PROBABILITY OF DEFAULT MODELLING USING MACROECONOMIC FACTORS

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ABSTRACT

PROBABILITY OF DEFAULT MODELLING USING MACROECONOMIC FACTORS

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As a consequence from the recent global financial crisis, regulatory frameworks are continuously improved in order to limit the banks' risk exposure. Two of the amendments are Basel III and IFRS 9. Basel III regulates the capital a bank is required to hold while IFRS 9 is an accounting standard for how banks should classify their assets and estimate their future credit losses. Mutually for both Basel III and IFRS 9 is the estimation of future credit losses which include the probability of default in the calculations.

The objective of this thesis is, therefore, to evaluate the relationship between the Probability of Default (PD) of small and medium enterprises and households with the evolution of the macroeconomic environment. This work contributes to the literature of credit risk proving the importance of macroeconomic variables in determining the PDs both for the sector of non-financial corporations and sector of households in Turkey. Evaluation of a long-run impact and short-run dynamics of the macro variables on the PDs are investigated by employing ARDL bound testing approach on quarterly data of probability of default ratio and other macroeconomic variables covering the period 2007:1-2018:4. The results of the ARDL bound tests suggest the probability of default is significantly impressed especially by interest rates, unemployment, inflation, reel exchange rates, volatility index (VIX) and economic growth rates. The estimated long-run relationships are found to be consistent with economic theory.

Keywords: Basel III, IFRS 9, Probability of Default, Credit Portfolio View, ARDL Bound Test

ÖZ

MAKROEKONOMİK DEĞİŞKENLERE DAYALI TEMERRÜT OLASILIĞI TAHMİNİ

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Son finansal krizin yansımaları dikkate alındığında bankaların riskli pozisyonlarının sınırlanması için yasal çerçevelerde sürekli gelişmeler yaşanmıştır. Yasal düzenlemelerdeki iyileştirme çalışmalarının en önemli gelişmeleri Basel ve UFRS mevzuatlarında alınmıştır. Basel-III bir bankanın tutması gereken sermaye tutarını düzenlerken UFRS 9 bankaların varlıklarını nasıl sınıflandırması gerektiğini ve beklenen kredi zararlarını tahmin yöntemlerini esas alan bir muhasebe standardıdır. İki düzenleme için de ortak olan nokta hesaplamalarda temerrüt olasılığını kullanan beklenen kredi kayıpları kavramıdır.

Bu tezin amacı makroekonomik değişimler ile tüketicilerin ve küçük ve orta büyüklükteki işletmelerin temerrüt olasılıkları arasındaki ilişkiyi tespit ederek ilgili finans literatürüne katkı sağlamaktır. 2007:1 ile 2018:4 arasındaki dönemi kapsayan temerrüt olasılığı ve diğer makroekonomik değişkenlerin çeyreklik verilerine ARDL sınır yaklaşımı uygulanarak makroekonomik değişkenlerin temerrüt olasılığı üzerindeki kısa dönem dinamikleri ile uzun dönem etkileri incelenmiştir. Yapılan analizler sonucunda, temerrüt olasılığının özellikle faiz oranı, işsizlik, enflasyon, reel efektif döviz kuru, volatilite endeksi ve ekonomik büyüme verilerinden önemli ölçüde etkilendiği saptanmıştır. Araştırma bulgularına göre modellerde kullanılan temerrüt olasılığı ile seçilmiş makroekonomik değişkenler arasındaki uzun dönemli ilişkinin ekonomik teoriye uygun olduğu söylenebilir.

Anahtar Kelimeler: Basel 3, UFRS 9, Temerrüt Olasılığı, Makroekonomik Kredi Riski Modelleri, ARDL Sınır Testi.

To My Family

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criteria
AR	Autoregressive Model
ARDL	Autoregressive Distributed Lag
BCBS	Basel Committee on Banking Supervision
BRSA	Banking Regulation and Supervision Agency
CCR	Credit Conversion Rates
CPI	Consumer Price Index
CPV	Credit Portfolio View
CUSUM	Cumulative Sum
EAD	Exposure at Default
EL	Expected Loss
ECL	Expected Credit Loss
GDP	Gross Domestic Product
IASB	International Accounting Standards Board
ICAAP	Internal Capital Adequacy Assessment Process
IFRS	International Financial Reporting Standards
IRB	Internal Ratings-Based
LGD	Loss Given Default
LLP	Loan-Loss Provision
NPL	Non-Performing Loans
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
PD	Probability of Default
RWA	Risk-Weighted Assets
SME	Small and Medium-Sized Enterprises

SUR	Seemingly Unrelated Regression
TSI	Turkish Statistical Institute
UECM	Unrestricted Error Correction Model
UL	Unexpected Loss
VAR	Vector Autoregression
VIX	Volatility Index

CHAPTER 1

INTRODUCTION

The probability of default is one of the most important risk parameters estimated in credit institutions, especially banks, and plays a major role in credit risk analysis and management. Given the fact that one of the fundamental activities of banks in granting loans, the banking industry attributes great importance to credit risk. Credit risk is commonly understood as the potential that a borrower or counterparty will fail to meet its contractual obligations (Basel Committee for Banking Supervision, 2000).

For a bank, it is crucial to evaluate the credit risk. A qualitative approach (based on the credit officer's judgment) dominated for this purpose up until the 1970s. However, this approach is associated with several obvious problems in particular subjectivity, inconsistency, inefficiency and incomprehensiveness. Since then, with the developments in information technology, a quantitative approach has prevailed and statistical credit risk evaluation models have been developed and enhanced. These models help to overcome the deficiencies of the qualitative approach based on the credit officer's judgment. Despite the fact that the quantitative approach may also be associated with several problems (development of models using historical data, the assumptions needed to apply certain statistical methods do not hold etc.), these models have become a standard technique for credit risk evaluation and estimation of the probability of default (Vanek & Hampel, 2017).

There are now four popular types of models of credit risk in the course of use at present in finance in general (Crouhy, 2000):

The structural models: there are two models of management of credit portfolio in the literature: Moody's KMV model (Portfolio Model) and CreditMetrics model by JPMorgan.

The actuarial models of Credit Suisse First Boston (CSFP): this model (CreditRisk+) was developed in 1997.

The Macro-factors model (Econometric model): The Credit Portfolio View model was introduced in 1998 by Mckinsey (Derbali, 2018).

All of these models are focused on the prediction of the probability of default of loans. Particularly in the banking industry, prediction of the probability of default gained even greater recognition with the introduction of the Basel II capital requirements framework in 2004 (Basel Committee for Banking Supervision, 2004). Within the Internal Ratings-Based Approach (IRB), PD constitutes one of the three fundamental parameters for the calculation of credit risk capital requirements, and, as it was mentioned in the beginning, one of the most important parameters in credit risk analysis and management. The other two parameters are Loss Given Default (LGD) and Exposure at Default (EAD). In this regard, banks are required to retain an adequate level of capital due to credit risk, especially to cover potential unexpected losses.

The initial Basel regulations (Basel-I) coined the term of credit risk and proposed capital requirements to strengthen the bank credit structure by quite pure methods (credit risk was only calculated according to credit ratings of the counterparties). After necessary improvements in the Basel regulations due to changes in the financial landscape, more complex models have been incorporated into the Accords under Basel-II. Expected Credit Loss (Loan loss provision) and Unexpected Credit Loss (Credit Risk Capital Requirements) formulas including PD, LGD and EAD emerged at this point. The development of those risk measures is a fundamental outcome reached by Basel II accords, but to reach the goal of having a safe banking system, they need to be as precise as possible. Furthermore, being well aware of the risks that a bank can face in its near future is essential for the proper functioning of the bank itself and the general banking system. Indeed, it is also important for customers (fiduciary risk) and governments. Thus, it is necessary to have model parameters (PD and LGD) that smoothly forecast future risk. In terms of a microeconomic perspective, capital requirements are imposed on banks in order to ensure that banks operate with a sufficient amount of capital to remain profitable and avoid insolvency. Moreover, from a macroeconomic perspective, as the Turkish banking system is overall interconnected, the miscalculation of a single bank's capital requirement -that can possibly end with its insolvency- could rapidly affect other banks and contribute to a general financial crisis or magnify an existing one.

The international financial reporting standard (referred to as the “IFRS 9”) emphasizes and deepens requirements in the area of credit risk analysis and management. In a sense, it will also create a stronger link between credit risk and accounting, and significantly impact the banks’ economic results. The key element of IFRS 9 is a forward-looking “expected loan loss provisions” model, representing a certain shift from the incurred loss model with what the new model brings to literature.

Loan-loss provision (LLP) is an accounting term that can be theoretically defined as the amount set aside to cover expected losses on loans in the future. So, the Loan-loss provision of a Bank is a useful and accurate measure of expected loan losses. Indeed, the Basel committee states that loan-loss provisioning should be robust and based on sound methodologies to reflect potential credit loss in the banks over the life of the loan portfolio.

There are several reasons why local and international regulations emphasize LLP. Firstly, given the fact that banking loans account for a high portion of a bank portfolio, the LLP should be a reliable indicator for the bank's financial condition and overall performance of a certain period. Hence, it should be carefully computed to avoid any inaccurate forecasts on banks' performances. Secondly, LLP figures help retrieve precious information about capital structure, bank’s ability to manage credits and its capacity to cover possible future losses. Then, LLPs are indicators used by financial institutions and stakeholders to gain information before investing in a bank for valuation purposes.

Additionally, LLPs are subjected to prudential regulations: a certain amount of provisions is required for each bank corresponding to its loans that guarantees safe banking activities and prevent customers from losing money due to banks’ insolvency.

Essentially, as IFRS9 refers, expected loss of a credit facility is calculated by PD *LGD* EAD. The definitions of PD, LGD, and EAD under IFRS 9 are exactly the same as those under Basel's IRB approach.

Consequently, Basel accords and International Financial Reporting Standards are regulations that require financial enterprises to estimate the unexpected loss (credit risk capital requirement) and the expected loss. Basel accords are the regulations developed in order to determine the amount of capital a bank is required to hold. IFRS 9 is an accounting standard that requires financial firms to classify and estimate their future credit losses and define them as a loss in the financial statements. Accurate estimation is vital as reservation of too much capital affects the return for the enterprise. An inaccurate estimation where too little capital is held does instead increase the risk for a financial enterprise and a default may occur. Probability of default is the critical factor that affects the estimation of credit risk capital requirement by IRB in Basel accords and the expected loss in IFRS 9.

The main objective of this study is to propose a straightforward, flexible and intuitive computational framework for PD estimation incorporating the macroeconomic forecast under IFRS 9 associated with expected credit losses and Basel accords associated with the Internal Ratings-Based approach in determining capital requirement. By assuming that improved macroeconomic conditions will reduce PD, the macroeconomic variables with possible impact on PD will be identified and The Credit Portfolio View model (an econometric model) introduced by Mckinsey will be employed. This paper will examine both non-financial corporations' sector and households' sector models of PD in the Turkish economy using quarterly data for inflation, interest rate, unemployment, exchange rate, GDP, and other determinants proposed by the literature. The primary sources of the data are the electronic data delivery system of the Central Bank of Turkey and Banking Regulation and Supervision Agency. The main models used in the analysis will be autoregressive distributed lag (ARDL) bound testing approach and the study will assess the long-run relationship and short-run dynamics between probability of default ratios and some macroeconomic variables.

The study proceeds as follows. Chapter 2 is a separate review of the development of the Basel Accords and IFRS 9. The reviews will detail the genesis of the requirements brought by regulations, discuss the principles contained therein and the proposed mechanism of implementation and analysis. Chapter 3 describes data and methodological framework and provides definitions of the probability of default as well as definitions of macroeconomic determinants. Chapter 4 involves the results of the quantitative models and lastly, Chapter 5 discusses the results of the models in terms of the Turkish banking system.

CHAPTER 2

THEORETICAL FRAMEWORK

2.1 Risk and Risk Management in Banking

Metalgschaft, Parmalat, Barings Bank, Long Term Capital Management, Enron and others... These institutions, called "Ivy League" compared to their terms, are among the leading ones in financial scandals now. While a part of these companies faced with heavy losses due to the operational risks that involved human factor, another group suspended their activities on account of market conditions and insufficient supervision systems. The Enron Company, collapsed in 2002 due to a fraudulent activity together with an auditing firm named Arthur Andersen, which was the motive behind the famous "Sarbanes-Oxley" act, which paved the way for new standards in institutional and supervisory terms. This regulation empowers the supervision function in public companies, encourages independent auditing, and increases the responsibility of the company. It has been positioned as an important regulation with its impact on business and finance culture. On the road towards the first major crisis of the millennium, this regulation, due to its costly business manner, was maybe the first sign of the "deregulation" madness that would start in the economy.

Banks, which are the centers for providing loans that are the lifeblood of real sector investments, have been the leading sector that has been influenced by the legal regulations in history. Banking is based on the principle that exposed risks are managed in order to maintain the existence of the bank as a healthy, reliable, and profitable enterprise. The most important facets of strict supervision and audit are the liquidity mismatch in their asset-liability structure and high risk/capital. Given the financial intermediation function of the banking, banks take risks not based on the transactions performed by their own resources, but by the external resources; effective management of foreign credits is the root of the survival of the banks in the economy. At this point, it is necessary to comprehend better the liquidity and capital adequacy notions that demonstrate the financial status of the bank. In terms of both human resources and software developments, all financial institutions have been more attentive to risk management particularly since the 2008 crisis. The 2008 Subprime Mortgage crisis, accepted as the biggest financial crisis since the 1929 Great Depression as a result of its widespread systemic risk, is a benchmark where the risk management participates in the decision making processes of companies as an independent unit. The Basel principles that became a generally accepted chain of regulations in the international arena overstepping its advisory role were the driving factor behind the rising awareness of risk management.

2.1.1 Concepts in Risk Management

Risk Management: There are two main purposes of risk management in banking, to prevent the banks from facing unbearable losses, and to improve the financial performance of the bank. (Altıntaş, 2006) It was stated in the Communique of the Internal Systems of the Banks, which was issued by the Banking Regulation and Supervision Agency (BRSA) in 2012, as follows: "The purpose of the risk management in banking is to determine the internal capital requirement complying with the risk profiles and to define, quantify, report, monitor, and check the exposed risks on consolidated and non-consolidated bases through policies, implementing procedures, and limits about monitoring, controlling, and if needed, changing the quality of the operations based on the risk-return profile that the future cash flows involve". (BRSA Regulation on the Internal Systems of Banks, 2012)

The risks that are common in the banking sector are Credit Risk, Counterparty Credit Risk, Market Risk, Exchange Rate Risk, Interest Rate Risk, Liquidity Risk, Operational Risk, Concentration Risk, Correlation Risk, Country Risk, and Legal Risk.

Credit Risk: These are the losses in case that a debtor is unable to repay a debt, or in case of deferrals. Among the reasons for credit risk are debtors getting into default, economic losses mostly ending in bankruptcy, low credit ratings of most of the companies using credits, depreciation of collaterals, and economic fluctuations. Additionally, banks make assessments about credit risk based on credit ratings. It is possible for the credit risk to decrease if the credit portfolio is diversified considering the target clients and general credit strategies.

Counterparty Credit Risk: It is defined as the default risk of one of the parties before the last repayment in contracts that impose obligations for both parties. Banks should well analyze the financial solvency of the counterparty before starting the transactions that might lead to the counterparty credit risk, and they should explicitly express the financial information demonstrating their creditworthiness, investment strategies, collateral management, and operational controls in the risk management policy documents. While managing the counterparty credit risk, banks can avoid the uncertainties particularly emanating from derivative transactions by implementing both internal and regulation-based limits.

Market Risk: Market risk, in general, is defined as the probability of loss due to a decrease in the current market values of assets and positions that the banks hold in their accounts. The assets and positions, which are the main subjects of the market risk, are the generally accepted accounts that the banks have to evaluate the current market prices according to international accounting standards. (Altıntaş, 2006) Additionally, the market risk stands for the possible losses in values of investment instruments such as stocks, securities, and derivative transactions. Interest rate risk, exchange risk, and concentration risk lay the groundwork for the market risk.

Exchange Rate Risk: It explains the probability of losses of a bank when the foreign currency liabilities are higher than its assets in case of exchange rate fluctuations in the market. Since the export loans are in foreign currency, the finance of these assets is provided through resources in foreign currency. Foreign exchange loans on the liabilities side of the bank can be more than its assets, and thus, the bank is exposed to exchange risk due to depreciation in local currency. This, in turn, has a negative impact on the profitability of the bank. In general, to avoid the exchange rate risk, banks resort to derivative instruments depending upon their borrowings, and thus, they are affected less from the fluctuations in the exchange rates. Among the elements that determine the extent of the exchange rate risk are the market rates, current deficit, inflation, economic and political conditions, and monetary and financial policy.

Interest Rate Risk: Interest rate risk represents possible losses due to irregularities in the interest rates, and it is the most important risk type that influences the asset-liability profiles of banks. As a result of the increase in the financial integration together with globalization in recent years, it is observed that the economic and political decisions of other countries influence the interest rates in our country. Accordingly, the quantification and management of interest rate risk have become the most important need. Repricing risk and structural interest rate risk are indicated among the most important risk types for the interest rate risk.

Liquidity Risk: It is a situation where the bank does not have sufficient cash inflow to ensure the cash outflows due to irregularities of the bank in the cash flows. This risk results from being unable to sell the assets, and thus, being unable to turn them into cash, in case of an urgent need for cash. The management of liquidity risk is one of the most important fields in terms of asset-liability compliance.

Operational Risk: It is defined as the risk of loss due to internal factors such as insufficient processes, failed transactions, and personal flaws as well as external factors such as natural disasters and policies of foreign countries. According to another view, operational risk means: A bank, operating in an environment where its costs exceed its revenues, loses resources or a serious decrease is experienced in its resources. Having insufficient controls in the payment systems or frauds conducted by depositors with the help of computer technology are among the operational risks as well. This risk has become a vital risk since banks operate in many countries together with the current technology-intense structure of ATM, EFT, and online systems. According to the "Guide of Good Practice"[1] issued by BRSA, which was prepared to manage the operational risks effectively and sufficiently, operational risk management framework, the structure of the organization, risk culture, strategy, procedures, and business continuity plan are of vital importance considering the complexity of the banking activities.

Country Risk: Country risk is the case, where the companies cannot fulfill their internal and external liabilities due to political, economic, and social conditions. "Country risk is a combination of economic risk, political risk, and regulatory risk. Economic indicators such as inflation, economic growth, and recession cause economic risk. Similarly, some factors such as wars, political crises, moratorium, expropriation, election, and customs constraints influence the political risk. Besides, country risk can arise from the regulations in the monetary and capital markets" (Coyle, 2000).

Concentration Risk: This type of risk occurs when a bank invests heavily in assets belonging to a specific sector or at specific maturities. Concentration risk can be classified on credit-basis, under categories of sector, collateral, currency, or country.

Correlation Risk: It is the probability of loss that can emerge from the bank portfolios might be subject to particularly market risk; the risk may be positive or negative in parallel with the increasing or decreasing values of different financial assets under market conditions with certain maturity dates.

Legal Risk: It represents the probability of a negative impact on the assets-liabilities structures of the banks due to changes in local and global regulations. Increasing international operations due to globalization and technological developments required financial institutions to abide by legal agreements. Complicating business models bring along controversies with third parties and increase the possibility of a legal risk.

[1] Guidance on the Operational Risk Management Framework.

2.1.2 Historical Development of Risk Management

As part of the "Young Plan", the Bank of International Settlements (BIS), which was founded in order to organize the collection activities of the war compensations based on "Versailles Treaty" signed in 1930 after the 1st World War, was the first international financial institution of the world. After the collapse of the Bretton Woods System in 1974, building the capital management systems of the banks on solid pillars became the focal point of the Bank, whose main purpose was to provide monetary and financial stability, and to ensure the coordination between national central banks and other financial institutions. Underlying factors of the collapse of Bretton Woods were leaving the fixed exchange rate policy, rapidly wide-spreading international trade, and the fluctuations in the financial markets caused by the crisis due to the oil prices raised by the Organization for Petroleum Exporting Countries (OPEC). The differentiated regulations of public authorities on the finance sector in the 1970s and 80s pushed the competing banks to open branches in countries with relatively soft limitations in order to preserve their strategic positions and profitability. This is defined as "regulation arbitrage". For instance, the first implementations for the capital adequacy constraints were the limitations[2] for the rate of the total equity to the total assets; however, these regulations were not applied in the same way by the audit institutions of relevant countries (Hull, 2015). Thus, banks created room for maneuver for themselves in whichever country they wanted. Lack of a useful anchor for capital regulation on a global scale caused such a complication.

On the other hand, the existence of high positioning in terms of international banks in developing countries (Mexico, Argentina, and Brazil) in the 1970s caused anxiety about the capital adequacy due to inaccurate quantification of the country risks. The diversity of the financial products (especially OTC derivative financial

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[2] In many countries, there was a law requiring that the ratio of a bank's total assets to its total equity does not exceed 20.

instruments, interest rate, currency swaps and currency options etc.) created after the rise in international trade increased the risk levels of transactions of banks. For instance, for a swap transaction, in which fixed interest rate and variable interest rate are exchanged, if one of the parties cannot fulfill the liabilities, it means that the bank loses money. Thus, there comes the counterparty credit risk. Additionally, adopting the derivative transactions as an off-the-balance sheet item demonstrates how the aforementioned capital/assets rate is insufficient in quantifying the risks of the bank. In addition to these developments, by the bankruptcy of the German bank "Herstadtt" in one day due to the problems in the balance of payments (the first example of settlement risk), it became the main topic to have a more sophisticated and holistic capital approach in the financial markets.

