due to the depreciation of the Turkish lira.

Chart V.3.1: Ratio of Closely Monitored Loans to Gross Loans on a Bank Basis (%)



Source: CBRT

Note: Based on data from 37 banks where the ratio of closely monitored loans to gross loans is different from zero in one of the two periods.

The variation of credit risk explanatory variables that banks use in internal credit models and expectations about macroeconomic indicators for the future period causes loans extended to the same firm/individual

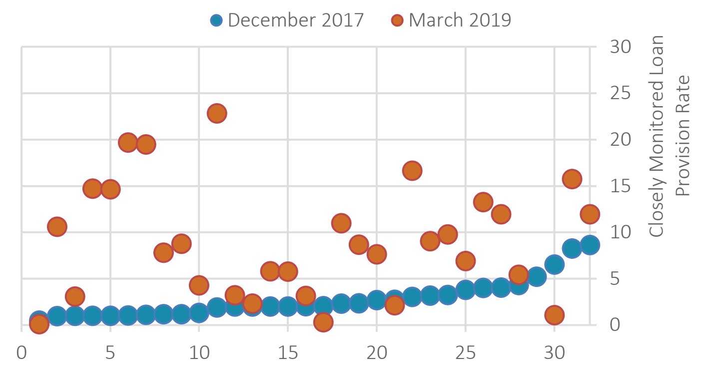
[1] According to the Regulation on Provisions, loans are classified under five groups: Loans of a standard nature (first group), loans under close monitoring (second group), loans with limited collectability (third group), doubtful loans (fourth group), and loans classified as loss (fifth group).

[2] In the Uniform Chart of Accounts, banks must recognize the closely monitored loan provisions under different account codes based on the use of TFRS-9 standard. These account codes have been used to identify the periods of banks' transition to the TFRS-9. Accordingly, 35 banks adopted the TFRS-9 as of January 2018 while a total of six banks – three in March 2018 and three in January 2019 – started using the TFRS-9 in their loan provisioning.

to be classified differently across banks. A bank-based comparison of the rates of closely monitored loans before and after the adoption of the TFRS-9 reveals that the variation in the rates of closely monitored loans has increased after the adoption of the TFRS-9. In fact, the standard deviation of closely monitored loan rates has increased to 8.9% from 3.8% at end-2017 (Chart V.3.1).

Loan classification also affects the financials of banks through the provisions channel. The rates of provisions for closely monitored loans can be used as an indicator of the increased credit riskiness after the shift to the TFRS-9. The increase in provision rates shows that a bank expects to write off a higher loss for the same amount of loan, which means that the credit risk has risen.

Chart V.3.2: Closely Monitored Loan Provision Rates on a Bank Basis (%)

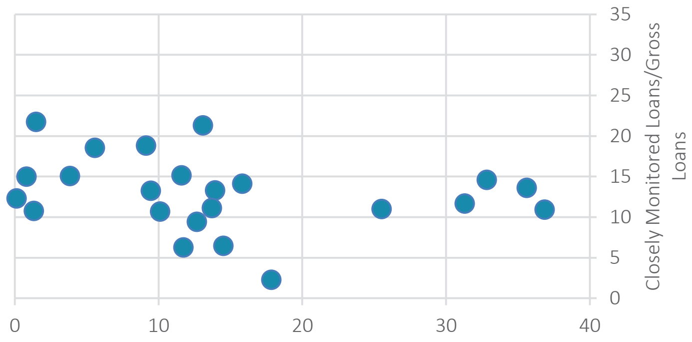


Source: CBRT Latest Data: 03.19

The cross-bank variation in closely monitored loan rates is also observed in provision rates. The standard deviation of provision rates for closely monitored loans rose to 8.1% in March 2019 from 3% in December 2017 (Chart V.3.2). The variation of the provision rates for closely monitored loans after the shift to the TFRS-9 is attributed to the projection of the probability of a firm's default based on its cash flow expectations as well as to assumptions for the loan collateral worth in case of default of a firm.

To decouple the effect of model assumption and the effect of a deterioration in solvency when using the internal model under the TFRS-9, the loan performance of closely monitored loans has been compared. Consistent with the closely monitored loan definition, the share of closely monitored loans with arrears of 30 days and longer has been analyzed. The ratio of closely monitored loans with arrears longer than 30 days to total closely monitored loans has decreased by 5 percentage points. This decrease shows that some non-impaired loans have also been classified as closely monitored loans due to the adoption of the internal credit modelling. A comparison of the share of loans that banks have classified as closely monitored loans under the TFRS-9 in the gross loan portfolio and the share of overdue closely monitored loans suggests that there is a horizontal rather than a linearly increasing relationship between the two. This also points to a variation in the prudence levels of banks in credit risk analysis and in the use of internal models. While banks with a lower ratio of overdue loans are expected to classify relatively smaller portion of their loans as closely monitored loans, banks' macroeconomic expectations for the future period and their prudence levels cause them to set the closely monitored loan rates at higher levels (Chart V.3.3).

Chart V.3.3: Share of Overdue Closely Monitored Loans on a Bank Basis (%)



Source: CBRT | Latest Data: 03.19

V.3.2 Conclusion

Since early 2018, banks have been using the TFRS-9 in their loan classification. Accordingly, loans that are not impaired but are found to have a significant increase in credit risk according to internal model results also started being classified as closely monitored loans. Consequently, the ratio of closely monitored loans to gross loans has increased and varied across banks. This variation is also driven by banks' internal model parameters, assumptions and expectations about macroeconomic indicators. An analysis of loan performance suggests that the impairment in loan performance has a limited effect on the increase and cross-bank variation in closely monitored loans whereas model assumption, parameter and expectation preferences of banks that reflect their prudent stance have a determining role.