Given those problematic developments, Basel Committee of Banking Supervision (Basel Committee) was founded in 1974 by the Bank of International Settlements in order to reach goals such as to stabilize the financial markets, to fill the deficiencies in the global audit system, and to bring minimum standard rules on a global scale for consistency and transparency in the quantification of capital adequacy, which reflects the financial power of a bank; this committee continues its operations today under the leadership of central banks of relevant countries[3] and supervisory authorities.

Meeting the unexpected losses and obligations is not only crucial for the financial institutions but also for the overall well-functioning of the financial system. In this context, capital adequacy is of vital importance in the banking system against the risks that may arise.

The classical dichotomy between the profitability and materialization of stability targets in the financial system is still open to the discussion today. Economic problems in the markets, which have been integrated to each other since 1980 owing to the foreign currency and derivative transactions, further deepened this dichotomy.

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[3] USA, Canada, Belgium, France, Germany, Italy, Japan, Luxembourg, Netherlands, Sweden, UK and Switzerland.

Considering these concerns, the Basel Committee determined two strict limitations in accordance with the "Basel Accord[4]" published in 1988 for only the large-scale banks operating in the international arena:

i) Assets/Capital < 20

ii) Capital Base / (Risk-Weighted Assets and Non-cash Liabilities) > = 8%

According to Basel-I regulations, grading and weighting of risks has emerged as a new requirement for the large financial institutions. In order to quantify the "Risk-Weighted Assets", which was introduced to the literature by the Basel rules, the assets in and off the balance sheet are multiplied by certain risk weights based on the counterparty categories. For instance, since the bankruptcy probability of a cash asset in the vault of a bank is zero, its risk weight is accepted as 0%, and giving privilege to the OECD countries, the risk weights of the credits provided through the guarantee of banks in the OECD countries are determined as 20%. Moreover, since the risk ratings, default risk, and collateral structures of the debtors were not differentiated, all of the loans, except the ones in exchange for residential mortgages, were accepted at the same level, and the risk weight was 100%. Off-the-balance-sheet items are also included in the capital adequacy rate; however, related amounts are converted into a loan through certain coefficients (Credit Conversion Rates—CCR) before being multiplied by risk weights. After conversion into credit by the CCR, they are multiplied by relevant risk weights and included in the capital adequacy calculations.

Basel-I, re-regulated the definition of the capital taking into consideration whether the items are liquid (Table 2.1):

Capital Base = Principal Capital (Tier I Capital) + Secondary Capital (Tier II Capital/ Supplementary Capital) — Assets Deducted from Capital

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[4] Basel-I.

Table 2.1 Capital Types and Main Items

PRINCIPAL CAPITAL	Paid-in Capital	Legal Reserves	Profit for the Period and total of the Previous Years' Profits	(-) The loss for the Period and total of the Previous Years' Losses
SECONDARY CAPITAL	General Credit Provision	Received Subordinated Debts	Free Provisions	Securities Increment Value Fund
ASSETS DEDUCTED FROM THE CAPITAL	Prepaid Expenses	Capitalized Expenses	Special Cost Expenses	

Source: Basel Committee on Banking Supervision (1988)

Although Basel-I was initially trying to limit the credit risk, the market risk was also indispensably included in the capital adequacy calculations. As a consequence of the increasing diversity of financial products by the time and instability in the prices, a need for capital emerged for open positions of the banks and the instruments traded in the secondary markets such as debt instruments, their subsidiaries, derivative productions and options. At the finalized draft in 1996, the concept of Risk-Weighted Assets (RWA) subject to market risk, calculated through "Standard Method", was added into the capital adequacy formula. Thus, the new capital adequacy formula took its final form: Capital Base / (RWA subject to Credit Risk + RWA subject to Market Risk).

Even though significant improvements have been introduced with Basel-I, there is also some criticism against its framework and implementation. These criticisms can be summarized as follows:

i) Evaluating all of the credit transactions through the same risk weight regardless of the default probabilities of the debtors,

ii) Disregarding the price uncertainties in the measurement of credit and market risks,

iii) Applying low risk weights to the OECD countries (Club Rule),

iv) Lack of the maturity item in the analyses,

v) Focus on the book values of the assets instead of their market prices,

vi) Existence of only 4 risk weights in the RWA subject to Credit Risk and turning the calculation into a mechanism with a low level of risk sensitivity.

These criticisms and the developments in the financial industry paved the way of Basel-II regulations related to the capital adequacy. Although Basel-I was a milestone in defining the capital requirements of the banks, the Basel Committee had to embark on a new quest due to the inadequacies. In pursuit of a more balanced understanding of capital for the changing and developing sector needs by the help of systems including more risk-sensitive and flexible approaches, the final Basel-II rules were published in 2004 following the implementation of Quantitative Impact Analyses (QIS).

Basel-II made significant changes in the framework for the international financial system, summarized as follows:

i) Using the ratings of external rating agencies or internal bank rating systems while quantifying the cash and non-cash credit risks (Differentiation of the credit risk in the Basel-I according to the debtor),

ii) Adding the operational risk to the denominator of the capital adequacy formula,

iii) Including the Internal Rating-Based Approach to the credit risk calculation options and giving an opportunity to the banks to create their own models on condition that they fulfill some criteria ("self-regulation" principle),

iv) Empowering the internal and external audit models.

The principles of Basel-II are gathered under three structural blocks, i.e., minimum capital requirement, supervision of the capital requirements and market discipline.

According to Basel-II, Minimum Capital Requirement is re-defined as presented below:

Capital Base / (RWA subject to Credit Risk + RWA subject to Market Risk+ RWA subject to Operational Risk) >=8%

Supervision of the capital requirements is the second block of Basel-II. The new system, providing independence to the financial audit organs in different countries by taking into consideration the local dynamics, looks out for the consistency in the implementation of the rules about capital adequacy. There should be a process in the banks for auditing the capital structures of the banks by their risk profiles. In order to keep the capital adequacy levels of the banks above a certain threshold, the auditing institutions should create early warning mechanisms. One of the most significant changes, with the adoption of a new approach including the risks[5] not inherent in the 1. Structural Pillar, is the annually prepared Internal Capital Adequacy Assessment Process (ICAAP) reports by which the regulatory organizations have a grasp of all the risks of banks.

Market Discipline, as the third pillar of Basel-II, requires the banks to share more information about the risks they take and the provisions they allocate in return. One of the most important justifications is that existing and future shareholders equipped with more information urge the banks to take more solid and efficient risk management decisions. Basel-II Accord aims at increasing market efficiency through information sharing and access to information in order to prevent the asymmetrical information flow between the banks and auditing authority and markets. Through the discipline built in the system, qualitative and quantitative data are started to be publicly announced about the financial status of the banks, risk levels, and capital adequacy levels.

Nevertheless, Basel-II could not prevent the capital loss for the large-scale banks during "Global Credit Crisis", whose impacts ever deepened in 2007. Thus, the deficiencies in the regulations have revealed distinctively. This situation has led to increased criticism against Basel-II with regard to specific issues, as summarized below.

a) Design flaws in the production and distribution channels of the housing loans,

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[5] Interest Rate Risk in The Banking Book, Liquidity Risk, Strategic Risk, Reputation Risk, Concentration Risk.

b) Credit derivative products with complex structures subject to risk measurement by the internal model and the necessary capital obligation were hard to be determined,

c) Shifting the positions from the banking book to the trading book, thus demonstrating a lower capital requirement[6],

d) Lack of systemic risk scenarios,

e) Having difficulties in pricing the assets during the liquidity squeezes,

f) Dependency on credit rating institutions.

These criticisms made it necessary to rearrange the rules on capital adequacy, which will be referred to as Basel-III, to the international financial system. When the results of the last banking crisis "2008 Global Credit Crisis" are examined, which became the hot agenda with its contributions, it is observed that banks lost excessive capital. The capital loss amount only due to the trading book was 124 billion Euros[7]. The most important factor behind this result is that the capital requirements were not quantified for the credit risks since the structured derivative products were kept in trading books. Actually, the values of these products were decreased not only due to market fluctuations but also with the change in the default risk or creditworthiness of the issuer. Taking into consideration these developments together with the criticisms mentioned in the previous chapter, the Basel Committee renewed Basel-II with three documents[8] published in 2009 and named these regulations as Basel-2.5.

Given the problems in Basel-2.5, the committee prepared a set of regulations, without changing the capital requirement calculations completely, covering the deficiencies observed in the last financial crisis with changes such as standards

[6] A banking book mainly contains long-term and held-to-maturity assets, such as loans while a trading book is the portfolio of financial instruments, which are purchased or sold, held by a brokerage or bank.

[7]http://www.garp.org/risk-news-and-resources/2010/december/the-regulatory-arbitrage-dilemma.aspx

[8] Revisions to the Basel II Market Risk Framework, Guidelines for Computing Capital for Incremental Risk in the Trading Book and Enhancements to the Basel II Framework.

increasing the qualities and quantities of the capital, additional capital buffer to be used based on procyclicality, liquidity coverage, additional capital buffer for the banks that are possible to create systemic risk, and non-risk-based leverage ratio. The new regulation, which was accepted by the Basel Committee member states in October 2011, was named as Basel-III. The committee determined a transition process in the implementation of the new rules related to capital adequacy.

The financial problems, which were deepened with the crisis, only can be resolved through a healthy and sufficient capital structure. Based on this philosophy, the Tier 1 capital concept was split into two; core capital and additional Tier 1 capital. Thus, the capital items of the highest quality were included through the core capital. On the other hand, in order to establish a solid structure on quantitative terms, the minimum core capital adequacy ratio was increased from 2% to 4,5%. Then, in case of a problem in the economic indicators, "Capital Conservation Buffer" implementation was decided for protecting the strong course of the capital with a proportion of 2,5% of the core capital, and "Countercyclical Capital Buffer" implementation for preventing the banks from the erosion of their resources due to excessive credit expansion conditions. Recently, the leverage ratios, which are among the most important milestones of the financial transformation, have also been included in the scope of regulations. Since the high leveraged transactions increase the possibility of loss, the draft, which prepared a non-risk-based leverage ratio, set a 3 % minimum for the ratio of the Tier 1 capital to the total of balance sheet and off-the-balance-sheet assets.

In recent years, research studies conducted by institutions such as Global Financial Markets Association, The Institute of International Finance, and The International Swaps and Derivatives Association demonstrated that, in contrast to the expectations of the committee, the regulations of Basel-III would bring higher capital requirements to the banks and will damage to the market liquidity (Upgrading the Basel standards: from Basel III to Basel IV, European Parliament, 2016). Therefore, the supervision body of the Basel Committee, “Group of Central Banks Governors and Heads of Supervision”, is working on a new package, which will take the Basel-III practices a step further.

2.2 Credit Risk in the Banks and its Quantification

2.2.1 Importance of Credit Risk

Considering that the most important and extensive source of the banks is the credits provided for their clients, it is a fact that the credit risk is a type of risk, which is the most frequent type, and it has serious consequences if necessary measures are not taken. In the "Guide for the Internal Control and Risk Management of the Banks", issued by the Banking Regulation and Supervision Agency, the credit risk was defined as "The case that a bank faces when a client, violating the contract, partially or completely cannot fulfill his/her liabilities due time". In a stricter sense, it is the risk of non-repayment of the credits provided by the bank and the risk of collaterals not covering the credit provisions. In such a case, we can mention the case of "default".

The most important part of risk management, which became popular in our country particularly after the 1994 and 2001 crises, is credit risk management. With the announcement of the Basel regulations, the credit risk gained particular importance in the integrated global markets. Considering the credit risk management parameters and capital requirements described in the Basel II, it is known that the banks, complying with the existing regulations, needed to create an internal new credit risk management policy.

2.2.2 Credit Risk Calculation Approaches in Terms of Basel

The banks need benchmarks that the investors can compare in order to explain their financial competencies. Legal and economic capital approaches seem to be the most important elements among these quantifications. While the legal capital is defined, within the framework of the Basel principles, as the capital amount that will meet the minimum capital adequacy ratio assigned to the institutions, the economic capital is a risk criterion, in which the unexpected declines in the revenues generated by an operation or a portfolio and unexpected losses in the assets are shown in certain statistical distributions. The legal capital adequacy ratio, which was determined by the Basel as 8%, takes 3 types of risk factors (market risk, credit risk, and operational risk) into consideration, while the economic capital approach, in a more inclusive manner, encompasses other risks as well, such as the liquidity, concentration, and credibility. Economic capital models provide clues for the bank managers, investors, creditors, and regulatory organizations about the risk profile of the institution. Additionally, the economic capital approach includes flexible parameters and it is economic-value based, regardless of the accounting-related asset valuation.

In the Basel-II capital adequacy accord, which was announced by the Basel Committee on Banking Supervision (BCBS) in 2004, two main options were presented substituting the credit risk method of the Basel-I. First of them, the 'standard approach' (Legal Capital Approach), which suggests varying risk weights based on the ratings provided by external credit rating institutions; the second option is the 'internal rating-based approach', which suggests determination of the credit risk weights based on the data and methodology provided by the internal rating systems established within the banks (Basel II, 2004).

The Standard Approach method includes quantification of the credit risk based on independent credit ratings. Banks, in determining the risk weights, can take the ratings issued by the independent rating institutions into consideration, which are approved by the national supervisory authorities. Banks implementing the standard approach can apply various techniques in order to decrease the credit risks they have due to the bank portfolio. These techniques, as mentioned in the Basel II, are guaranteed transactions, netting in the balance sheet, guarantees, credit derivatives, and maturity mismatch.

One of the most important criticisms about credit risk measurement through the standard method is that the implementation of credit risk weights, most likely, provides a rough measurement of the economic risk. The main reason for this is that credit risk ratings are not differentiated enough to separate the different default risks of each different debtor. The concept of 'capital', used in the risk-based capital approach, does not sufficiently represent the capacity of a bank to cover its expected or unexpected losses (for example, loan reserve requirements go above the risk level that is common in better business cycles, and it becomes insufficient under converse developments) (Jackson, 2000).

Internal Ratings-Based Approach is the second option to use for quantifying the credit risk to determine capital requirement, according to the Basel-II. Provided that certain minimum standards are compiled and the obligation to inform the public is fulfilled, the banks, after approval from supervisory authority to use the Internal Ratings-Based (IRB) approach, can determine the capital requirement for a certain loan based on internal estimations conducted for the risk components. Risk components include the probability of default, loss given default, and exposure at default. (Basel II, 2004).

IRB Approach is split into two methods as the basic approach and advanced approach. In the basic approach, banks estimate the probability of default on their own, while they take into consideration the estimations of the supervisory authority for other risk components. In the advanced approaches, provided that they comply with the minimum standards, banks are free to calculate all risk components (probability of default, loss given default, and exposure at default) by their own estimation methodologies and effective maturity. Internal rating approach is based on the calculation of 'expected loss' and 'unexpected loss' amounts about the credit portfolio. While capital requirements are for unexpected losses, the expected loss should be reduced from the capital as a part of the impairment of the loans. (Altıntaş, 2006).

2.2.3 Basics about Credit Risk

There are two elements of credit risk: Expected Loss (EL) and Unexpected Loss (UL). Expected loss is related to the average value that a single credit or a total credit portfolio can lose in a certain period of time, while the unexpected loss is related to the volatility that is observed in the value of the credit or a portfolio in the same period. Capital, in the risk management approach, is evaluated as the reserve for the unexpected losses, since the risk is a concept that stands for uncertainty. Banks allocate provision for expected losses. As per capital, it is like insurance to be used in case the risks are materialized; therefore, economic capital, technically, is the required amount of capital to cover unexpected losses in a certain confidence range.

Within the framework of the Basel II criteria, important concepts about the credit risk can be listed as the probability of default, loss given default, and exposure at default. RWA subject to credit risk is calculated as the multiplication of the economic capital figure, which is obtained through the unexpected loss formula —to be explained in the later chapters, by 12.5 and 1.06[9].

Expected Loss (EL) is one of the key items in calculating the credit risk. Although it is not directly used in the capital adequacy calculations, its sub-items play a role in the calculation of the unexpected loss as well. It is the average loss in one year emerging from a single credit or the entire credit portfolio. It has three components as Probability of Default, Loss Given Default, and Exposure at Default and the formula is as follows:

$$EL = \text{Probability of Default} * \text{Loss Given Default} * \text{Exposure at Default} \tag{2.1}$$

Expected loss model is not only important for the standards of the ICAAP requirements, but also for the accounting standards developed in the IFRS 9 published by the International Accounting Standards Board (IASB). The motive behind is that it is necessary for the banks to allocate provisions for the impairment of the expected losses, and the amount of these provisions must be deducted from the capital.

IAS 39 for the impairment, adopted the Financial Instruments: Recognition and Measurement Standard 'incurred loss' model. As a repercussion of the 2008 financial crisis, the anticipation of future risks was added to the agenda. For this purpose, in July 2014, the International Accounting Standards Board completed and

[9] Basel conversion factor.

published the last version of the IFRS 9 Financial Instruments standards replacing the IAS 39 Financial Instruments: Recognition and Measurement standards. IFRS 9 financial instruments standards changed the classification of financial instruments and impairment. One of these changes about the impairment issue was the 'expected credit loss' model.

As will be explained in the next chapter in detail, International Financial Reporting Standards IFRS 9 published by the IASB influence banks and capital market institutions to a considerable extent with this new understanding about provisions for the expected losses in credit risk. Since the IFRS 9 is also based on the expected loss approach mentioned in the Basel standards, it will share the same infrastructure about the loan provisions. Contrary to the IAS 39, IFRS 9 embraces a forward-looking approach, therefore, it will attempt to realize this estimation through modeling and thus, it will benefit from the PD, LGD, and EAD models in the Basel III. About the estimation of the expected losses, although there are some differences— to be explained in the next chapters— about parameters between the Internal Ratings Based Approach capital requirements standards of the Basel Committee for Banking Supervision and IFRS 9 published by the International Accounting Standards Board within the framework of the IFRS 9 Financial Instruments, the expected credit loss (ECL) is calculated as follows:

$$ECL = PD * LGD * EAD * \text{Effective Interest Rate (EIR)} \tag{2.2}$$

Unexpected Loss (UL) is another item to calculate in this regard. This concept, which is also known as the volatility of the expected loss, is a method of the measurement of the economic capital. The unexpected loss is calculated through the formulas in the documents prepared by the BRSA. In order to reach the CAR (capital adequacy ratio) figures, the economic capital figures calculated below, as mentioned earlier in this chapter, are multiplied by 12.5 and 1.06, which is the Basel conversion factor; thus, converted to the risk-weighted assets. The amount of Risk-Weighted Assets is calculated as follows:

Risk-Weighted Amount = Risk Weight (RW) x Risk Amount

$$\mathrm{RW} = \left[\mathrm{LGD} \times \mathrm{N}\left(\frac{\mathrm{G(PD)}}{\sqrt{1-\mathrm{R}}} + \sqrt{\frac{\mathrm{R}}{1-\mathrm{R}}} \times \mathrm{G}(0{,}999)\right) - \mathrm{LGD} \times \mathrm{PD}\right] \times \frac{(1+(\mathrm{V}-2.5)\times \mathrm{b})}{(1-1.5\times \mathrm{b})} \times 12{,}5 \times 1{,}06 \quad (2.3)$$

In the formula,

N(x), is the cumulative distribution function for a standard normal random variable (stands for the probability of normal random variable —with 0 mean and 1 variance— to be lower from or equal to x),

G (z), is the inverse cumulative distribution function for a standard normal random variable (stands for the x value where N(x)=z),

"R" is the correlation which is calculated through the following formula,

$$R = 0{,}12 \times \frac{(1-e^{(-50\times PD)})}{(1-e^{(-50)})} + 0{,}24 \times \left[1 - \frac{(1-e^{(-50\times PD)})}{(1-e^{(-50)})}\right] \quad (2.4)$$

"b" is the maturity adjustment factor calculated via the following formula,

Maturity adjustment (b) = $(0.11852 - 0.05478 \text{ x In (PD)})^2$ (2.5)

V, is the effective maturity which is determined as 2,5 years for corporate loans and 6 months for quasi-repo transactions, but which can also be demanded by the national supervisory authorities to be calculated by the banks for each loan.

The concept of probability of default is highly fundamental in managing credit risk. Default is the case, when the debtor cannot repay the debt on due time, and its equivalence in the Basel rules is 90 days overdue of the debt. Probability of default, on the other hand, is the possibility of the counterparty to be unsuccessful in fulfilling his/her liabilities. While there are various approaches in modeling the credit risk based on the estimation of the probability of default, four models that are mostly used in the literature will be presented. Although these models are different from each other, the common goal is to estimate future periods based on past data. Even though distinct models are being used, all of them were prepared for loans of less qualified or already gone default. In this study, inspiring from the studies adapting the Credit Portfolio View approach, which was developed by Thomas Wilson in 1997 as a macroeconomic credit risk model in forecast of probability of default; it is aimed at developing models and methodologies that will enable the use of macroeconomic variables in forecast of probability of default in Turkish Banking System.

The Credit Metrics model, developed by JP Morgan, is an approach of credit transition based-on an analysis of the change in the credit ranking. In this model, which is also known as Value at Risk Model, the possibilities of transition from a credit rating to another in a certain period of time, and the probability of default are being evaluated. According to this model, where transition matrices are being used, each debtor has a credit rating, and the possibility of improvement/worsening in the rating or probability of default is being determined in this model. While the default causes a decrease in the value of the credit, the value of credit decreases either as its rating worsens (Diaz & Gemmill, 2011).

Credit Metrics is a tool used in estimating the future possible credit asset allocation due to the change in the credit value of the liable firm generally in an annual period. The 'change in the value' stands for the credit rating of the debtor passing from the existing rating to another rating at lower or higher direction as well as the probability of default. (Morgan, J.P., 1997).

The model randomly determines the distribution of the debtor based on ratings by making probability estimations for each rating; moreover, the value of the credit is re-calculated by using the forward premiums of the ratings and the portfolio value, which was calculated by adding these premiums. This model, which takes these assumptions into consideration, is generally known as a prospective model, it is only made up of the adaptation of transition matrices that do not depend on any economic or financial variables (Mérõ, 2003).

Moody's KMV model (The Merton model) is another widely used approach in modeling the credit risk based on the estimation of the probability of default. KMV model is a simulation application, which envisages separate ratings for each firm rather than an objective single rating and which explains that the past mean default ratios and transition probabilities significantly differ from the real ratios. Additionally, this model reveals through empirical implementations that significant differences may occur about default ratios in the same rating classification and overlapping can be realized in the probability of default range (Crouhy, Michel, Galai & Mark, 2000).

KMV, based on Merton Model for each debtor, obtains the expected default frequency; in this model, the probability of default is considered as a function of capital structure, return-on-assets variability, and current asset value of the company. The expected default frequency values are observed in a main listing of the probability of default of the debtor rather than more traditional listings such as AAA or AA that are suggested by the rating institutions.

In this regard, the third model is Credit Risk+ (Credit Suisse) where only the default risk is calculated, and this model has no assumptions about the default process. While it is assumed that the probability of default is the same for the credit in all periods, it is estimated through the Poisson distribution in the model.

The probability of a credit to be on conditional default is weighted according to the sectors, the realization of default is only a statistical probability. This model, which excludes the changes in the quality of credit by focusing on the losses due to non-repayment, is based on a method that is formulated according to the probability of default (Wehrspohn, 2002).

Credit Portfolio View (Mckinsey) Model is the fourth commonly used model for calculating credit risk. This model adapts the transition probabilities, matrices, and probabilities of default according to macroeconomic variables. The values differ according to the countries and sectors and based on the improvement/worsening in the economy, the credit ratings are reviewed.

Credit Portfolio View is an econometric model, which takes the macroeconomic environment into consideration as a determinant variable; for instance, the probability of default for a debtor with BBB rating is higher in the contraction periods compared to that of expansion period. Additionally, this is a multiple-factor model used for simulating the transition probabilities for the various rating groups in different sectors; moreover, it accepts that default is based on the values of macroeconomic elements for each country such as unemployment rate, Gross Domestic Product growth rate, long term interest rate, exchange rates, public expenditures, and total saving rate.

There are also some parameters such as Loss Given Default and Exposure at Default required to calculate expected loss and capital. To this end, Loss Given Default represents the economic loss emerging from the credit in case of a default of a debtor, and it is shown as a rate. Loss given default rate represents the unreimbursable part of the amount at default, in other words, the possible loss to become definite. In determining the Loss Given Default rate, there are two approaches as "basic" and "advanced". Within the framework of the "basic" approach, the estimations of the supervisory authority are used. In this approach, the loss given default is accepted as 45% for the prioritized and non-collateralized receivables, and 75 % for others. In the advanced approach, supervisory authorities permit the use of internal models for the forecast of loss given default rate. It is assumed that the data set to be used in the estimation should cover at least a complete economic period and the estimated data should not be less than 7 years.

Another credit risk parameter is Exposure at Default, which is the expected gross (economic) credit balance in case of a default of the debtor. While calculating the expected loss, the possible risk amount at the assumed date of default should be used instead of the risk amount at the calculation date. The risk amount in case of a default to be encountered in the future should be estimated considering the characteristics of each credit type.

2.3 IFRS 9: A New Model for Expected Loss Provisions

Started by the IASB after the 2008 crisis, the IFRS 9 Financial Instruments is a comprehensive financial reporting standards project, which is comprised of three phases, to replace the IAS 39 Financial Instruments: Recognition and Measurement. There are new regulations and amendments about classification and measurement in Phase-1, about impairment in Phase-2, and about hedge accounting in Phase-3 (IFRS 9 Financial Instruments-replacement of IAS 39). The whole of the mentioned project was concluded in July 2014, and IFRS 9 Financial Instruments was implemented in Turkey for the period starting on 1 January 2018 and afterward.

During the 2008 financial crisis, the delayed recognition of credit losses (impairments), emerged at the credit receivables and other financial assets, was defined as a deficiency of the accounting standards being used until then. The main reason for this mismatch is that the impairment conditions in the IAS 39 were based on the incurred loss model and it proposed to make provisions after a loss is incurred. In the incurred loss model, the recognition was not being employed upon credit default losses until the credit risk was realized, the existing model in the IAS 39 then, was presenting an opportunity of income management to companies via postponement of credit losses. The "too little and too late" criticism of FSB and G20 about the mentioned approach, urged the IASB to terminate its approach, which was considering only past for the loan loss provisions, and it encouraged the board to develop a forward-looking methodology. Thus, IFRS 9 became an approach named as expected loss model, which is based on expected losses and changes in credit losses. Contrary to the approach of IAS 39, which was merely based on the preceding provisions, IFRS 9 envisages benefiting from all existing and past data that might influence the cash flow estimations about the credit in the future.

IFRS 9 approach, which ensures making provisions in advance against impairments in credits, has more prudent practices compared to the IAS 39. Contrary to the IAS 39, IFRS 9 takes into consideration the macroeconomic predictions and calculated credit losses in the future (for instance, at the start of an expected crisis). Therefore, the profit and loss fluctuations emerging from the business cycle decrease. Through this approach, some opportunities are provided such as preventing the fluctuating course of bank profits and making capital adequacy assessments for longer terms. Additionally, a further opportunity arises such as receiving more information by the investors and depositors at the right time about expected credit losses of the bank.

In order to fulfill other deficiencies determined in the IAS 39 about the recognition of impairments, a 3-stage model was developed in the IFRS 9 for the expected loan loss provisions. The new model requires recognition of the expected credit loss in each reporting period, and it requires a review of expected credit losses according to the changes in the credit risk about the financial assets (IASB, 2014). IFRS 9 developed a credit provision model with two different methods named as 12-month and lifetime expected credit losses. The transition from the first stage to the second was hinged on a significant change in credit risk and in this case, a lifetime (for the remaining maturity period of the credit) expected credit loss assessment was envisaged rather than a 12-month expected credit loss assessment. It was defined as the third stage default status. Although there is not a conceptually deep basis for using 12-month periods in calculating the expected credit losses, IASB accepts this as an appropriate time period for the costs emerging from the implementation of expected credit loss estimation. It's because many institutions are using 12-month time periods based on IRB approach in calculation of credit risk capital requirements.

Loan loss provisions of IFRS 9 is quite similar to the IRB approach within the framework of Basel for the banks. Both of them are based on expected loss calculation. IRB approach requires the calculation of the expected loss through internal models. In Basel, the expected loss, as explained in the previous part, is the decrease in the value of the receivables in an annual period or the expected loss amount due to a possible default of the counterparty. While the Basel is based-on covering the expected losses through loan provisions like IFRS 9, it emphasizes that the capital is retained for the unexpected losses.

As mentioned before, there are two types of expected credit loss in IFRS 9 Financial Instruments as 12-month and lifetime. Although quantification of the lifetime expected credit losses has some differences from the 12-month expected credit losses, the expected credit losses can basically be calculated through formula 2.2 (KPMG, 2015).

The definitions of PD, LGD and EAD are basically the same as those in the IRB approach of Basel, and they were explained in detail in the previous part. However, the PD, LGD and EAD parameters, whose annual estimations were made in Basel, should be calibrated for IFRS 9. EIR represents the effective interest rate for the financial asset. In order to calculate the PD, LGD, and EAD parameters, each bank needs to establish its own internal credit rating system and should model the mentioned PD, LGD and EAD parameters through credit risk models such as Moody’s KMV, JP Morgan Credit Metrics and Credit Portfolio View (Macroeconomic Model).

2.3.1 IFRS 9 Impairment Model

IFRS 9 basically replaced the IAS 39 Financial Instruments: Recognition and Measurement. The replacement was employed in three phases. 1st Phase: Calculation and classification of the financial assets and financial liabilities; 2nd Phase: Impairment methodology, and the 3rd Phase: Hedge Accounting. The phase, which is the most important characteristic of banking institutions, with the strongest effect on the business processes is the impairment methodology phase. The new impairment methodology includes a framework calculating the expected credit losses (and thus, loss provisions) and it suggests a 'three-stage' model for the impairment due to changes in the credit quality after the first recognition:

1st Stage; It includes the financial instruments with low credit risk at the date of reporting. For these assets, the recognition of the expected credit losses for 12 months is employed and the interest revenue is calculated over the gross book value of the asset (in other words, without cutbacks for the loan provisions). 12-month ECL is the credit losses emerging from possible defaults in the 12 months after the reporting date.

2nd Stage; It includes the financial instruments, whose credit risk has a significant increase after the first recognition (as long as it does not have a low credit risk at the reporting date), but whose impairment was not proven with objective evidence. The recognition is employed as a lifetime for the ECL of these assets; however, the interest revenue is calculated over the gross book value. The lifetime ECL is the expected credit loss emerging from all possible default cases during the expected lifetime of the financial instrument.

3rd Stage; It involves the financial instruments with objective evidence about impairment. The recognition is employed as a lifetime for the ECL of these assets and the interest revenue is calculated over the net book value. For the amounts with decreasing credit value, the probability of default is 100% since the default has become realized and it is not used in the reserve accounts.

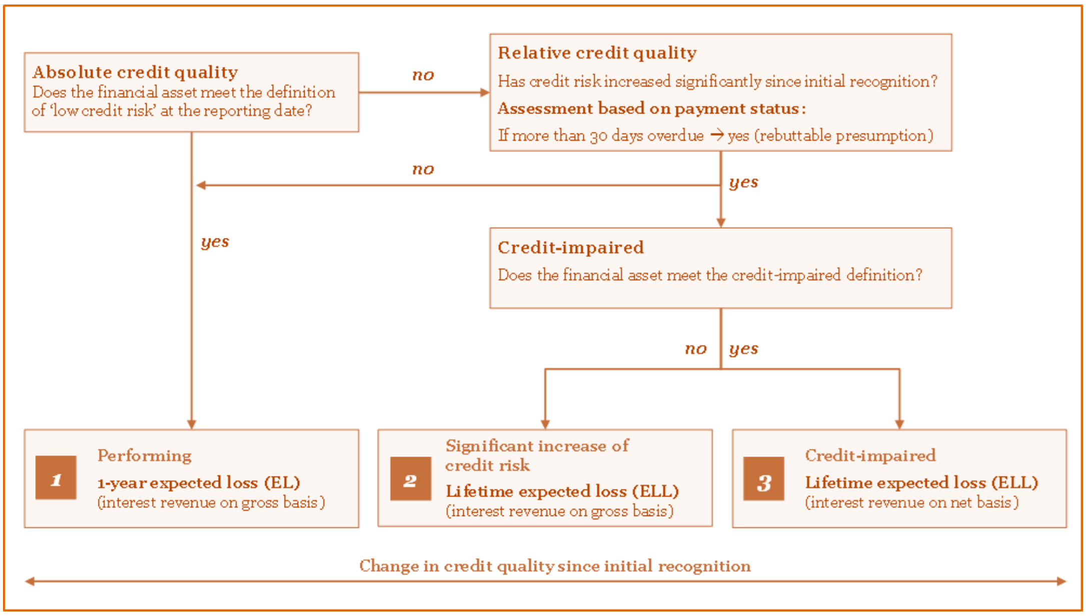

Figure 2.1 An overview of general impairment suggested by the IFRS 9

Source: PricewaterhouseCoopers (2014)

The aim of the impairment requirements is, considering the prospective data, the recognition of the lifetime expected credit losses of all financial instruments with significant increases in credit risks since the first recognition. Accordingly, it was revealed that banks needed to analyze credit default scenarios and credit loss risks based-on and sensitive to macroeconomic scenarios. The assessment whether the recognition of lifetime expected credit losses is needed or not for a financial instrument is based on significant increases in the probability of default or default risk since the first recognition.

2.3.2 Quantification of Credit Losses

While the 12-month ECL is estimated based on the PD, LGD, and EAD model elements for the 1st stage, the lifetime ECL is estimated based on very significant PD, LGD, and EAD model estimations for the 2nd and 3rd stages. IFRS 9 made consideration of prospective, credit specific, macroeconomic, and market-specific developments obligatory in the estimation of PD, LGD, and EAD model elements that are used in the quantification of the expected credit losses. However, it is remarkable that since the default case has become a reality in the 3rd stage ECL estimation, the probability of default cannot be modeled and it is included in the ECL calculation as 100%. Subsequent to the estimation of the model parameters, another significant point is to deduct the relevant discount factor, which reflects the time value of money, from the ECL value of each period. It is because, since the calculated expected loss represents the future value, it is emphasized that the present value of this amount should be calculated through the effective interest rate.

At 1st Stage of ECL calculation, the ECL for the 1st stage debts at the reporting date is calculated with the formula (2.2). In the formula, PD is the anticipatory PD of the debt for a year, while LGD is the Loss Given Default provided that the default takes place in the next year, and the EAD is the existing anticipatory Exposure at Default estimation provided that the default takes place in the next year.

At the 2nd Stage, the ECL for each period is calculated as follows:

$$ECL_t = PD_t \times LGD_t \times EAD_t \tag{2.6}$$

Where ECL_t is the ECL value for the t period, PD_t is the anticipatory PD of the debt for the (t-1,t] period, LGD_t is the anticipatory LGD estimation provided that the default takes place within the (t-1,t] period, and EAD_t is the anticipatory EAD estimation provided that the default takes place within the (t-1,t] period. In order to calculate the present value of the ECL estimation, a discount should be made from each period's ECL based on the effective interest rate of the amount:

$$ECL = \sum_{t=1}^{T} \frac{ECL_t}{(1+r)^t} \tag{2.7}$$

At the 3rd and the last stage of ECL calculation, interest revenues are to be reconsidered. Since the PD is 100 % for the amounts with a decreased credit value, the probability of default is not applied. The ECL is estimated based on normal LGD and EAD values. However, the difference between the 2nd stage and the 3rd stage is related to how the interest revenue will be recorded. The interest revenues in the 1st and 2nd stages are quantified over the gross book value. In the 3rd stage, the interest revenue is based on the netting-employed gross book value as provisions for losses.

2.3.3 Credit Risk and IFRS 9 Impairment Model Parameters

IFRS 9 creates a strong relationship between credit risk and accounting, influencing the economic results of the bank. There are some differences between the Basel III and IFRS 9, that are shown in the following table. Since, similar to Basel III, IFRS 9 is based on the expected loss approach, it will share the same infrastructure for the loan provisions. Because IFRS 9, in contrast with the IAS 39, has a prospective approach, it will attempt estimation through modeling, and therefore, it will benefit from the PD, LGD, and EAD models in the Basel III. However, there are some differences between the capital requirements standards based on Internal Ratings Based Approach published by the Basel Committee of Banking Supervision and the model shaped in the IFRS 9 published by the International Accounting Standards Board.

At this point, it is highly important to outline the definition of default. According to the law, the debtor is accepted in default:

i) in case the bank believes that, without guarantees, the debtor is not going to be able to repay the complete debt and/or

ii) in case the debtor is over 90 days overdue in fulfilling his/her significant amount of liabilities to the bank

According to IFRS 9, there is a rebuttable presumption that the default will not emerge after the 90 days overdue of the financial instrument, as long as there is no reasonable and supportable information about that default emerges in case of a longer overdue. The definition of default in IFRS 9 complies with credit risk management practice.

Table 2.2 BASEL III and IFRS 9

PARAMETERS	**BASEL III**	**IFRS 9**
Default Definition	Definition based on the number of overdue days (>90) and solvency	Complying with the credit risk management practice - assuming that the default emerged during the period of 90 overdue days
PD Model		
To be estimated	The average loss ratio for the next 12 months	The loss ratio expected for 12-month or for lifetime
The period is taken into consideration in the modeling	The historical data should be as large as including at least one economic cycle. Thus, the probability of default estimations should be Through-the-cycle.	It is necessary that the expected loss should reflect the current conditions, far from good and bad scenarios. Thus, the probability of default estimation should be point-in-time.
LGD Model		
To be estimated	Average estimation of the amount to be collected after default (should reflect the 12-month period)	It is the estimation of the amount to be collected after the default, and it is determined according to the terms left. (For the rest of the asset life)
The status of cost of collection	Direct and indirect, all the costs are taken into consideration.	It only takes into consideration the direct costs.
Exposure at Default	The risk amount in the 12-month period	It requires the calculation of the cash flows during the lifetime of the financial instruments and it should reflect the early payment and early termination.

Source: Avul (2018)

There are some points to consider in PD modeling. The PD estimations are employed through either Point-in-time or Through-the-cycle. The PDs are generally estimated through-the-cycle under the Basel framework due to the demanded low volatility level of the credit risk capital requirements (economic fluctuations are neutralized). However, the PD estimations under IFRS 9 should be rather "real-time", and thus, including the prospective information (particularly macroeconomic predictions), they should be point-in-time. Another important point is that the current PD model should caliber the maturity structure in order to reach the lifetime expected credit loss rate.

Paying attention to certain issues in LGD Modeling is also needed. Similar to the PD model, the maturity structure should be calibrated in the LGD model to reach the expected credit loss ratio. Additionally, the indirect costs considered in the LGD model should be eliminated for the model that will be calculated in terms of IFRS 9.

$$LGD = \frac{EAD - Collection\ Amount + Costs}{EAD} \tag{2.8}$$

According to Basel; Costs = direct + indirect expenses

According to IFRS 9; Costs = direct expenses.

While calculating the parameter Exposure at Default some points are to reconsidered. Although the calculation of Exposure at Default is pretty much similar in IFRS 9 and Basel, within the framework of IFRS 9, it is necessary to determine the EAD value considering the cash flow expectations of each financial instrument for each period, and historical course information (early payment or early termination) should also be included into the calculation.

CHAPTER 3

METHODOLOGICAL FRAMEWORK

This study seeks to identify key macroeconomic determinants of the probability of default for the Turkish banking system and formulate econometric models capable of describing and predicting their movements. Such a model will improve the precision of balance sheet values and be a useful aid in allocating provisions.

Various models have been developed to model the probability of default and have been put into implementation by banks. Among such models, the Credit Portfolio View (CPV) model is an approach that is commonly used for forecasting the probability of default employing macro variables (Wilson, 1997a, 1997b, 1998). In the present study, by assuming that improved macroeconomic conditions will reduce credit risks, the macroeconomic variables with possible impact on the probability of default will be identified and an econometric model will be established.

Since this study aims to detect the short-run as well as the long-run relationships between probability of default and macro variables, the Autoregressive Distributed Lag (ARDL) approach (Pesaran & Shin, 1999) will be employed to capture the long-run relationship and the short-run dynamics for the probability of default and its determinants. The existence of a long-run / cointegrating relationship will be tested based on the Error Correction (EC) representation. The ARDL / EC model is useful for forecasting and to disentangle long-run relationships from short-run dynamics.

3.1 Credit Portfolio View Conceptual Framework

Credit Portfolio View is a model with multiple factors that are used to link default probabilities to macro variables. The model was developed by Wilson within McKinsey. The approach developed by this author bases itself on the hypothesis that the probability of default is connected to macroeconomic factors such as the growth rate of the GDP, interest rate, unemployment rate, the exchange rate or the inflation ratio.

While in the growth/expansion phase of the economy, a decrease is observed in the cases of credit default; an opposite trend is observed in the recession. In other words, the cycles of credit follow the tendency of economic cycles. Because the state of the economy is widely driven by macroeconomic factors, CPV proposes a methodology to connect these macroeconomic factors to the probability of default.

CPV model has three main steps.

1) Logistical Conversion: Primarily, the historical default rates are converted into logistical forms; thus, the macroeconomic index series is obtained which reflects the general condition of the economy. Index is a time series that is highly negatively correlated with default rates (for instance, default rates decrease while the macroeconomy improves, and the index increases). The logistical conversion ensures breaking the linearity between the probability of default and independent variables.

2) Credit risk model: In the Wilson model, the macroeconomic index-based variable obtained through the conversion in the logistical form is used instead of default rates; as per the macroeconomic factors, they are used as the independent variables. In the linear estimation equation, the part that is explained by the macroeconomic variables represents the systematic credit risk, and the error terms represent the specific credit risk.

3) Macro Model: Wilson suggests univariate second-level autoregressive (AR(2)) equations for estimating the values to be gained in future periods by a macroeconomic variable used in explaining the macroeconomic index (thus, the default rates). In other words, each independent variable will be explained by the first and second lag of its value. The unexplained part that is represented by the error terms will reflect the impact of other factors. However, in practice, it is observed that various methods can be preferred instead of AR(2).

In the process of forecasting the default rate in the Credit Portfolio View model, the probabilities of default are modeled as being a Logit function. The Logit function allows that the values of probability of default are included between 0 and 1 and this is exactly what we need for something to be considered as a probability.

$$p_{j,t} = \frac{1}{1+e^{-Yj,t}} \qquad (3.1)$$

Here, $Y_{j,t}$ is an index value derived using a multi-factor regression model that considers a number of macroeconomic factors, j representing the industry or the country and t the time period. $P_{j,t}$ varies between 0 and 1, and indicates the probability of default. From equation 1, the value of macro index given default rate is calculated as:

$$y_{j,t} = \ln\left(\frac{1-Pj,t}{Pj,t}\right) \qquad (3.2)$$

In order to find the empirical link to macro variables, the transformed default rate is assumed to be determined by a number of macro variables as shown by equation 3.3.

$$y_{j,t} = \beta_{j,0} + \beta_{j,1} X_{1,t} + \beta_{j,2} X_{2,t} + \ldots\ldots + \beta_{j,n} X_{n,t} + \varepsilon_{j,t} \qquad (3.3)$$

$\beta_{j,0}, \beta_{j,1}$ ... $\beta_{j,n}$ are coefficients to be estimated by the method of Ordinary Least Squares (OLS). $X_{1,t}$, $X_{2,t}$, … , $X_{n,t}$ are values of economic variables (GDP, unemployment rate, exchange rate etc.) in the date t of the industry or the country j. $\varepsilon_{j,t}$ represents a term of error which is identically normally distributed and independent of $Y_{j,t}$. In the equation, the systematic effect is captured by macroeconomic variables $X_{i,t}$ (i = 1,2,…,n), and $\varepsilon_{j,t}$ defines a sector or country-specific effect.

As the next step, the evaluations of individual macro variables are modelled by using ARIMA models. For this step, Wilson (1997) originally used an Autoregressive model of order 2 (AR2) but added that different ARMA structures or even any type of model could be used.

$$x_{i,t} = \gamma_{i,0} + \gamma_{i,1} X_{i,t-1} + \gamma_{i,2} X_{i,t-2} + \omega_{i,t} \tag{3.4}$$

where $\gamma_{i,0}, \gamma_{i,1}, \gamma_{i,2}$ are coefficients to be estimated and $\omega_{i,t}$ is a term of error that is normally distributed and independent of $X_{i,t}$.

3.2 The Literature on Macroeconomic Variables

The relationship between credit risk modeling and conjuncture has become a rising mainstream in credit risk literature lately. Allen ve Saunders (2004) made extended micro-level research trying to explore the cyclical effects on the probability of default, loss given default and exposure on default accepted as basic components of credit risk. It has been revealed that all of these variables were affected by cyclical situations and cyclical fall downs had important implications over the parameters according to the study.

Empirical studies have looked into the linkage between NPLs and business cycles. Marcucci and Quagliariello (2008) used the Italian banking sector input over the period of 1990-2004 and employed Vector Auto-Regression (VAR) to examine the effects of changes in the business cycle on the repayment capability of loans. They proved that NPLs follow a cyclical pattern, increase during boom and decline during depression.

Arpa, Giulini and Pauer (2001) investigated the banks’ provisions whether they were associated with operating income by employing Austrian banks' data. They conducted regression analysis and found that risk provisions share in total banking sector loans have a negative relationship with real interest rate and real GDP growth, whereas provisioning varies positively with real estate price inflation and consumer price index.

Kalirai and Scheicher (2002) studied the credit risk dependency on the macroeconomic variables over the period of 1990-2001 by employing simple regression analysis. They selected real GDP, CPI, industrial production, money growth, stock market indices, interest rates and other macroeconomic variables as explanatory variables. It is understood that interest rates, stock market indices, industrial production and business confidence index are significant factors in the measurement of the loan quality.

Shu (2002) applied to a similar model as Kalirai and Scheicher (2002) to investigate the relation between macroeconomic variables and loan quality. They took Hong Kong data over the period of 1995-2002 and realized that an increase in interest rate has a considerable positive impact on NPLs, whereas growth in CPI, real GDP and property prices has a significant negative impact on NPLs. They deduced that the performance of equity prices and unemployment had little impact on NPLs.

Babou. ek and Janèar (2005) employed Czech banking data over the period of 1993-2004 to investigate the impact of macroeconomic development, represented by unemployment, exports, imports, real GDP growth, CPI, credit growth rate and real effective exchange rate on the NPLs by the help of unrestricted VAR model. They suggested a positive relationship between NPL and CPI and unemployment. They also inferred that appreciation of real effective exchange rate has no effect on NPLs, whereas growth in GDP reduces the NPLs level.

Gerlach, Peng and Shu (2005) resorted to regression analysis by using Hong Kong statistics and regressed NPLs against nominal interest rates, equity prices, CPI, number of bankruptcies, property prices, real GDP and the unemployment rate. The results showed that an increase in nominal interest rates and bankruptcies raised the NPLs ratio, whereas an increase in economic growth, CPI and property price inflation lowered the NPLs ratio. They also found that deflation in the economy undermines the economic growth, subsequently harming the profitability and inhibiting the debt-paying ability of borrowers.

Babihuga (2007) compiled the data of Asian, European and Sub-Saharan African countries to draw attention to the linkages between financial stability indicators and macroeconomic variables. He regressed NPL data over banking sector regulations, business cycle component of GDP, terms of trade, real lending rates, unemployment, and real effective exchange rate. The results suggested that financial stability indicators (capital adequacy, profitability and asset quality) are strongly dependent on phases of the business cycle. On the other hand, the inflation rate and real GDP have a negative impact on NPLs.

Jakubík (2007) made an econometric analysis to measure the impact of a set of explanatory variables such as real GDP, the loan to GDP ratio, real effective exchange rates, unemployment, real interest rate and CPI on the dependent variable NPL by employing Czech Republic banking sector input. The results pointed that corporate default rate is significantly determined by the growth in loan to GDP ratio and real effective exchange rate appreciation whereas, in the case of households, growth in the interest rate and unemployment leads to deterioration in NPLs.

Recognized Credit Portfolio View adaptations mostly consist of the studies made by central banks due to credit risk stress tests. To exemplify, Boss (2002), an employee in the Austrian Central Bank, established three separate credit risk equations including corporations, household and exporters. The macro index series retrieved after logistic transformation of historical default rates have been employed in the model and inflation, Austrian stock index, interest rates and oil prices were selected as explanatory macro variables in the linear estimation equation generated by the least-squares method. Apart from these, macro variables specific to sectors have been added to the equation. Fixed asset investments, disposable income and exportation amount were selected as independent variables to the corporation, household and exporter models respectively. Interest rates and oil prices affect the probability of default negatively whereas inflation and stock index have a positive impact. Selected specific variables also vary with PD positively. AR (2) process has been used for explanatory macro variables as Wilson suggested.

Virolainen (2004) from Finland Central Bank determined the macroeconomic variables which affected the credit risk the most as notably GDP, interest rates and corporate debt, additionally inflation, production, reel wages, oil prices and stock indices in the macroeconomic credit risk modeling and stress test prepared for Finland commercial sector. The macro index series retrieved after the logistic transformation of historical default rates related to the commercial sector have been employed in the model. Estimations were built by Seemingly Unrelated Regression. A negative relationship between GDP and PD was detected, on the other hand, a positive relationship between interest rate, indebtedness ratio and PD emerged. AR (2) process has been used for explanatory macro variables as Wilson suggested.

Wong, Choi and Fong (2006) from the Hong Kong Monetary Authority used PD as a dependent variable in logistic form. Moreover, real GDP ratios for China and Hong Kong, real interest rates and real estate price index for Hong Kong has been employed as independent variables. Estimations were built by SUR method. A negative relationship between GDP, real estate price index and PD was detected, on the other hand, a positive relationship between interest rates and PD emerged.

A Credit Portfolio View version introduced by Otani, Shiratsuka, Tsurui ve Yamada (2009) from Japan Central Bank has been employed in macroeconomic credit risk models in the Central Bank since 2007. Real GDP, consumer price index, total loan amount, nominal exchange rate and money market rates were included in the VAR model as macroeconomic factors.

Avouyi-Dovi, Bardos, Jardet, Kendaoui and Moquet (2009) from the French Central Bank generated only one VAR model for the macro index produced by the logistic transformation of historical default rates. The real GDP growth in logistic form, 3-month nominal interest rates and credit spreads reflecting the difference between corporate bonds and the risk-free rate has been added to the model as macroeconomic variables. Equations acquired from VAR (1) model were used in the estimation of default rates and explanatory variables. In other words, four variables in the model are explained with the one lag of both their own and other variables.

3.3 A Short Introduction of the ARDL Model

Modeling time series in order to keep their long-run information intact can be done through cointegration. However, long-term relationships cannot be investigated when some series are stationary while others not. That is, cointegration involves a certain stationary linear combination of variables that are individually non-stationary but integrated to order, I(d). Cointegration is an econometric concept that mimics the existence of a long-run equilibrium among underlying economic time series that converges over time. Traditionally, the cointegration tests of Engle-Granger (1987), Phillips and Ouliaris (1990), Park (1990), or Johansen (1991; 1995), typically require all variables to be I(1). To overcome this problem, Pesaran, Shin and Smith (2001) in the econometrics literature in their study on England propose a test for cointegration that is robust when dealing with variables that are integrated of a different order, I(0), I(1) or combination of the both. (Pesaran, etc., 2001).

Cointegration is concerned with the analysis of long-run relations between integrated variables and reparameterizing the relationship between the considered variables into an Error Correction Model. The ARDL cointegration technique is used in determining the long-run relationship between series with different order of integration. Autoregressive Distributed Lag (ARDL) cointegration technique or bound test of Cointegration is based on the estimation of an Unrestricted Error Correction Model (UECM) with the Ordinary Least Squares (OLS) method. Unconstrained error correction model can be expressed as follows:

$$\Delta y_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta y_{t-i} + \sum_{i=0}^{p} \beta_{2i} \Delta x_{t-i} + \beta_3 y_{t-1} + \beta_4 x_{t-1} + e_t \qquad (3.5)$$

Where β_0 is the drift term, the terms with the first-order difference operator ("Δ") represent short-run dynamics and the terms with β_3 and β_4 correspond to the long-run relationship. Lastly, "p" represents the lag length of the model.

The choice of the appropriate lag length is crucially important for the ARDL procedure. To this end, Akaike Information Criterion (AIC) or the Schwarz Bayesian

Criteria (SBC) information criteria are often used. At the selected lag length, the model should not have autocorrelation in the error terms. Therefore, if the model created with the lag length of the selected critical value has autocorrelation problem, then the lag length that provides the second smallest critical value is taken, if the problem of autocorrelation is still ongoing, this process should be continued until the problem is resolved. To test for cointegration, the following hypotheses are considered:

$H_0: \beta_3 = \beta_4 = 0$ (null, i.e. the long-run relationship does not exist) (3.6)

H_1: At least one different from zero (Alternative, i.e. the long-run relationship exists) (3.7)

The long-run relationship of the underlying variables is detected through the F-statistic (Wald test). Once the test statistic is computed, it is compared to two asymptotic critical values. These critical values consist of two parts: while the first one is assumed to be I(1) and the other is assumed to be I(0). In this case, a range is formed between these values. If the calculated F-statistic exceeds the upper limit, the null hypothesis is rejected. Otherwise, if the calculated value is below the lower limit, the null hypothesis is not rejected. However, it is not possible to reach any result if the calculated value is between the range. In short, if the calculated F-statistic value is above the upper limit, there is a cointegrated relationship.

It is necessary to estimate the appropriate ARDL model to reveal long-term and short-term relationships after it has been determined that there is a cointegrated relationship between the variables. The long-term relationship between variables can be expressed as follows:

$$y_t = \beta_0 + \sum_{i=1}^{q} \beta_{1i}\, y_{t-i} + \sum_{i=0}^{p} \beta_{2i}\, x_{t-i} + e_t \qquad (3.8)$$

The parameters of the ARDL model should be estimated if there is a long-term relationship. In the equation above, q represents the lag length of the dependent variable (Yt), and p is the lag length of the independent variable (Xt). The model to be estimated is expressed as ARDL (q, p). ARDL (q, p) model should be estimated based on R Square, Akaike Information Criterion (AIC), Schwarz Bayesian Criteria (SBC) and Hannan-Quinn (HQ).

After finding the long-term parameters between the variables, the short-term relationship can be found with the error correction model based on the ARDL method. The error correction model based on the ARDL method is expressed as follows:

$$\Delta y_t = \beta_0 + \sum_{i=1}^{q} \beta_{1i} \Delta y_{t-i} + \sum_{i=0}^{p} \beta_{2i} \Delta x_{t-i} + \beta_3 EC_{t-1} + e_t \quad (3.9)$$

In the above equation, the ECt-1variable is the one period lagged error-correction term derived from the long-run cointegrating vector. The β3 parameter in the ARDL model indicates that there is an error-correction mechanism driving the variables back to their respective steady-state after a temporary shock and is called the speed of adjustment parameter. When this parameter is found to be significant, it is stated that the model expressing the short-term relationship between variables can be used as long-term and long-term relationships between variables are valid. The equilibrium/error term coefficient β3 must be negative and significant to represent adjustment towards equilibrium. Finally, several diagnostic tests should be conducted to assess the goodness of fit of the chosen model specification, including the test for serial correlation, normality and heteroskedasticity. We also examine model stability by inspecting the plot of the cumulative (CUSUM) and cumulative sum of square (CUSUMSQ) statistics. This approach assesses the parameter stability of the chosen specification.

3.4 The Data and Variables

The independent variables to be investigated within the scope of models to predict the probability of default for Turkish banking system based on macroeconomic variables will be chosen from macroeconomic data set that has been found to affect credit risk in the current literature and from the data set which will be determined by evaluating the structure of Turkish economy. Considering that the probability of default variable subject to the study covers balance sheet periods, it has been decided that the frequency should be quarterly and the data between 2007 and 2018 years have been analyzed.

The time interval which is the period in which all the selected variables have been shared covering the first quarter of 2007 and the last quarter of 2018, has been chosen as the data set period. Time series data used in the study has been compiled from the data distribution systems of Central Bank of the Republic of Turkey (CBRT), Banking Regulation and Supervision Agency and Bloomberg Terminal. The analyses have been performed with Eviews 10 software pack.

3.4.1 Probability of Default

The most important variable in the models is the probability of default variable, which is used in the credit risk assessment and will be estimated within the scope of the model. The reason that will be explained in detail in Chapter 2, the probability of default concept is used as an input factor by the Basel Committee on Banking Supervision's Internal Rating Based method, which determines the minimum capital requirements of banks with its own internal evaluation system.

The probability of default is not only a credit risk parameter but it is also used as an important parameter in the IFRS 9 Expected Loss Provision Model issued by the International Accounting Standards Board. IFRS 9 is an approach that enables provisioning of impairment for loans before default and will attempt to make an estimate of the modeling, as it is adopted as a forward-looking approach. In summary, the probability of default constitutes one of the three basic parameters required to calculate credit risk capital requirements within the IRB approach as well as to allow IFRS 9 to be set aside for loan loss through the Expected Loss Provision Model. (The other two parameters are Loss in Default and Exposure at Default) Therefore, an accurate estimation of the probability of default enables banks to effectively manage their balance sheets and economic policies.

The data set proposed to be used as a probability of default in the literature is the historical default rates in case of existence and these rates can be calculated by two different methods.

$$1)\ \text{Default Rate} = \frac{The\ Number\ of\ Customers\ in\ Default\ within\ the\ Period}{Total\ Number\ of\ Customers\ At\ The\ Beginning\ of\ Period} \quad (3.10)$$

$$2)\ \text{Default Rate} = \frac{The\ Amount\ of\ Credit\ in\ Default\ within\ the\ Period}{The\ Total\ Amount\ of\ Credit\ at\ the\ Beginning\ of\ the\ Period} \quad (3.11)$$

However, in the absence of the historical default rates based on the number of customers or the amount of credit, the account-based “Nonperforming Loans Ratio” is used as a substitution data which is calculated by dividing of nonperforming loans to total loans within periods. In this study, a historical nonperforming loans ratio will be used to substitute historical default rates as shown in the following equation. (Altıntaş, 2012)

$$\text{Non-performing Loans Ratio} = \frac{Non-performing\ Loans\ by\ the\ End\ of\ Period}{Performing\ Loans\ at\ Beginning\ of\ Period\ (Prior\ Period)} \quad (3.12)$$

The amount included in the numerator of the NPL ratio presented in the equation is the gross sum of the loans (principal and interest) under the administrative or legal proceedings which installment payments are delayed at the end of a certain period and the average default rate of exposure to the total risk amount multiplied by the total amount of risk (PD * EAD) is considered as the resulting balance. The denominator denotes the total risk amount (EAD) in the case of accounting-based default. Consequently, the non-performing loan ratio can be used as an indicator of the average default rate in an environment where historical default rates cannot be reached.

The average gross follow-up credits, calculated on a quarterly basis, are divided into the average total loan balance regarding the previous three months due to the fact that there is a minimum period of three months between the use of loans and transition to follow-up situation. In the denominator of the ratio, the reason for not using the total loan amount by adding the non-performing loans to the normal loans is to avoid the assumption that the loans that have already been followed up in the previous period may be in default again in the current period. (Altıntaş, 2012)

Given the classification of loans in the banking sector by the BRSA as corporate, SME and consumer loans, the non-performing loans ratio calculation was conducted separately for SME and consumer (household) loans, and analyses and examinations were conducted under two headings as SME and Consumer.

3.4.2 Development of Nonperforming Loans in Banking Sector

Considering the classification of loans as corporate, SME, and consumer loans in the banking sector, the following analysis was made with this classification.

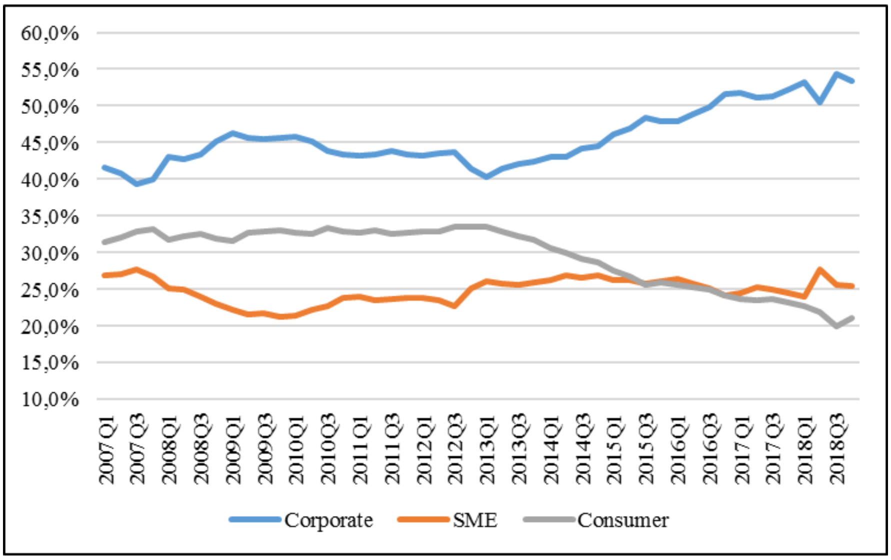

Figure 3.1 Distribution of the Loans in Turkey, by Credit Types, %

Source: BRSA.

When we look at the distribution of the loans in Turkey by credit types, in terms of corporate, SME and consumer loans; In the same period, the share of corporate loans, which was 39.95% in 2007, followed a horizontal course with slight fluctuations up to 2012, and reached an upward trend as of that date and reached

53.4% in 2018. The share of consumer loans followed a flat course until 2012 as in the corporate loans series, but by 2012, the share of 33.45%, which followed a downward trend in the economy, declined to 21% in 2018. The share of SME loans remained stable only with a slight decrease in the given period.

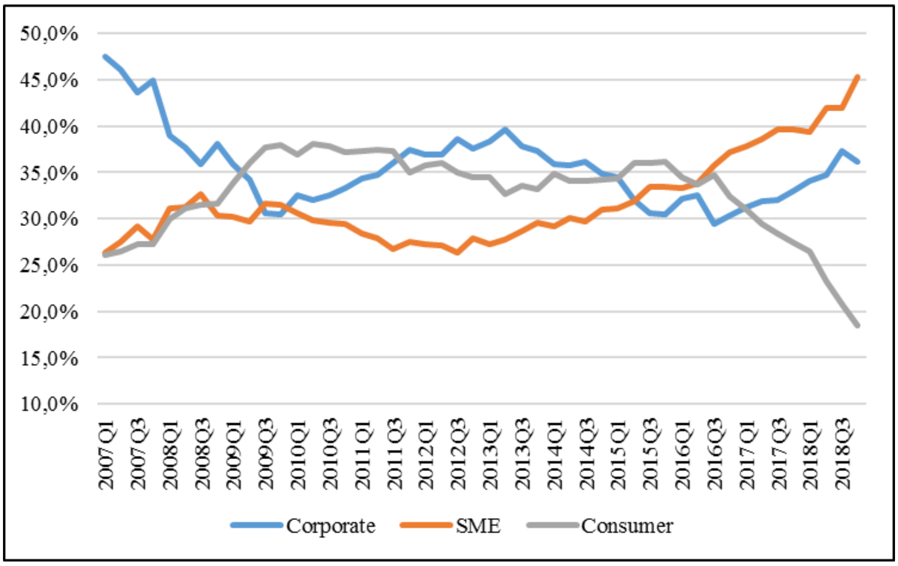

Figure 3.2 The Share of Non-Performing Loans by Credit Types, %

Source: BRSA

The share of corporate, consumer and SME loans in the non-performing loans is high, respectively. In 2012, there was a sharp increase in SME loans and a sharp decrease in consumer loans by 2017. The non-performing SME loans started to decline in the third quarter of 2009 until the end of 2012. Since then the share of SME loans in non-performing credits has been on the rise. On the other hand, After a rise till 2010 in the share of non-performing credits, non-performing consumer loans followed a horizontal course with slight fluctuations down until 2017.

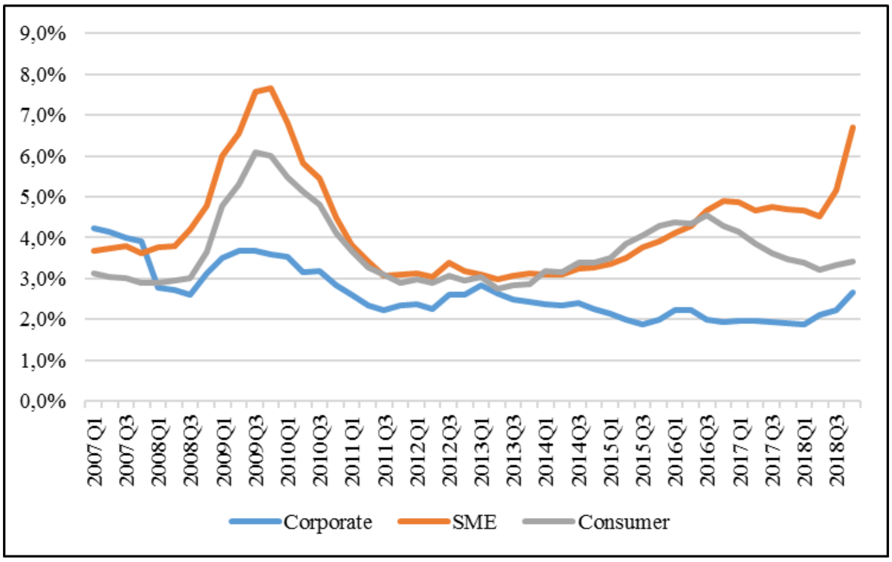

Figure 3.3 The ratio of Non-Performing Loans, %

Source: BRSA

As of the last quarter of 2018, the NPL ratio is the highest in SME loans, followed by consumer loans. The non-performing loan ratio for the SME loan portfolio was highest in the period of 2007Q1-2018Q4 with a rate of 7.64% (2009Q4) and the lowest with a figure of 2.97% (2013Q2). For the consumer loan portfolio, the highest non-performing loan ratio was 6.1% (2009Q3) and the lowest was 2.74% (2013Q2). The rates, which tend to increase in general terms in all loan portfolios due to the global crisis in the 2007Q1-2009Q3 period, have started to decline again after the decreasing impact of the global crisis since 2009Q4. While the downward trend for corporate loans portfolio continued until the last quarter of 2018, it has started to increase again in the SME and consumer loan portfolios by 2013 and continued its development until the last period.

3.4.3 Nonperforming Loans as Dependent Variable

The dependent variable that will represent the probability of default in the linear regression model is the index series that will be obtained by the logistic transformation of the historical non-performing loans ratio. In the following equations, the non-performing loans ratio is calculated as it is stated in equation 3.16 and the ratio is converted into logistical forms.

$$\text{INDEX} = \ln(\frac{1-NPLt}{NPLt}) \tag{3.13}$$

INDEX is a time series that is highly negatively correlated with the non-performing loans ratio. Correlation coefficient between INDEX and NPL series is - 0,9804 for SME loans and - 0,9816 for consumer loans. INDEX reflects the general situation of the macroeconomy in the country and as the situation of the economy improves, the INDEX gets higher values. The higher value of the INDEX means that the NPL decreases. The conversion of the INDEX variable predicted by the linear regression equation to the NPL will be made by the following formula:

$$\text{NPL} = \frac{1}{1+e^{-INDEXt}} \tag{3.14}$$

As previously explained, the purpose of the logistic transformation for the dependent variable is to ensure breaking the linearity between the macro shocks and the non-performing loans ratio.

3.4.4 Macroeconomic Variables

All indicators affecting the economy in macroeconomic markets will also have an impact on the banking sector. The risk factors that have the power to explain the systematic part of the credit risk (cannot disappear by diversification) are not an unlimited number, as shown in the previous literature, GDP growth, interest and inflation rates, unemployment rates and exchange rates are the basic macroeconomic variables that are expected to explain the systematic credit risk. When the different types of loans are analyzed in risk analysis, more specific macroeconomic variables can be used to differentiate the credit risk according to the type of credit. However, it should be taken into consideration that the explanatory macro variables preferred in the credit risk methodology should be among the main elements suitable for stress tests, in other words, the variables should describe the macroeconomic scenario and control the stress test results.

Gross Domestic Product (GDP) Growth is one of the most important variables that determine the probability of defaults. The growth rate in GDP is expected to affect every economic unit as it is an indicator that reflects the economy in its entirety. Real economic growth increases the possibility of debtors to pay their debts. Overall, the volume of non-performing loans (NPLs) is decreasing under better financial conditions of households and companies.

On the contrary, the volume of loans that cannot be paid up in economic downturns increases and economic actors have problems paying their debts. We consider “seasonally and calendar adjusted chain-linked volume index and percentage chain” real GDP variable over the 2007-2018 period. The GDP variable data are from Turkish Statistical Institute (TSI).

Another variable in the model is Industrial Production Index. The production index is a business cycle indicator that aims to measure changes in value added at factor cost of the industry for a given reference period. The index is closely related to economic growth. Therefore, if there is an increase in the industrial production index, the nonperforming credits become negatively affected and the non-performing loans ratio is expected to decrease.

Another important variable for an economy is the interest rate. Higher interest rates increase the debt burden by increasing interest payments. In general, the higher the interest rate, the more difficult it is to pay the customer's debt. However, it should be noted that the effect of interest will be different for consumer loans and for companies. The real sector firms with a high rate of debt will increase their financing costs and will have difficulty in paying their debts in time when interest rate rises. In the long term, the quality of credit users will deteriorate. Therefore, higher interest rates should increase the NPL ratio of companies. As the borrowing costs are fixed in consumer loans, it would be more accurate not to expect a direct increase in NPL ratio when interest rate increases on individual loans. In this study, we consider the "average interest rates applied to banks' loans", of the Central Bank of Turkey.

The Real Exchange Rate Index, which is nominal exchange rates adjusted for domestic and foreign inflation rates, is among the most important macro variables that can describe the effect of the foreign currency on the default rates. The effect of the increase in exchange rates (or the decline in the real exchange rate index) on the default rates is generally expected to be negative. The real exchange rate index can be used to represent the risk factor in the analysis for SMEs. Within the scope of the amendment, published in the Official Newspaper dated 16.08.2018, it is prohibited to use foreign currency and foreign currency indexed loans to the consumers. Therefore, in the Turkish Banking System, 100% of the cash loans used by the consumers are TL loans and the analysis made for the consumer loans in the exchange rate is not included in the macroeconomic variables that explain the NPL ratio. We consider the CPI-Based Real Effective Exchange Rate (2003 = 100) series of the Central Bank of Turkey in the analysis for SMEs.

The inflation rate may be another important determinant for the probability of default. In general terms, inflation is the transfer of welfare from the lender to the borrower, because over time, the value of the loan falls. Therefore, as high inflation helps borrowers to pay their debts, there is a perception that there is an inverse relationship between inflation and NPL ratio. Considering the fact that the rise in inflation is expected to increase the ability to pay the debt for the consumers, it is expected that inflation will have a negative effect on the NPL ratio. The annual percentage change of the Consumer Price Index (2003 = 100), which was announced by TSI for the inflation rate used as an explanatory variable in the analysis for the individual loans.

The unemployment variable should be particularly important for the household sector. When the unemployment rate rises, the number of people who will have difficulty paying their debts due to decreasing levels of welfare will be larger. Therefore, a positive relationship between unemployment and NPL should be expected. We consider the unemployment rate series of TSI in the analysis for consumer loans.

The Volatility Index (VIX), is a real-time market index that represents the market's expectation of 30-day forward-looking volatility. It is often seen as the best gauge of 'fear' and uncertainty in the market. The high volatility index indicates financial stress, which is often accompanied by steep market declines. The volatility index variable should be very important, especially for SMEs. We consider the VIX variable data from Bloomberg.

Besides basic macro indicators in this study, domestic consumption, capacity utilization ratio, foreign trade indicators, consumer confidence index, Turkey Credit Default Swaps (CDS) have been tested as other indicators. Whereas some of these indicators (domestic consumption, capacity utilization ratio, industrial production index) are leading indicators or derivative of the real GDP data, the correlation between those variables and NPL has the expected sign.

CHAPTER 4

EMPIRICAL RESULTS BASED ON THE ARDL APPROACH

Given the classification of loans in the banking sector by the BRSA as corporate, SME and household loans, the non-performing loans ratio calculation was conducted separately for SME and household loans, and analyses and examinations were conducted under two headings as SME and households.

4.1 PD of Households

The main purpose of this section is to examine the relationship between the probability of default of consumer loans and selected macroeconomic variables. In light of this aim, various quantitative models including many macroeconomic variables were tested broadly in scope with regard to the probability of default which is calculated by non-performing consumer loan ratio and used as the dependent variable in the analysis and what are the macroeconomic variables affecting the PD. Inappropriate variables were removed and the fittest models were put forward. Within this context, the impact of inflation, industrial production growth and unemployment rate data over non-performing consumer loans was measured.

Correlation analysis was employed to analyze the relationship between the selected macroeconomic variables and the corresponding correlation coefficients were calculated in order to determine whether the variables move together. These coefficients are in the correlation matrix of Table 4.1.

Table 4.1 Correlation of Employed Macroeconomic Variables (2007q1-2018q4)

	Growth	**Inflation**	**Unemployment**
Growth	1	-0.0773	-0.5182
Inflation	-0.0773	1	-0.0122
Unemployment	-0.5182	-0.0122	1

The consequence of high correlation is called multicollinearity and it might cause problems in estimation. Accordingly, the correlation coefficient between the explanatory variables is expected to be below the acceptable limits. When Table 4.1 is examined, it is seen that the correlation between the variables is low.

Before going to a statistical analysis of a time series, the concept of stationarity of the series that will be included in the developed model should be investigated. A non-stationary time series is a stochastic process with unit-roots or structural breaks. Empirical studies so far have revealed that most of the macroeconomic time series are non-stationary. In the establishment of econometric models with non-stationary series, Granger and Newbold (1974) stated that the problem of spurious regression may occur. When the problem of spurious regression is encountered among the series containing unit-roots, various methods have been proposed to find a solution. One of these suggestions is to take the differences in the series. However, in this case, a new problem is encountered and leads to the loss of information that is important for long-run relationships.

The ARDL method has been extensively utilized as it has several advantages for the assessment of cointegration and short/long-run relationships. Firstly, in contrast to the other methods such as Granger (1981) and, Engle and Granger (1987) cointegration analysis, ARDL cointegration technique can be utilized to test for a level relationship for variables that are either I(0) or I(1) as well as for a mix of I(0) and I(1) variables.

Moreover, most cointegration techniques are sensitive to the sample size while the ARDL method provides robust and consistent results for small sample sizes (Pesaran & Shin, 1999, Pesaran et al., 2001).

Lastly, Pesaran and Shin also note that unlike other methods of estimating cointegrating relationships, the ARDL representation does not require symmetry of lag lengths; each variable can have a different number of lag terms.

4.1.1 Unit Root Tests

ARDL framework depends on the time series characteristics of the data sets. So, initially, we have to investigate the order of integration. This is to ensure that the variables are not integrated of order, I(2). The order of integration is the number of unit roots contained in the series or the number of differencing operations it takes to make the series stationary. The integration properties of all the variables included in the study are investigated by the Augmented Dickey-Fuller (ADF) unit root tests before investigating the long-term relationships between the dependent and independent variables.

Table 4.2 ADF Test Results

Variable	No. of lags	Specification	Test Statistic	Test Critical Value	Prob.	Conclusion
PD_Consumer Index	1	Constant	-4.133123	-3.581152 (%1)	0.0022	Stationary
Growth	1	Constant	-4.982726	-3.581152 (%1)	0.0002	Stationary
Inflation	1	Trend and Constant	-1.264054	-3.185512 (%10)	0.8843	Non-Stationary
Unemployment	2	Constant	-1.721893	-2.602225 (%10)	0.4136	Non-Stationary
ΔInflation	2	Trend and Constant	-5.276347	-4.180911 (%1)	0.0005	Stationary
ΔUnemployment	1	Constant	-3.862747	-3.584743 (%1)	0.0047	Stationary

Automatic lag length selection is employed using Akaike Information Criteria to determine the length of a lag. EViews reports the critical values at the 1%, 5% and

10% levels. When the test statistic value is greater than the critical values, we do not reject the null hypothesis. Findings from ADF unit root tests point out that unemployment and inflation are stationary in their first difference and all other variables are stationary at level. The results of the unit root test are given in Table 4.2.

The results in Table 4.2 show that there is a mixture of I(1) and I(0) of underlying regressors and therefore, the ARDL testing could be proceeded with.

4.1.2 ARDL Bound Testing

After examining the stationary properties of the series, the ARDL bound test was used for co-integration analysis. The Unrestricted Error Correction model should be constructed to perform ARDL Bound Test approach and UECM specification used in this study is shown in the following equation.

$$\Delta\, PD\_\text{Consumer Index}_t = \beta_0 + \beta_1\, PD\_\text{Consumer Index}_{t-1} + \beta_2 \text{Growth}_{t-1} + \beta_3 \text{Inflation}_{t-1} + \beta_4 \text{Unemployment}_{t-1} + \sum_{i=1}^{p} \beta_{5\text{i}}\, \Delta\, \text{PD\_Consumer Index}_{t-i} + \sum_{i=1}^{p} \beta_{6\text{i}}\, \Delta\, \text{Growth}_{t-i} + \sum_{i=1}^{p} \beta_{7\text{i}}\, \Delta\, \text{Inflation}_{t-i} + \sum_{i=1}^{p} \beta_{8\text{i}}\, \Delta\, \text{Unemployment}_{t-i} + e_{\text{t}} \tag{4.1}$$

In the equation, Δ represents the first difference operator, β_0 is the constant term; β_{5i}, β_{6i}, β_{7i}, β_{8i} represents the short-run coefficients, β_1, β_2, β_3, β_4 are the long-run coefficients, p shows the number of lag length and e_t refers to the error term of a time series.

We formulate the H0 hypothesis as shown below so as to test for the existence of cointegration.

$$\text{H0: } \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0 \tag{4.2}$$

We will test the null hypothesis of our study and cointegration relation will be compared with calculated F statistics and tabulated F statistics values in Pesaran et al.

(2001). So, deciding on either to reject or accept H0 (no cointegration among the variables) is based on the following criteria:

If F-Statistics (Fs) > upper bound, then we reject H0, thus the variables are cointegrated.

If Fs < lower bound, then we accept H0, thus we conclude that the variables are not co-integrated.

But if Fs ≥ lower bound and ≤ Upper bound, under this condition, the decision is inconclusive.

In the UECM model, the cointegration relation between the series was investigated with the ARDL bound test approach. The results of the bound test indicate that the calculated F-statistic reject the null hypothesis of no co-integration between variables since the calculated values of F-statistics (5.913871) are greater than the upper bound critical value of 4.66 at the significance level of 1%. These results point out that there is a cointegration relationship between series.

4.1.3 Long-run and Short-run ARDL Estimates

Since the Bound test supported the evidence of a long-run equilibrium among variables, we can employ ARDL model to determine the long and short-run static relationship. Long term test results of models and long-run coefficients are shown in Table 4.3.

According to the results of the analysis, the consumer index[10] moves in concert with the unemployment series, inflation rate and industrial production growth. In short, selected independent variables are important determinants of the probability of default in the long-run. According to the figures on the table, the existence of a statistically significant and negative relationship between consumer index and

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[10] PD_Consumer Index is a time series that is highly negatively correlated with non-performing loans ratio of consumer.

unemployment indicates the positive relationship between unemployment and the probability of default due to the fact that probability of default and consumer index are parametrically inverse. Similarly, a statistically significant and positive relationship between consumer index and growth or inflation shows that there is an inverse relationship between the probability of default and those variables. These consequences are in line with the expectations.

Table 4.3 Estimated Long-Run Coefficients of ARDL (2,0,2,2)

Variable	**Coefficient**	**t-Statistic**	**Prob.**
Growth	1.310193	2.045279	0.0482
Inflation	5.636545	4.771909	0.0000
Unemployment	-15.00028	-9.573934	0.0000
C	4.163425	19.16716	0.0000

After estimating the long-term coefficients, we obtain the error correction version of the ARDL model. To investigate the short-run relationship between variables the vector error correction model is specified as follows.

$$\Delta\, PD\_\text{Consumer Index}_t = \beta_0 + \sum_{i=1}^{p1} \beta_{1\mathrm{i}}\, \Delta\, PD\_\text{Consumer Index}_{t-i} + \sum_{i=0}^{p2} \beta_{2\mathrm{i}}\, \Delta\, \text{Growth}_{t-i} + \sum_{i=0}^{p3} \beta_{3\mathrm{i}}\, \Delta\, \text{Inflation}_{t-i} + \sum_{i=0}^{p4} \beta_{4\mathrm{i}}\, \Delta\, \text{Unemployment}_{t-i} + \beta_5 EC_{t-1} + e_{\mathrm{t}} \tag{4.3}$$

Where β_{1i}, β_{2i}, β_{3i}, and β_{4i} are the short-run dynamic coefficients of the model's convergence to equilibrium, and β_5 is the speed of adjustment.

Table 4.4 reports the short-run coefficient estimates obtained from the ECM version of the ARDL model. The PD_Consumer index is affected by changes in index itself with lag, unemployment and inflation. In the short-run, the estimated coefficient of PD_Consumer index with lag and inflation are statistically significant and have a positive impact on the PD_Consumer index. But, the estimated coefficient of inflation with lag and unemployment are statistically significant and have a negative impact on the Consumer index.

Table 4.4 Error Correction Representation of ARDL (2,0,2,2)

Variable	**Coefficient**	**t-Statistic**	**Prob.**
ΔPD_Consumer Index(-1)	0.687316	6.855795	0.0000
Δ Unemployment	-12.94689	-5.953690	0.0000
Δ Inflation	2.001771	2.822100	0.0077
Δ Inflation(-1)	-2.285493	-3.018719	0.0046
CointEq(-1)	-0.360088	-5.731914	0.0000
Test	**Test Statistic**		
R-squared	0.986376		
Adjusted R-squared	0.982970		
F-statistic	289.5942	0.0000	
Jarque-Bera Normality Test	1.032521	0.5967	
Breusch-Godfrey Serial Correlation LM Test	2.001420	0.1508	
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.740404	0.6698	

The results for the model estimated show that the cointegration equation (ECM) is both statistically significant and negative thus signaling that there exist short-run relationships amongst the variables in the model. The coefficient of ECM (Cointeq (-1)) term of -0.36 suggests an adjustment of approximately 36 percent of disequilibria in the previous year's shock adjust back to the long-run equilibrium level in the current year.

The ARDL model tries to find the best linear unbiased estimator (BLUE) and thereby diagnostic tests need to be conducted. We can validate the results and ensure that the results are statistically robust by utilizing tests for stability, serial correlation, heteroscedasticity and normality in the residuals. The diagnostic test results of the model are shown in Table 4.4.

The diagnostic test suggests that the estimation of long-run coefficients and ECM are free from serial correlation, heteroscedasticity and nonnormality at the 10 percent level of significance. Lastly, the ARDL model is quite sensitive to structural breaks and as we are using financial time series that are sensitive to worldwide events the stability of the coefficients needs to be analyzed. So, in the last step, the stability test is required to confirm the stable short-run and long-run relationship. To assess the stability of the long-run and short-run coefficients CUSUM and CUSUMSQ tests can be used.

CUSUM and CUSUMQ tests were proposed by Brown, Durbin and Evans in 1975. The tests are applied to the residuals of the model. The CUSUM test is based on the cumulative sum of residuals based on is first set of n observations. It is updated recursively and is plotted against the break points. If the plot of CUSUM stays within 5% significance level, then the coefficient estimates are said to be stable. Similar procedure is used to carry out the CUSUMQ which is based on the squares recursive residuals.

The figure shows the CUSUM and CUSUMSQ tests for the parameter instability from ARDL model. Since the plots in the CUSUM and CUSUMSQ lie within the 5% significance level, the parameter of the equation is stable enough to estimate the long-run and short-run relationship in the study.

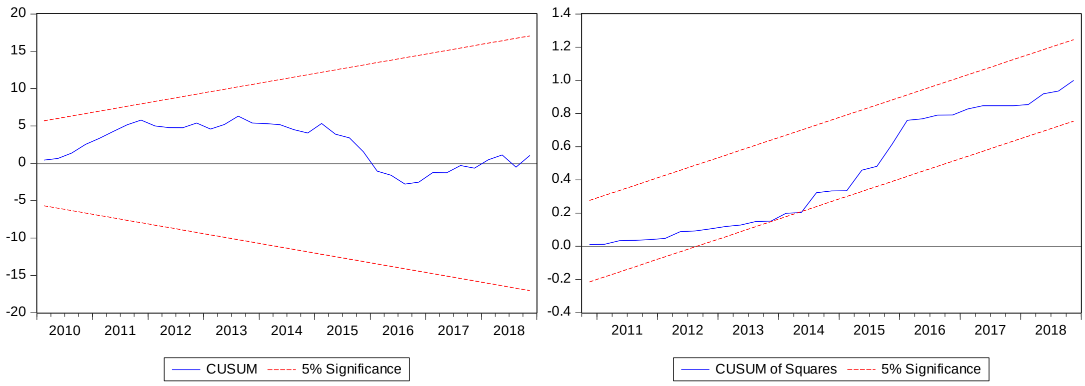

Figure 4.1 CUSUM and CUSUMQ Plot

4.2 PD of Small and Medium-Sized Enterprises

The purpose of this section is to estimate the macroeconomic factors determining the probability of default of commercial loans calculated by non-performing commercial loan ratio that gives clues about the firms' repayment capacity and used as a dependent variable in the analysis and to detect the direction and degree of the relationship between PD and those factors. Within this context, the impact of commercial interest rate (IR), industrial production growth (Growth), the real effective exchange rate (REER) and VIX index (VIX) were selected as explanatory variables. Growth represents the economic growth, REER corresponds to the risk component, IR shows the commercial loan cost whereas VIX was incorporated into the model for global risk.

Correlation analysis was employed to analyze the relationship between the selected macroeconomic variables and the corresponding correlation coefficients were calculated in order to determine whether the different data sets move together. These coefficients are in the correlation matrix of Table 4.5. When the Table is examined, it is seen that there is no evidence of multicollinearity.

Table 4.5 Correlation of Employed Macroeconomic Variables (2007q1-2018q4)

	Growth	**REER**	**VIX**	**IR**
Growth	1	-0.0435	-0.4530	-0.1062
REER	-0.0435	1	0.5769	-0.5543
VIX	-0.4530	0.5769	1	-0.2242
IR	-0.1062	-0.5543	-0.2242	1

4.2.1 Unit Root Tests

The ADF test results are presented in Table 4.6.

Table 4.6 ADF Test Results

Variable	No. Of lags	Specification	Test Statistic	Test Critical Value	Prob.	Conclusion
PD_SME Index	1	Constant	-2.822815	-2.601424 (%10)	0.0629	Stationary
Growth	1	Constant	-4.982726	-3.581152 (%1)	0.0002	Stationary
REER	2	Trend and Constant	-1.722071	-3.186854 (%10)	0.7249	Non-Stationary
VIX	1	Constant	-2.239363	-2.601424 (%10)	0.1957	Non-Stationary
IR	1	Constant	-1.097275	-2.601424 (%10)	0.7091	Non-Stationary
Δ REER	3	Trend and Constant	-5.780785	-4.186481 (%1)	0.0001	Stationary
Δ VIX	1	Constant	-3.527661	-2.926622 (%5)	0.0115	Stationary
Δ IR	1	Constant	-4.524084	-3.581152 (%10)	0.0007	Stationary

The ADF test results suggest that Growth and PD_SME Index series are an I(0) process and other series (VIX, REER and IR) are I(1) process therefore, the ARDL testing could be proceeded with.

4.2.2 ARDL Bound Testing

The Unrestricted Error Correction model should be constructed to perform ARDL Bound Test approach and UECM specification used in this study is shown in the following equation.

$$\Delta\, PD\_\text{SME Index}_t = \beta_0 + \beta_1\, PD\_\text{SME Index}_{t-1} + \beta_2 \text{Growth}_{t-1} + \beta_3 \text{REER}_{t-1} + \beta_4 \text{VIX}_{t-1} + \beta_5 \text{IR}_{t-1} + \sum_{i=1}^{p} \beta_{6\text{i}}\, \Delta\, D\_\text{SME Index}_{t-i} + \sum_{i=1}^{p} \beta_{7\text{i}}\, \Delta\, \text{Growth}_{t-i} + \sum_{i=1}^{p} \beta_{8\text{i}}\, \Delta\, \text{REER}_{t-i} + \sum_{i=1}^{p} \beta_{9\text{i}}\, \Delta\, \text{VIX}_{t-i} + \sum_{i=1}^{p} \beta_{10\text{i}}\, \Delta\, \text{IR}_{t-i} + e_{\text{t}} \quad (4.4)$$

In the equation, Δ represents the first difference operator, β_0 is the constant term; β_{6i}, β_{7i}, β_{8i}, β_{9i}, β_{10i} represents the short-run coefficients, β_1, β_2, β_3, β_4, β_5 are the long-run coefficients p shows the number of lag length and e_t refers to the error term of a time series. There exist several methods for determining the optimal lag length and a common method is to minimize the value of information criterion using the AIC.

We formulate the H_0 hypothesis as shown below so as to test for the existence of cointegration.

$$\text{H0: } \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0 \quad (4.5)$$

We will test the null hypothesis of our study and cointegration relation will be compared with calculated F statistics and tabulated F statistics values in Pesaran et al. (2001)

The results of the bound test indicate that the calculated F-statistic reject the null hypothesis of no co-integration between variables, since calculated values of F-statistics (14.44201) is greater than upper bound critical value of 4.37 at the significance level of 1%. These results point out that there is a cointegration relationship between series.

4.2.3 Long-run and Short-run ARDL Estimates

Since Bound test supported the evidence of a long-run equilibrium among variables, we can employ ARDL model to determine the long and short-run static relationship. Long term test results of models and long term coefficients are shown in Table 4.7.

Table 4.7 Estimated Long-Run Coefficients of ARDL (1,2,0,0,2)

Variable	Coefficient	t-Statistic	Prob.
Growth	5.469221	4.108617	0.0002
REER	4.827071	3.568720	0.0010
VIX	-1.137822	-2.803803	0.0081
IR	-4.754861	-2.997736	0.0049
C	-4.946009	-1.980443	0.0553

The SME Index[11] moves in concert with the commercial interest rate, the real effective exchange rate, VIX index, and industrial production growth. According to the figures on the table, the existence of a statistically significant and negative relationship between SME index and commercial interest rate or VIX indicates the positive relationship between the probability of default and those variables due to the fact that probability of default and SME index are parametrically inverse. Similarly, a statistically significant and positive relationship between SME index and growth or real effective exchange rate shows that there is an inverse relationship between the probability of default and those variables. These consequences are in line with the expectations either.

[11] PD_SME Index is a time series that is highly negatively correlated with non-performing loans ratio of SME.

After estimating the long-term coefficients, we obtain the error correction version of the ARDL model. To investigate the short-run relationship between variables the vector error correction model is specified as follows.

$$\Delta \text{PD\_SME Index}_t = \beta_0 + \sum_{i=1}^{p1} \beta_{1\text{i}}\, \Delta\, \text{PD\_SME Index}_{t-i} + \sum_{i=0}^{p2} \beta_{2\text{i}}\, \Delta\, \text{Growth}_{t-i} + \sum_{i=0}^{p3} \beta_{3\text{i}}\, \Delta\, \text{REER}_{\,t-i} + \sum_{i=0}^{p4} \beta_{4\text{i}}\, \Delta\, \text{VIX}_{\,t-i} + \sum_{i=0}^{p4} \beta_{5\text{i}}\, \Delta\, \text{IR}_{t-i} + \beta_6 EC_{t-1} + e_{\text{t}} \qquad (4.6)$$

Where $\beta_{1i,}$ $\beta_{2i,}$ β_{3i} β_{4i} and β_{5i} are the short-run dynamic coefficients of the model's convergence to equilibrium and β_6 is the speed of adjustment. Table 4.8 reports the short-run coefficient estimates obtained from the ECM version of the ARDL model.

Table 4.8 reports the short-run coefficient estimates obtained from the ECM version of the ARDL model. All the coefficients of the lagged-ECM terms in the model are significant. The PD_SME index is affected by changes in growth, interest rate and with their lag. In the short-run, the estimated coefficient of growth with lag and interest rate are statistically significant and have a negative impact on the PD_SME index. But, the estimated coefficient of interest rate with lag and growth are statistically significant and have a positive impact on the SME index.

The results for the model estimated show that the cointegration equation (ECM) is both statistically significant and negative thus signaling that there exist short-run relationships amongst the variables in the model. The coefficient of ECM (Cointeq (-1)) is -0.17 and is significant at 1% level. It means the coefficient term of -0.17 suggests an adjustment of approximately 17 percent of disequilibria in the previous year's shock adjust back to the long-run equilibrium level in the current year.

Table 4.8 Error Correction Representation of ARDL (1,2,0,0,2)

Variable	**Coefficient**	**t-Statistic**	**Prob.**
Δ Growth	1.182363	3.727112	0.0007
Δ Growth(-1)	-0.840984	-2.130568	0.0400
Δ IR	-0.203155	-0.682581	0.0449
Δ IR(-1)	1.266884	4.101565	0.0002
CointEq(-1)	-0.171426	-9.934135	0.0000
Test	**Test Statistic**		
R-squared	0.984787		
Adjusted R-squared	0.980984		
F-statistic	258.9346		0.0000
Jarque-Bera Normality Test	2.774970		0.2497
Breusch-Godfrey-Serial Correlation LM Test	1.932819		0.1603
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.677367		0.7239

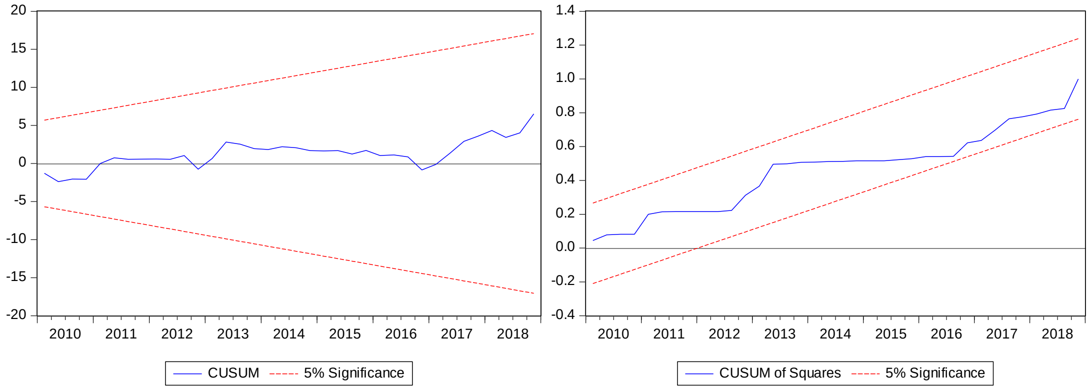

Figure 4.2 CUSUM and CUSUMQ Plots

The diagnostic test suggests that the estimation of long-run coefficients and ECM are free from serial correlation, heteroscedasticity and nonnormality at the 10 percent level of significance. Figure 4.2 shows the CUSUM and CUSUMSQ tests for the parameter instability from ARDL model. Since the plots in the CUSUM and CUSUMSQ lie within the 5% significance level, the parameter of the equation is stable enough to estimate the long-run and short-run relationship in the study.

CHAPTER 5

CONCLUSIONS AND FINAL REMARKS

Credit risk is the most important financial risk carried by banks. Therefore, accurate estimation of credit risk is a vital issue for both the financial system and the real sector, especially in the banking sector. The value at credit risk, which is the sum of expected and unexpected credit losses, is the probabilistic measure of the total credit risk of any bank or banking sector. Expected loss is the expected average loss of any credit transaction or loan portfolio. Unexpected loss is the statistical estimate of the expected volatility and the determinant of the minimum economic capital to be kept for credit risk. The most important risk factor determining the level of expected and unexpected credit losses is the default probabilities of creditors. Therefore, in credit risk analysis and loss estimation, it is essential to examine the factors affecting the default probabilities of creditors and the possible developments in these factors.

The strong and meaningful statistical relationships known to exist between default probabilities and macroeconomic variables provide significant opportunities to anticipate expected and unexpected credit losses for both the banks and for the authorities which are responsible for the supervision and/or financial stability of the financial sector. The macroeconomic credit risk models developed within this framework make possible the estimation and analysis based on the relationships between probability of default or non-performing loan ratio as determinants of credit losses and macro risk factors with systemic effects.

In this study, it was aimed to develop models and methodologies that would enable macroeconomic variables to be utilized in the estimation of credit losses in the

Turkish Banking Sector, inspired by the Credit Portfolio View approach as the macroeconomic credit risk model developed by Wilson in 1997.

In the study, in the absence of historical credit default data, non-performing loan ratios were calculated by proportioning the total non-performing amount in each period to the total performing loan amount by quarterly periods, and by the transformation of the non-performing ratios in logistic form, macro index has been obtained, describing the general economic conditions. The macro index, which has a very close to -1 correlational relationship with the non-performing ratios, was used as dependent variable indices in the credit risk model. The use of default or non-performing rates in logistic form is an accepted practice that aims to break the linearity between macro-variables and default probabilities.

Quarterly data were analyzed separately for companies and households. In the research, many models have been tested extensively on what are the macroeconomic variables affecting the ratio of non-performing loans in both consumer loans and commercial loans, inappropriate variables were extracted, and finally, the most appropriate models were tried to be revealed.

In the study, the relationship between the probability of default for both models and the macroeconomic variables was examined for the period of 2007-2018. First of all, the stationarity of the series was examined. For the analysis of stationarity, ADF test, which is frequently used in the applied literature, was used and it was found that some variables were stationary in the level values according to the ADF test and some variables were stationary in the first differences. After the stationary analysis, the cointegration relationship was examined with the bound test approach proposed by Peseran (2001) and others. According to the bound test results, the co-integration relationship between the probability of default in both models and macroeconomic variables were found.

Lastly, long and short term relations between macroeconomic variables and the probability of default were analyzed with ARDL method. According to the results of ARDL model established for consumer loans, long-term unemployment positively affects the probability of default as expected. There is a statistically significant and negative correlation between industrial production growth and the probability of default and inflation and the probability of default.

According to the research findings, it can be said that the relationship between the probability of default of consumer loans and the selected macroeconomic variables is in accordance with the economic theory. For example, the improvement in the financial situation of consumers is likely to reduce their possibility of avoiding from performing their debts, given the rise in industrial production indices pointing to direct growth. On the other hand, the increases observed in the country's inflation level triggered the rise in the growth side and the decrease in the debt level in real terms (also contributing to the increase in employee wages). At this point, the probability of default shows an adverse tendency with inflation. On the other hand, unemployment figures indicate that consumers are struggling to repay the debt because they trigger a contraction in contrast to industrial production.

According to the results of ARDL model established for commercial loans, there was a statistically significant and positive relationship between the probability of default in the long term and the VIX volatility index and the probability of default and the commercial loan interest rate. It is observed that there is a statistically significant negative correlation between the industrial production growth and the probability of default and real effective exchange rate index and the probability of default in the long term.

According to the research findings, the relationship between the probability of default of commercial loans and the selected macroeconomic variables can be explained by the existing conceptual frameworks. For example, the VIX index is a tool to measure the global risk level, and any rise in this indicator brings capital outflows and makes it difficult for companies to pay their debt. In this aspect, there is a positive relationship between VIX and the probability of default. Similarly, the rise in commercial loan interest rates makes the cost of companies increase and makes it difficult to find new loans. In this case, there is a risk that they will not be able to continue their activities. On the other hand, the increase in the real effective exchange rate index indicates the value gain in the local currency and facilitates the payment of debts, especially in foreign currency. Lastly, the rise in the industrial production index is an indicator of the economic growth of the companies operating commercially. In this case, the probability of default of companies seems declining.

Given the vitality of borrowing and lending functions of banking for real sector firms, the management of the risk emanated from those activities should be emphasized. Credit risk modeling has an important place in economics in order to be resistant to probable shocks and crises in financial markets gained a new identity with respect to wide-spread globalization, to accommodate with both Basel and IFRS 9 standards and to get rid of sudden inevitable shocks with minimum loss by precautionary measures foreseeing the credit risk-oriented problems in macro and micro level. When viewed from this aspect, the necessity of the facts that the management process of the credit risk, the utmost influencer of the banking business should be emphasized and fruitful researches should be done on this issue taking the past crises in Turkey and the reality that reinforcement experiences of the system were not dated further back into consideration. This work will contribute to the literature regarding the macroeconomic credit risk modeling for the Turkish Banking System.

After the literature review, it is seen that the main macroeconomic variables for the consumer loans in Turkey are growth, interest rates, monetary expansion, current account balance, unemployment, exchange rates and inflation rate. Important studies and findings regarding the credit risk until today have been included in this work after giving a primary place to the description, types and significance of the risks. This study made in light of the past works in the literature building relationships between credit risk and macroeconomic variables did not produce a result on contrary to those works.

In-depth models involving many macroeconomic variables on what kind of macro variables change the probabilities of default of consumer loans and corporate loans for SMEs at large scale have been tested and finally, the fittest models have been put forth. In this context, the effects of growth in industrial production index, unemployment and inflation rates in consumer loans and effects of industrial production index, real effective exchange rate, interest rates and VIX volatility index over the corporate loans have been measured. The diversity of macroeconomic variables rendered this work quite important. The researches examining the long-term effect of VIX on loans seem to be very limited according to literature. In this respect, this study is worthy to see the long-term reverberations of VIX on the corporate loans used by SMEs.

The findings about the macroeconomic variables have policy related implications for the commercial banks. The commercial banks can use the results to predict changes in the NPLs in the name of precautionary measures to stop any financial crisis. The bank can reshape its loan extension policy according to the performance of the economy, interest rate, inflation rate, exchange rate and industrial production. On the other hand, BRSA may revise its supervision principles by the suggestions of this study. They can develop a framework which includes the macroeconomic variables such as GDP growth, real interest rate, inflation, exchange rate, exports and industrial production to monitor the stability and soundness of the banking sector.

REFERENCES

Adom, P.K., Bekoe,W., Akoena, S.K.K., (2012). Modelling Aggregate Domestic Electricity Demand In Ghana: An Autoregressive Distributed Lag Bounds Cointegration Approach", *Energy Policy*, Elsevier, vol. 42(C), pp.530–537.

Allen, L. & Saunders, A., (2004). Incorporating Systemic Influences Into Risk Measurements: A Survey of the Literature, *Journal of Financial Services Research*, *26*(2), p. 161-191. doi:10.1023/B:FINA.0000037545.38154.8a

Altıntaş, A., (2012). Kredi Kayıplarının Makroekonomik Değişkenlere Dayalı Olarak Tahmini ve Stres Testleri - Türk Bankacılık Sektörü için Ekonometrik Bir Yaklaşım, Türkiye Bankalar Birliği.

Arpa, M., Giulini, I., Ittner, A., & Pauer, F. (2001). The influence of macroeconomic developments on Austrian banks: implications for banking supervision. *Bis Papers*, 1, 91-116.

Avouyi-Dovi, S., Mireille, B., Jardet, C., Kendaoui, L., & Moquet, J. (2009). Macro stress testing with a macroeconomic credit risk model: Application to the French manufacturing sector, *Banque de France Working Paper,* 238.

Babihuga, R. (2007). Macroeconomic and financial soundness indicators: An empirical investigation (No. 7-115). International Monetary Fund.

Babouček, I., & Jančar, M. (2005). Effects of macroeconomic shocks to the quality of the aggregate loan portfolio (Vol. 22). Czech National Bank.

Bahmani-Oskooee, M. (2001). Nominal and real effective exchange rates of Middle Eastern countries and their trade performance. *Applied economics*, *33*(1), 103-111.

Basel Committee on Banking Supervision, & Bank for International Settlements. (2000). *Principles for the management of credit risk*. Bank for International Settlements.

Basel Committee on Banking Supervision. (2004). *International convergence of capital measurement and capital standards: A revised framework*, Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision. (2009). *Revisions to the Basel II market risk framework*, Basel, Switzerland: Bank for International Settlements.

Basel Committee on Banking Supervision. (2009). *Enhancements to the Basel II framework*, Basel, Switzerland: Bank for International Settlements.

Basel Committee on Banking Supervision. (2009). *Guidelines for computing capital for incremental risk in the trading book*, Bank for International Settlements, Basel, Switzerland.

Boss, M. (2002). A macroeconomic credit risk model for stress testing the Austrian credit portfolio. *Financial stability report*, *4*, 64-82.

Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society: Series B (Methodological)*, *37*(2), 149-163.

Coyle B. (2000). *Introduction to Currency Risk*, Financial World Publishing, United Kingdom, pp.4-5.

Crouhy, M., Galai, D., & Mark, R. (2000). A comparative analysis of current credit risk models. *Journal of Banking & Finance*, *24*(1-2), 59-117.

Derbali, A. (2018). The credit portfolio management by the econometric models: A theoretical analysis. *Acta Universitatis Danubius. Œconomica*, *14*(4).

Diaz, D., & Gemmill, G. (2002). A systematic comparison of two approaches to measuring credit risk: CreditMetrics versus CreditRisk+. *Trans. 27th ICA*.

Duasa, J. (2007). Determinants of Malaysian trade balance: An ARDL bound testing approach. *Global Economic Review*, *36*(1), 89-102.

Engle, R.F., Granger C.W.J. (1987). Co-integration and error correction: representation, estimation and testing, *Econometrica* 55, 251–276.

Gerlach, S., Peng, W., & Shu, C. (2005). Macroeconomic conditions and banking performance in Hong Kong SAR: a panel data study. *BIS Papers*, *22*(2), 481-497.

Granger, C.W.J., Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111-120.

Mérõ, K., Zsámboki, B., Horváth, E., Bethlendi, A., Naszodi, A., Szombati, A., & Czajlik, I. (2003). *Studies On The Potential Impacts Of The New Basel Capital Accord* (No. 2003/27). Magyar Nemzeti Bank (Central Bank of Hungary).

Hull, J. (1946). *Risk management and financial institutions*, Wiley Finance, Fourth Edition.

International Accounting Standards Boards. (2014). International Financial Reporting Standards 9, Financial Instruments.

Jackson, P., Perraudin, W. (2000). Regulatory Implications of Credit Risk Modelling, *Journal of Banking and Finance* 24, 1-14.

Jakubík, P. (2007). Macroeconomic environment and credit risk. *Czech Journal of Economics and Finance*, *10*(1): 133-166.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica: Journal of the Econometric Society*, 59, 1551-1580.

J.P. Morgan. (1997). CreditMetrics ™ - Technical Document: The Benchmark for Understanding Credit Risk.

Kalirai, H., & Scheicher, M. (2002). Macroeconomic stress testing: preliminary evidence for Austria. *Financial Stability Report*, (3), 58-74.

KPMG. (2015). International Financial Reporting Standards 9, Content, Challenges and Tools.

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*, *36*(4), 1012-1027.

Marcucci, J., & Quagliariello, M. (2008). Is bank portfolio riskiness procyclical ?: Evidence from Italy using a vector autoregression. *Journal of International Financial Markets, Institutions and Money*, *18*(1), 46-63.

Otani, A., Shiratsuka, S., Tsurui, R., & Yamada, T. (2009). Macro stress-testing on the loan portfolio of Japanese banks. *Bank of Japan, Financial Systems and Bank Examination Department*.

Pesaran, H., Shin, Y. (1999). An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis, In S. Strom (eds.) *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium,* Cambridge University Press.

Pesaran, M. H., & Shin, Y. (1998). An autoregressive distributed-lag modelling approach to cointegration analysis. *Econometric Society Monographs*, *31*, 371-413.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289-326.

Pricewaterhouse Coopers. (2014). International Financial Reporting Standards 9, Expected credit losses.

Quagliariello, M. (2003). Are macroeconomic indicators useful in predicting bank loan quality: Evidence from Italy. *Bank of Italy*, Rome.

Shu, C. (2002. The Impact of Macroeconomic Environment on the Asset Quality of Hong Kong's Banking Sector. *Hong Kong Monetary Authority Research Memorandums.*

Vaněk, T., & Hampel, D. (2017). The Probability of Default Under IFRS 9: Multi-period Estimation and Macroeconomic Forecast. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *65*(2), 759-776.

Virolainen, K. (2004). Macro stress testing with a macroeconomic credit risk model for Finland, *Bank of Finland Discussion Papers*, 2004/18.

Wehrspohn, U. (2002). Credit Risk Evaluation: Modeling-Analysis-Management (Doctoral dissertation).

Wilson, T.C., (1997). Portfolio Credit Risk I, *Risk Magazine 10*(9).

Wilson, T.C., (1997). Portfolio Credit Risk II, *Risk Magazine 10*(10).

Wilson, T.C., (1998). Portfolio Credit Risk, *FRBNY Economic Policy Review 4*(3), 71-82.

Wong, J., Choi, K. F., & Fong, T. (2006). *A Framework for Stress Testing Bank's Credit Risk* (No. 0615). Hong Kong Monetary Authority.

APPENDICES

APPENDIX-A: TURKISH SUMMARY / TÜRKÇE ÖZET

Temerrüt olasılığı, kredi kuruluşlarında, özellikle de bankalarda tahmin edilen en önemli risk parametrelerinden birisidir ve kredi riski analiz ve yönetiminde önemli bir rolü vardır. Bankaların en önemli görevlerinden birinin kredi vermek olduğu göz önüne alındığında, bankacılık endüstrisi kredi riskine büyük bir önem vermektedir. Kredi riski genel olarak borçlunun ya da karşı tarafın kontrattaki yükümlülüklerini yerine getirememe riski olarak tanımlanır. Kredi risk değerlendirmesi, bir kredi müşterisinin temerrüde düşme olasılığını tahmin eden bir (istatistiksel yaklaşım) süreç olan, kredi derecelendirmesi ile gerçekleştirilmektedir.

Bankalar, işlerinin çok önemli bir kısmını kredi verme işlemi teşkil ettiği için, geçmişten bu yana kredi derecelendirmesi uygulamalarına odaklanmışlardır. Özellikle bankacılık endüstrisinde, Basel prensiplerinin yayımlanması ile birlikte temerrüt olasılığının tahmini daha da çok önem kazanmaya başlamıştır. İçsel Derecelendirme Metodu içinde, Temerrüt Olasılığı kredi riski sermaye gereksinimlerinin hesaplanabilmesi için gerekli olan üç temel parametreden birini oluşturmaktadır ve başlangıçta da belirtildiği gibi, kredi riski analiz ve yönetimindeki en önemli parametrelerden birisidir. Diğer iki parametre Temerrüt Halinde Kayıp ve Temerrüt Halinde Riske Maruz Kredi Tutarıdır. Bu açıdan, özellikle de beklenmedik kayıplarını karşılamak üzere, bankaların yeterli bir miktarda sermaye bulundurmaları şart koşulmuştur. 2013 yılında, bu gereklilikler Sermaye Gereksinimleri Yönergesi ve Sermaye Gereksinimleri Yönetmeliğinin yayımlanması ile Avrupa Birliği kanunu çerçevesine de dahil edilerek uygulanmıştır.

Kredi riskinin iki temel unsuru vardır: Beklenen Kayıp ve Beklenmeyen Kayıp. Beklenen kayıp, tek bir kredi veya toplam kredi portföyün belli bir zaman periyodu içinde alabileceği ortalama değerle, beklenmeyen kayıp ise kredi veya portföy değerinin aynı periyotta gösterebileceği dalgalanma (volatilite) ile ilgilidir. Risk yönetimi yaklaşımında sermaye, beklenmeyen kayıpların karşılığı olarak değerlendirilir, çünkü risk belirsizliği işaret eden bir kavramdır. Beklenen kayıplar için bankalar karşılık ayırırlar. Sermaye ise risklerin gerçekleşmesine karşı bir sigorta niteliğindedir, bu nedenle ekonomik sermaye belirli bir güven aralığında beklenmeyen kayıpları karşılamak için gerekli sermaye tutarıdır.

Diğer bir taraftan muhasebe alanında Uluslararası Finansal Raporlama Standardı 9 (UFRS 9), 1 Ocak 2018'den itibaren yürürlüğe girmiş ve kredi risk analizleri ve yönetimi alanındaki gereksinimleri vurgulayarak daha da derinleştirmiştir. Bir bakıma, kredi riski ve muhasebe arasında daha güçlü bir ilişki oluşturmuş ve bankaların ekonomik sonuçlarını önemli ölçüde etkilemeye başlamıştır. Finansal Raporlama Standartları temel olarak Uluslararası Muhasebe Standartları: Muhasebeleştirme ve Hesaplama'nın yerine geçmiştir. Yerine geçme süreci üç aşamada gerçekleşmiştir. 1. Aşama: Finansal varlıkların ve finansal borçların hesaplama ve sınıflandırılması; 2. Aşama: Değer düşüklüğü metodolojisi ve 3. Aşama: Finansal riskten korunma muhasebesi. Yeni değer düşüklüğü metodolojisi beklenen kredi kayıplarının (ve dolayısıyla kayıp karşılıklarının) hesaplanmasına yönelik bir çerçeve ihtiva etmektedir.

Küresel finansal krizin bir sonucu olsa da, Uluslararası Muhasebe Standartları 39'un en büyük zayıf noktası, finansal varlıklarla ve onların kayıp karşılıklarının muhasebesi ile ilintili değer düşüklüğü (kredi kayıpları) hesaplama mekanizmasıdır. Yetersiz değer düşüklüğü çerçevesi, onun UFRS 9 ile değiştirilmesinin en güçlü nedeni olmuştur. Uluslararası Muhasebe Standartları 39'a göre, bahse konu süreç Gerçekleşen Zarar Modeli esas alınarak gerçekleşmekte, bu da kayıp karşılıklarının bazı olumsuz olaylar, tipik olarak bir müşterinin kredisini ödeyememesi gibi, meydana geldikten "sonra" muhasebeleştirilmesi anlamına gelmektedir. UFRS 9' un yürürlüğe girmesinden sonra, bu konuda bir değişim yaşanmakta ve değer düşüklüğü hesaplamaları ve muhasebe gereksinimleri Tahmini Kredi Kayıpları Modellerine dayandırılmaktadır. Dolayısıyla, kredi kayıpları ve neticesi olarak kayıp karşılıkları tahminlere dayalı olarak, bu da olumsuz bir olay henüz gerçekleşmemiş (potansiyel) haldeyken, muhasebeleştirilmektedir.

UFRS 9'un kredi karşılıkları yaklaşımı bankalar açısından Basel çerçevesi altında geliştirilen İçsel derecelendirmeye dayalı yaklaşımı hatırlatmaktadır. Zira ikisi de beklenen kayıp hesaplamasına dayalıdır. Basel III, beklenen kayıpların içsel modeller kullanılarak hesaplanmasını gerektirmektedir. Beklenen kayıp Basel'de, bir yıllık dönemde, alacağın değerinin azalması veya karşı tarafın muhtemel temerrüdü nedeniyle kaybedilmesi beklenen tutardır. Basel beklenen kayıpların UFRS 9 gibi kredi karşılıklarıyla karşılanmasını esas alırken, sermayenin beklenmeyen kayıplar için tutulduğunu vurgulamaktadır. UFRS 9 kredi riski ve muhasebe arasında güçlü bir ilişki oluşturmakta ve bankanın ekonomik sonuçlarını önemli ölçüde etkilemektedir. Hem Basel tarafından açıklanan hem de UFRS 9 Finansal Araçlar kapsamında belirtilen, beklenen kredi zararları aşağıdaki formül ile hesaplanır:

Beklenen Kredi Kaybı = Temerrüt Olasılığı * Temerrüt Halinde Kayıp * Temerrüt Halinde Riske Maruz Kredi Tutarı (2.1)

Temerrüt Olasılığı; karşı tarafın ya da borçlunun yükümlülüklerini yerine getirmede başarısız olma ihtimali, Temerrüt Halinde Kayıp; karşı taraf ya da borçlunun temerrüde düşmesi durumunda oluşacak kayıp oranı, Temerrüt Anında Riske Maruz Kredi Tutarı ise her bir karşı taraf ve borçlunun temerrüt riskine maruz kaldıklarındaki portföyünün büyüklüğüdür.

Bu yazının temel amacı, kolay, esnek, sezgisel ve sayısal bir çerçeve oluşturarak, gelecek dönemler için temerrüt olasılığını tahminleyebilmektir. Temerrüt olasılığını tahmin edebilmek için, araştırmacının öncelikle uygun bir kredi risk modeli seçmesi gerekmektedir. Böyle bir modelin seçimi, kredi risk yönetimi açısından çok önemlidir. Yetersiz bir model, model hataları içerebilir. Bu model hataları da kredi risk yönetim sürecinde belirsizliklere yol açar. Son yıllarda, uzmanlık sistemi ve derecelendirme sistemi gibi geleneksel sistemlerden farklı olarak, yeni yaklaşımlar geliştirilmiştir. Bu yeni yaklaşımlar farklı varsayımlar ve bilgilerden istifade etmektedir ve genellikle dört kategori altında tasnif edilmektedirler:

Riske Maruz Değer Modeli : CreditMetrics

Merton Modeli: Moody’s KMV

Aktüerya Modeli: Credit Risk +

Makroekonomik Model: Credit Portfolio View

Bu çalışmada 1997 yılında Wilson tarafından geliştirilen makroekonomik kredi riski modeli Credit Portfolio View yaklaşımından esinlenerek Türk Bankacılık Sektörü’nde kredi kayıplarının tahmininde makro ekonomik değişkenlerden yararlanılmasını mümkün kılacak model ve metodolojilerin geliştirilmesi hedeflenmiştir. Credit Portfolio View modeli, temerrüt olasılıklarını makro ekonomik değişikliklere göre uyarlamaktadır. Hesaplanan değerler, ülkelere ve sektörlere göre farklılaşmakla beraber ekonominin genelindeki iyileşme ya da kötüleşme durumuna göre hesaplanan temerrüt olasılıkları gözden geçirilmektedir. Model, mevcut makroekonomik ortamı kredi riski değerlendirmesinde belirleyici unsur olarak ele alan ekonometrik bir model olup; bu model, temerrüdün her bir ülke için işsizlik oranı, Gayrisafi Yurtiçi Hasıla büyüme oranı, faiz oranı, döviz kurları, kamu harcamaları ve toplam tasarruf oranı gibi makroekonomik etmenlerin değerine bağlı olduğunu kabul eden değişik sektörlerdeki temerrüt olasılıklarını tahmin etmek için kullanılan çoklu-faktör modelidir.

Çalışmada, Türk bankacılık sistemi için temerrüt olasılığını makroekonomik değişkenlere dayalı olarak tahmin edecek modeller kapsamında araştırılacak olan bağımsız değişkenler, mevcut literatürde kredi riskini etkilediği tespit edilmiş olan makroekonomik veriler ve Türkiye ekonomisinin yapısı değerlendirilerek belirlenecek olan verilerden seçilmiştir. Bu tezin amacı makroekonomik değişimler ile tüketicilerin ve küçük ve orta büyüklükteki işletmelerin temerrüt olasılıkları arasındaki ilişkiyi tespit ederek ilgili finans literatürüne katkı sağlamaktır. Çalışmaya konu olan bağımlı değişken temerrüt olasılığının bilanço dönemlerini kapsadığı dikkate alındığında, frekansın çeyreklik olması gerektiğine karar verilmiş ve 2007Q1-2018Q4 yıllarına ait çeyrek dönemlik veriler kullanılarak analizler yapılmıştır. Seçilen değişkenlerin hepsinin ortak olarak bulunduğu ilk dönem olan 2007 yılının ilk çeyreği ile 2018 yılının son çeyreğini kapsayan 2007-2018 aralığı veri seti dönemi olarak seçilmiştir. Çalışmada kullanılan zaman serisi verileri; Türkiye İstatistik Kurumu, Türkiye Cumhuriyet Merkez Bankası Elektronik Veri Dağıtım Sistemi ve Bankacılık Düzenleme ve Denetleme Kurumu'ndan derlenmiştir. Analizler Eviews 10 programı ile gerçekleştirilmiştir.

Makroekonomik piyasalarda ekonominin genelini etkileyen tüm indikatörler bankacılık sektörü üzerinde de etkisini gösterecektir. Kredi riskinin sistematik (çeşitlendirme ile yok edilemeyen) bölümünü açıklama gücüne sahip, sistemik etkiye sahip risk faktörleri sınırsız sayıda olmayıp, dünya örneklerinde olduğu gibi büyüme, faiz ve enflasyon oranları, işsizlik oranları ve döviz kurları sistematik kredi riskini açıklaması muhtemel temel makroekonomik değişkenlerdir. Risk analizinde farklı kredi türlerine inildiğinde, bu temel faktörlere kredi riskini açıklama gücü kredinin türüne göre farklılaşabilecek daha özel nitelikli makroekonomik değişkenler kullanılabilir. Ancak bu çalışmanın konusu olmasada, çalışmanın sonucuna göre uygulanabilecek kredi riski stres testi çalışmalarında tercih edilecek açıklayıcı makro değişkenlerin, stres testlerine uygun, diğer bir ifade ile sonuçları test edilecek makroekonomik senaryoyu betimleyebilecek ana unsurlardan olmasına özen gösterilmelidir.

Temerrüt Olasılığı ve Tarihsel Takip Oranları: Modelde yer alan en önemli değişken kredi riski değerlendirmesinde kullanılan ve model kapsamında tahmin edilecek olan temerrüt olasılığı değişkenidir. Bunun nedeni, Temerrüt Olasılığı kavramının Basel Bankacılık Denetim Komitesinin İçsel Derecelendirmeye Dayalı yöntemini kullanan ve bankaların asgari sermaye gereksinimlerini belirlemede yararlanılan girdi faktörü olarak kullanılmasıdır. Temerrüt olasılığı sadece bir kredi riski parametresi olmamakla birlikte Uluslararası Muhasebe Standartları Kurulu 'nun yayımladığı UFRS 9'un Beklenen Zarar Karşılığı Modelinde de önemli bir parametre olarak kullanılmaktadır. UFRS 9, kredilerdeki değer düşüklükleri için temerrüt öncesinde karşılık ayrılmasını sağlayan bir yaklaşımdır ve ileriye dönük bir yaklaşım olarak benimsendiği için modellemeyle ilgili tahmini gerçekleştirmeye çalışacaktır. Özetle, temerrüt olasılığı hem İçsel Derecelendirmeye Dayalı yaklaşım içinde kredi riski sermaye gereksinimlerinin hesaplanabilmesi hem de UFRS 9'un Beklenen Zarar

Karşılığı Modeli ile kredi karşılığı ayrılabilmesi için gerekli olan üç temel parametreden birisini oluşturmaktadır. Bu nedenle temerrüt olasılığı değişkeninin sağlıklı bir şekilde tahmin edilmesi bankaların bilançolarını ve ekonomi politikalarını etkin bir şekilde yönetmelerine imkân tanır. Bu çalışmada tarihsel temerrüt oranlarını ikame etmek üzere, aşağıdaki denklemde gösterildiği şekilde hesaplanacak, tarihsel takip oranları kullanılmıştır.

$$\text{Takip Oranı} = \frac{Dönem\ Sonu\ İtibariyle\ Takipteki\ Krediler}{Dönem\ Başı\ (Önceki\ Dönem\ Sonu)\ İtibariyle\ Normal\ Krediler} \tag{3.12}$$

Gayrisafi Yurtiçi Hasıla büyümesi: Temerrüt olasılığı değerini belirleyen en önemli değişkenlerden birisi büyümedir. Büyüme oranı da aslında bütünüyle ekonomiyi yansıtan bir gösterge olduğundan ekonomik her birimi etkilemesi beklenecektir. Reel ekonomik büyüme borçluların borçlarını ödeme imkanlarını artırır. Genel olarak, ödenmeyen kredilerin hacmi, hanehalkı ve şirketlerin daha iyi finansal koşulları altında azalmaktadır. Aksine, ekonomik gerileme süreçlerinde ödenemeyen kredilerin hacmi artmakta ve ekonomik aktörler borçlarını ödemekte problemler yaşamaktadır.

Sanayi Üretim Endeksi: Belirli zaman aralığında faktör maliyetleri karşılığında sanayi katma değerindeki değişimi ölçen bir iş çevrimi göstergesidir. Bu endeks büyüme ile yakın ilişki içerisindedir. Bu sebeple, sanayi üretim endeksinde artış gözleniyorsa , takipteki kredi tutarı azalmakta ve takipteki kredi oranının düşmesi beklenmektedir.

Faiz Oranı: Her bir ekonomide önemli bir diğer belirleyici de faiz oranlarıdır. Daha yüksek faiz oranları, artan faiz ödemeleriyle borç yükünü artırır, böylece ekonomik aktörler ekonomik anlamda daralma yaşayabilir. Genel anlamda, faiz oranı ne kadar yüksekse, müşteri borcunu ödemede o kadar çok zorlanır. Ancak faizin etkisinin bireysel krediler ve şirketler için farklı olacağı unutulmamalıdır. Faiz artışı bilançolarında yüksek oranda borç bulunduran reel sektör firmalarının finansman maliyetlerini artıracak ve zamanla borçlarını ödemede güçlük yaşamalarına neden olacaktır. Uzun vadede ise kredi kullanıcılarının kalitesinde kötüleşmeye yol açacaktır. Bu nedenle, yüksek faiz oranları şirketlerin temerrüt olasılığını yükseltmelidir. Bireysel kredilerde ise borçlanma maliyetleri sabit olduğundan bireysel kredilerde faiz oranlarındaki artışa karşı aynı yorumu yapmak doğru olmayabilir.

Reel Kur Endeksi: Ulusal paranın, önemli yabancı paralar ile mübadelesinde geçerli olan nominal kurlar ve döviz kurlarındaki nominal değişimlerinin enflasyondan arındırıldığı reel kur endeksleri, dış dünyanın takip oranları veya temerrüt olasılığı üzerindeki etkisini betimleyebilecek en önemli makro değişkenler arasındadır. Döviz kurlarındaki artışın (veya reel kur endeksindeki düşüşün) takip veya temerrüt oranları üzerindeki etkisinin genelde olumsuz olması beklenir. Reel kur endeksi küçük ve orta büyüklükteki şirketler içi yapılan analizde risk unsurunu temsilen kullanılabilir. 16.08.2018 tarihli Resmi Gazete'de yayımlanan karar ile 32 sayılı kararda yapılan değişiklik kapsamında tüketicilere döviz ve dövize endeksli kredi kullandırılması yasaklanmıştır. Bundan dolayı Türk Bankacılık Sisteminde tüketicilerin kullandığı nakdi kredilerin %100'ü Türk Lirası kredisidir ve döviz kuruna tüketici kredileri için yapılan analizde temerrüt olasılığını açıklayan makroekonomik değişkenler arasında yer verilmemiştir.

Enflasyon Oranı: Fiyat seviyelerindeki değişme temerrüt olasılığı için diğer bir önemli belirleyici olabilir. Genel anlamda, enflasyon refahın borç verenden borç alana transferidir, çünkü zamanla kredinin değeri düşmektedir. Bu nedenle, yüksek enflasyon borç alanların borçlarını ödeyebilmelerine yardımcı olduğundan, enflasyon ve temerrüt olasılığı arasında ters bir orantı olduğuna dair seziler bulunmaktadır. Nitekim Bireysel krediler için yapılan analizde faiz oranlarından bağımsız olarak düşünüldüğünde, enflasyondaki yükselmenin (parasal gevşemenin) borç ödeme kabiliyetini arttırması beklendiğinden enflasyonun temerrüt olasılığını negatif etkilemesi beklenmektedir.

İşsizlik Oranı: İşsizlik değişkeni özellikle hanehalkı sektörü için oldukça önemli olmalıdır. İşsizlik oranı yükseldiğinde, azalan refah seviyelerinden dolayı borçlarını ödemekte zorlanacak olan kesim daha büyük oranda hane halkı olacaktır. Bu nedenle, işsizlik ve temerrüt olasılığı arasında bir doğru orantı beklenmelidir.

VIX volatilite endeksi: Oynaklık endeksi piyasanın geleceğe dönük 30 günlük oynaklık beklentisini yansıtan gerçek zamanlı bir endekstir. Özellikle piyasadaki korku ve belirsizliği en iyi ölçen araç olarak bilinir. Yüksek oynaklık endeksi finansal stresi göstermekte ve beraberinde sert piyasa düşüşleri getirmektedir. Firmalar için VIX önemli bir değişken olmaktadır.

Diğer Göstergeler: Çalışmada temel makro göstergeler yanında, yurtiçi tüketim, dış ticaret göstergeleri, tüketici güven endeksi, Türkiye Kredi Risk Swapı, kapasite kullanım oranı, gibi diğer göstergeler ile takip oranları arasındaki ilişkiler de test edilmiştir. Bu göstergelerden bazıları (yurtiçi tüketim, kapasite kullanım oranı) Gayrisafi Yurtiçi Hasıla verisinin öncüsü veya türevi mahiyetinde olup, korelasyon ilişkileri beklenen işarettedir.

Çalışmanın modellerinin kurulduğu bölümde ilk olarak Türkiye'de tüketici kredilerin temerrüt olasılığını ile seçilen makroekonomik değişkenler arasındaki ilişki incelenmiştir. Bu amaç doğrultusunda takibe düşen tüketici kredileri ile hesaplanan ve bağımlı değişken olarak analizde kullanılan tüketici kredilerinin temerrüt olasılığı ve onu etkileyen makroekonomik değişkenlerin neler olduğu konusunda geniş kapsamlı olarak birçok makroekonomik değişkenin yer aldığı modeller sınanmış, uygun olmayan değişkenler çıkarılmış ve nihayetinde ise en uygun modeller ortaya konmaya çalışılmıştır. Bu bağlamda işsizlik verisi, enflasyon ve sanayi üretim endeksindeki büyümenin takipteki tüketici kredileri üzerindeki etkileri ölçülmüştür.

Seçilen değişkenler arasında seri korelasyon problemi olup olmadığı korelasyon matrisi ile incelenmiştir. Bu doğrultuda açıklayıcı değişkenler arasındaki korelasyon ilişkisinin kabul edilebilir sınırlar altında olması beklenir. Tablo 4.1 incelendiğinde değişkenler arasında korelasyon ilişkisinin düşük olduğu görülmüştür.

Zaman serisi analizinde serilerin durağanlığının test edilmesi büyük önem arz etmektedir. Şimdiye kadar gerçekleştirilen ampirik çalışmalar makroekonomik zaman serilerinin büyük bölümünün durağan olmayan zaman serileri olduğunu ortaya çıkarmıştır. Birim kök içeren bu seriler arasında sahte regresyon sorunuyla karşılaşıldığından, bu duruma çözüm bulabilmek için çeşitli yöntemler önerilmiştir. Bu önerilerden bir tanesi, serilerin farklarının alınıp regresyona sokulmasıdır. Ancak bu durumda da yeni bir problemle karşılaşılmakta ve uzun dönem dengesi için önemli olan bilgilerin kaybedilmesine yol açmaktadır. Çünkü değişkenlerin birinci farkları kullanıldığından bu değişkenler arasında olması muhtemel uzun dönemli ilişkiyi görme olasılığı ortadan kalkmaktadır.

Pesaran vd. (2001) tarafından geliştirilen ARDL sınır testi yaklaşımına göre Engle-Granger ve Johansen eşbütünleşme testlerinin aksine serilerin I(0) veya I(1) olmalarına bakılmaksızın seriler arasında eşbütünleşme ilişkisinin varlığı araştırılabilir. Ayrıca bu yaklaşım düşük sayıda gözlemi içeren verilerde de sağlıklı sonuçlar verebilmektedir.

Zaman serileri ile yapılan çalışmalarda kullanılan değişkenlerin durağanlık şartını sağlamaları istatistiki açıdan güvenilir sonuçlar elde edilebilmesi için aranılan bir önkoşuldur. Bu nedenle bağımlı ve bağımsız değişkenler arasındaki uzun dönemli ilişkilerin araştırılmasından önce, çalışmaya dâhil edilen tüm değişkenlerin durağanlığı ADF birim kök testi ile incelenmiştir. Kullanılacak ADF Modelinde, Akaike bilgi kriterince tavsiye olunan gecikme sayılarına itibar edilmiştir. Yapılan birim kök sınamaları sonucunda işsizlik ve enflasyon serilerinin birinci farkı alındığında durağan olduğu kanaatine ulaşılmış, diğer değişkenlerin de %1'in daha altındaki olasılık değerleriyle birim köke sahip olmadıkları yani durağan oldukları sonucuna ulaşılmıştır. Birim kök sınamasına ilişkin ADF Testi sonuçları Tablo 4.2.'da sunulmaktadır. Tablo incelendiğinde bütün değişkenler aynı düzeyde durağan olmadıklarından değişkenler arasındaki uzun dönem ilişkilerini görebilmek için ARDL eş bütünleşme testi yapılacaktır.

Serilerin durağanlığı incelendikten sonra eş bütünleşme analizi için Paseran (2001)'ın geliştirdiği sınır testi kullanılmıştır. Sınır testi için ilk önce kısıtlanmamış hata düzeltme modeli kurulmalıdır. Hata düzeltme modelinin bizim çalışmamız için uyarlanmış hali aşağıdaki eşitlikte gösterilmektedir.

$$\Delta\, PD\_\text{Consumer Index}_t = \beta_0 + \beta_1\, PD\_\text{Consumer Index}_{t-1} + \beta_2 \text{Growth}_{t-1} + \beta_3 \text{Inflation}_{t-1} + \beta_4 \text{Unemployment}_{t-1} + \sum_{i=1}^{p} \beta_{5\text{i}}\, \Delta\, \text{PD\_Consumer Index}_{t-i} + \sum_{i=1}^{p} \beta_{6\text{i}}\, \Delta\, \text{Growth}_{t-i} + \sum_{i=1}^{p} \beta_{7\text{i}}\, \Delta\, \text{Inflation}_{t-i} + \sum_{i=1}^{p} \beta_{8\text{i}}\, \Delta\, \text{Unemployment}_{t-i} + e_{\text{t}} \qquad (4.1)$$

Denklemde yer alan hata düzeltme modelinde p gecikme sayısını göstermektedir. Eş bütünleşme ilişkisinin varlığının test edilmesi için bağımlı ve bağımsız değişkenlerin birinci dönem gecikmelerine F testi yapılır. Bu test için temel hipotez (H0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$) şeklinde kurulur ve hesaplanan F istatistiği Pesaran (2001)'daki tablo alt ve üst kritik değerleri ile karşılaştırılır. Hesaplanan F istatistiği Pesaran alt kritik tablo değerinden düşük ise seriler arasında eş bütünleşme ilişkisi bulunmaz iken hesaplanan F istatistiği alt ve üst tablo kritik değeri arasındaysa kesin bir yorum yapılamamaktadır. Eğer hesaplanan F istatistiği tablo üst kritik değerin üzerindeyse seriler arasında eş bütünleşme ilişkisi vardır.

Eşbütünleşme test sonuçlarına göre hesaplanan F-istatistiği % 1 anlamlılık düzeyinde üst sınırın üzerinde yer almaktadır. Peseran vd. (2001) varsayımı göz önüne alındığında eşbütünleşmenin olmadığını ifade eden boş hipotezi reddederek bağımlı ve bağımsız değişkenler arasında eşbütünleşme ilişkisi tespit edilmiştir.

Seriler arasında eşbütünleşme ilişkisi tespit edildikten sonra makroekonomik değişkenler ve temerrüt olasılığı arasında uzun ve kısa dönem ilişkileri belirlemek için ARDL modeli kurulmuştur. ARDL modelinde gecikme sayılarının belirlenmesi için Akaike bilgi kriterinden yararlanılmış olup ARDL (2,0,2,2) modeli uygun ARDL modeli olarak seçilmiş ve modelden hesaplanan uzun dönem katsayıları Tablo 4.3'de yer almaktadır.

Elde edilen sonuçlara göre temerrüt olasılığının uzun dönemde işsizlik serisi, enflasyon ve sanayi üretim endeksindeki büyüme ile birlikte hareket etmektedir. Yani seçilen bağımsız değişkenler uzun dönemde temerrüt olasılığının önemli belirleyicileridir. Tablo incelendiğinde uzun dönemde temerrüt olasılığı ile işsizlik arasında istatistiksel olarak pozitif yönlü ve anlamlı bir ilişkinin bulunması beklentiler dahilinde bulunmaktadır. İktisadi büyümeyi temsil eden sanayi üretim endeksi büyümesi ve enflasyondaki ile temerrüt olasılığı arasında ise uzun dönemde istatistiksel olarak negatif yönlü ve anlamlı bir ilişkinin bulunması, yine beklentiler dahilinde bulunmaktadır.

Değişkenler arasındaki kısa dönemli ilişkinin araştırılması için ARDL yaklaşımına dayalı hata düzeltme modeli çalışmamıza uyarlanmakta ve ARDL (2,0,2,2) modelinden elde edilen hata düzeltme modeli sonuçları Tablo 4.4'te sunulmaktadır. Tablo'daki CointEq(-1) değişkeni uzun dönem ilişkisinden elde edilen hata terimi serisinin bir dönem gecikmeli değeridir. Bu değişkenin katsayısı kısa dönemdeki dengesizliğin ne kadarının uzun dönemde düzeltileceğini göstermektedir. Hata düzeltme değişkeni ise beklendiği gibi negatif ve istatistiksel olarak anlamlı çıkmıştır. Katsayı modelde -0,36 olarak bulunmuştur. Modele ilişkin heteroskedasite (değişen varyans), otokorelasyon ve normallik testleri bulgularına ilişkin sonuçlar da gene aynı Tablo'da verilmiştir. Buna göre kurulan model için otokorelasyon, heteroskedasite ve normallik problemleri bulunmamaktadır. Son olarak modele ilişkin Cusum ve CusumQ test sonuçlarına göre test istatistikleri %5 anlamlılık düzeyinde kritik sınırlar içinde bulunduğundan söz konusu dönemde yapısal bir değişim tespit edilmemiştir. Yani parametrelerin %5 anlamlılık düzeyinde istikrarlı olduğu görülmektedir.

Kurulan ikinci modelin amacı, ülke ekonomileri açısından hayati öneme sahip olan bankaların aktif büyüklüklerini etkileyen en önemli faktörlerden birisi olan ve firmaların ödeyebilme güçlerini gösteren takipteki ticari krediler ile hesaplanan ve bağımlı değişken olarak analizde kullanılan ticari kredilerinin temerrüt olasılığını belirleyen makroekonomik faktörleri bulmak ve bu faktörlerin temerrüt, olasılığını etkileyiş yönünü ve derecesini tespit etmektir. Bu açıdan, bu çalışmada ticari kredilerin temerrüt olasılığını belirleyen makro ekonomik faktörler olarak ticari kredi faiz oranı, sanayi üretim endeksindeki büyüme, reel efektif döviz kuru ve VIX volatilite endeksi açıklayıcı değişken olarak kullanılmıştır. Üretim endeksindeki büyüme ülkemizdeki iktisadi büyümeyi temsilen, reel efektif döviz kuru risk unsurunu temsilen, faiz oranı ticari kredi maliyetini temsilen ve VIX endeksi ise küresel riski temsilen modele alınmıştır.

Seçilen değişkenler arasında seri korelasyon problemi olup olmadığı korelasyon matrisi ile incelenmiştir. Tablo 4.5 incelendiğinde değişkenler arasında korelasyon ilişkisinin düşük olduğu görülmüştür.

Tüm değişkenlerin durağanlığı ADF birim kök testi ile incelenmiştir. Birim kök sınamasına ilişkin ADF Testi sonuçları Tablo 4.6.'da sunulmaktadır. Tablo incelendiğinde bağımlı değişkenin ve büyüme verilerinin ADF testi sonucuna göre düzeyde durağan oldukları görülürken, diğer değişkenlerin düzey seviyede birim köke sahip olduğu görülmektedir. Değişkenlerin birinci farkı alındığında değişkenler durağan hale gelmiştir. Bütün değişkenler aynı düzeyde durağan olmadıklarından değişkenler arasındaki uzun dönem ilişkilerini görebilmek için ARDL eş bütünleşme testi yapılacaktır.

Serilerin durağanlığı incelendikten sonra eş bütünleşme analizi için Paseran (2001)'ın geliştirdiği sınır testi kullanılmıştır. Sınır testi için ilk önce kısıtlanmamış hata düzeltme modeli kurulmalıdır. Hata düzeltme modelinin bizim çalışmamız için uyarlanmış hali aşağıdaki eşitlikte gösterilmektedir.

$$\Delta\, PD\_\mathrm{SME\ Index}_t = \beta_0 + \beta_1\, PD\_\mathrm{SME\ Index}_{t-1} + \beta_2 \mathrm{Growth}_{t-1} + \beta_3 \mathrm{REER}_{t-1} + \beta_4 \mathrm{VIX}_{t-1} + \beta_5 \mathrm{IR}_{t-1} + \sum_{i=1}^{p} \beta_{6\mathrm{i}}\, \Delta\, D\_\mathrm{SME\ Index}_{t-i} + \sum_{i=1}^{p} \beta_{7\mathrm{i}}\, \Delta\, \mathrm{Growth}_{t-i} + \sum_{i=1}^{p} \beta_{8\mathrm{i}}\, \Delta\, \mathrm{REER}_{t-i} + \sum_{i=1}^{p} \beta_{9\mathrm{i}}\, \Delta\, \mathrm{VIX}_{t-i} + \sum_{i=1}^{p} \beta_{10\mathrm{i}}\, \Delta\, \mathrm{IR}_{t-i} + e_{\mathrm{t}} \qquad (4.4)$$

Denklemde yer alan hata düzeltme modelinde p gecikme sayısını göstermektedir. Çalışmada gecikme sayısının belirlenmesi için Akaike bilgi kriterinden faydalanılmış olup bu kriteri en küçük yapan gecikme uzunluğu modelin gecikme uzunluğu olarak belirlenmiştir. Sınır testi sonuçlarına göre hesaplanan F-istatistiği % 1 anlamlılık düzeyinde üst sınırın üzerinde yer almaktadır. Bir başka ifade ile bağımlı ve bağımsız değişkenler arasında eşbütünleşme ilişkisi tespit edilmiştir.

Seriler arasında eşbütünleşme ilişkisi tespit edildikten sonra Akaike bilgi kriterine göre ARDL (1,2,0,0,2) modeli uygun ARDL modeli olarak seçilmiş ve modelden hesaplanan uzun dönem katsayıları Tablo 4.7'de sunulmuştur. Elde edilen sonuçlara göre temerrüt olasılığının uzun dönemde ticari kredi faiz oranı, sanayi üretim endeksindeki büyüme, reel efektif döviz kuru ve VIX volatilite endeksi ile birlikte hareket ettiği görülmektedir. Yani seçilen bağımsız değişkenler uzun dönemde temerrüt olasılığının önemli belirleyicileridir. Tablo incelendiğinde uzun dönemde temerrüt olasılığı ile VIX volatilite endeksi ve ticari kredi faiz oranı arasında istatistiksel olarak pozitif yönlü ve anlamlı bir ilişkinin bulunması beklentiler dahilinde bulunmaktadır. İktisadi büyümeyi temsil eden sanayi üretim endeksindeki büyüme ve reel efektif döviz kuru ile temerrüt olasılığı arasında ise uzun dönemde istatistiksel olarak negatif yönlü ve anlamlı bir ilişkinin bulunması gene beklentiler dahilinde yorumlanmaktadır.

Değişkenler arasındaki kısa dönemli ilişkinin araştırılması için ARDL yaklaşımına dayalı hata düzeltme modelinin çalışmamıza uyarlanmış ve ARDL (1,2,0,0,2) modelinden elde edilen hata düzeltme modeli sonuçları Tablo 4.8'te sunulmaktadır. CointEq(-1) değişkeni beklendiği gibi negatif ve istatistiksel olarak anlamlı çıkmıştır. Katsayı modelde -0,17 olarak bulunmuştur. Modele ilişkin heteroskedasite (değişen varyans), otokorelasyon ve normallik testleri bulgularına ilişkin sonuçlar da gene aynı Tablo'da verilmiştir. Buna göre kurulan model için de otokorelasyon, heteroskedasite ve normallik problemleri bulunmamaktadır. Son olarak modele ilişkin Cusum ve CusumQ test sonuçlarına göre test istatistikleri %5 anlamlılık düzeyinde kritik sınırlar içinde bulunduğundan söz konusu dönemde yapısal bir değişim tespit edilmemiştir. Yani parametrelerin %5 anlamlılık düzeyinde istikrarlı olduğu görülmektedir.

Kredi alma ve kredi verme fonksiyonlarının bankacılık sektörünün temel fonksiyonları olduğu düşünüldüğünde, bunlardan kaynaklanan riskin yönetiminin önemi de ortaya çıkmaktadır. Küreselleşme ile global bir kimlik kazanan finansal piyasalarda gerçekleşmesi muhtemel şoklara ve krizlere karşı dayanıklı olmak hem Basel kriterlerine hem de UFRS 9 standartlarına uyum sağlamak ve hem makro hem de mikro düzeyde kredi riski kaynaklı sorunları öngörüp gerekli önlemleri alarak, kaçınılmaz ve önlenemez bazı şoklardan mümkün olan en az zararla kurtulabilmek için, kredi riski modellemeleri büyük önem taşımaktadır. Bu açıdan bakıldığında, Türk bankacılık sisteminin kriz geçmişi ve sistemin güçlendirilme çalışmalarının çok eskiye dayanmadığı da göz önünde bulundurulursa, sektörü en çok etkileyecek olan kredi riskinin yönetim sürecinin daha çok üzerinde durulmasının ve bu konuda ciddi çalışmaların yapılmasının gerekliliği ortaya çıkmaktadır. Yapılan bu çalışma, Türk bankacılık sistemi için makroekonomik kredi riski modellemesi ile ilgili literatürde önemli bir katkı sağlayacaktır.

Literatür incelendiğinde Türkiye'de bankacılık sisteminde kredileri etkileyen başlıca makroekonomik değişkenlerin iktisadi büyüme, faiz oranları, parasal genişleme, cari işlemler dengesi, enflasyon, işsizlik oranları ve kur endeksleri olduğu görülmüştür. Öncelikli olarak kredi riskinin tanımı, çeşitleri ve önemi üzerinde durduğumuz bu çalışmada günümüze kadar bu konuda yapılmış olan önemli çalışmalar ve bulgulara yer verilmiştir. Kredi riskinin makroekonomik çevreyle olan ilişkisinin varlığını gösteren literatürdeki diğer çalışmaların ışığında yapılan bu çalışma o çalışmaların aksine bir sonuçla noktalanmamıştır.

Bu araştırmada tüketici kredilerinin ve küçük ve orta büyüklükteki işletmelerin kullandığı ticari kredilerin temerrüt olasılıklarını belirleyen makroekonomik değişkenlerin neler olduğu konusunda geniş kapsamlı olarak birçok makroekonomik değişkenin yer aldığı modeller sınanmış, uygun olmayan değişkenler çıkarılmış ve nihayetinde ise en uygun modeller ortaya konmaya çalışılmıştır. Bu bağlamda sanayi üretim endeksindeki büyüme, işsizlik ve enflasyon oranlarının tüketici kredilerin temerrüt olasılıkları üzerindeki etkileri ile sanayi üretim endeksi, reel efektif döviz kuru, faiz oranları ve VIX volatilite endeksinin işletmelerin kullandığı ticari krediler üzerindeki etkisi ölçülmüştür. Araştırmada bu kadar çok makroekonomik değişkenin yer alması çalışmayı önemli kılmıştır. Özellikle literatür incelendiğinde uzun dönemde VIX' in temerrüt olasılıkları üzerindeki etkisini inceleyen araştırmaların çok sınırlı olduğu görülmüştür. Bu bakımdan araştırma VIX endeksinin Türkiye'de küçük ve orta büyüklükteki işletmelerin kullandığı kredilerin temerrüt olasılıkları üzerindeki uzun dönem etkilerinin görünmesi bakımından önemlidir.

Çalışma sonuçlarına göre, seçili makroekonomik değişkenler ile tüketici kredilerinin temerrüt olasılıkları arasındaki ilişkinin ekonomik teorilere uygun olduğu söylenebilir. Örneğin, sanayi üretimindeki artışın büyümeyi işaret etmesi dikkate alındığında, tüketicilerin finansal durumlarındaki iyileşme borçlarını ödemekten kaçınma olasılıklarını azaltacaktır. Ek olarak, enflasyondaki artışlar bir ülkenin büyüme oranında artışı ve reel borç seviyesindeki azalışı tetiklemektedir (Çalışan maaşları da artacaktır). Böylece temerrüt olasılığı ile enflasyon arasında negatif bir ilişki olduğu ortaya çıkmaktadır. Öte yandan, işsizlik artışı da sanayi üretiminin tersine bir küçülmeyi göstermesi açısından tüketicilerin borçlarını çevirmekte zorlandıklarına işaret etmektedir.

Seçili makroekonomik değişkenler ile ticari kredilerin temerrüt olasılıkları arasındaki ilişki bilinen ekonomi ana akımları üzerinden açıklanabilmektedir. Örneğin, korku endeksi olarak bilinen VIX küresel risk seviyesini göstermekle birlikte bu endeksteki artış sermaye çıkışlarını tetiklemekte ve şirketler için borç ödemelerini zorlaştırmaktadır. Bu açıdan, VIX ile temerrüt olasılığı arasında pozitif bir ilişki bulunmaktadır. Benzer şekilde, ticari kredi faiz oranları firmaların maliyetlerini artırmakta ve yeni kredi bulunmasını zorlaştırmaktadır. Bu durum firmaların faaliyetlerine devam etmelerine engel olabilmektedir. Öte yandan, reel efektif kur düzeyinde yaşanacak artış yerel paranın değerlenmesine, dolayısıyla da borçların ödenmesinde (özellikle yabancı para cinsinden) kolaylık sağlanmasına yardımcı olmaktadır. Son olarak, sanayi üretim endeksindeki artış şirketlerin büyümesine olanak verirken temerrüt olasılıklarının da azalmasına sebep olmaktadır.

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TEZİN TÜRÜ / DEGREE: **Yüksek Lisans** / Master **Doktora** / PhD

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