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THE FACTORS INFLUENCING BANKS' RISK-TAKING BEHAVIOR: EVIDENCE FROM THE TURKISH BANKING INDUSTRY [*]

Bankaların Risk Alma Davranışını Etkileyen Faktörler: Türk Bankacılık Sektöründen Kanıtlar

Erdal DEMİR[**] **& Yüksel AYDIN**[***]

Anahtar Kelimeler: Banka Risk Alma, Ticari Bankalar, Türk Bankacılık Sistemi, Panel Veri Analizi

JEL Kodları: G21, G32, C33

Öz

Bu araştırma, 2010-2023 dönemi için Türkiye'deki ticari bankaların risk almasını etkileyen faktörleri ampirik olarak analiz etmektedir. Geliştirilen panel veri regresyon modellerinde banka risk alma ölçütü olarak ters Z skoru kullanılırken, bağımsız değişken olarak çeşitli banka düzeyi ve makro düzey değişkenler kullanılmıştır. Bu makalede geliştirilen modeller, tüm bankaları içeren ana örneklem ve oluşturulan alt örneklemler için ayrı ayrı tahmin edilmiştir. Sabit etkili regresyonlardan elde edilen sonuçlara göre, banka büyüklüğü, banka sermayesi, banka mevduatı ve net faiz marjı değişkenleri ana örneklem açısından banka risk alma düzeyini azaltma eğilimindedir. Ancak likidite riski, kredi riski, enflasyon oranı, ekonomik büyüme ve COVID-19 pandemi krizi banka risk alma düzeyini artırma eğilimindedir. Halka açık, halka açık olmayan, yerli ve yabancı bankalardan oluşan alt örneklemlerden elde edilen bulgular, banka büyüklüğü, banka sermayesi ve net faiz marjının banka risk alma düzeyini azaltma eğiliminde olduğunu göstermektedir ki bu da ana örneklemden elde edilen bulguları desteklemektedir. Son olarak, bu makalenin sonuçları, bankaların risk alma davranışlarının kontrol edilmesi, bankacılık sektöründe istikrarın sağlanması ve sürdürülebilir bir bankacılık sektörünün oluşturulması açısından banka yönetimi, düzenleyici mekanizmalar ve politika yapıcılar için önemli çıkarımlara sahiptir.

Keywords: Bank Risk Taking, Commercial Banks, Turkish Banking System, Panel Data Analysis

JEL Codes: G21, G32, C33

Abstract

This research employs an empirical approach to analyse the factors affecting the risk-taking of commercial banks in Turkey for the period 2010-2023. The inverse Z score was utilised as a measure of bank risk-taking in the developed panel data regression models, while various bank-level and macro-level variables were employed as independent variables. The developed models in this article are estimated separately for the main sample, which includes all banks, and for the sub-samples that have been formed. According to the results based on fixed effects regressions, bank size, bank capital, bank deposit and net interest margin variables tend to reduce the level of bank risk taking in terms of the main sample. However, liquidity risk, credit risk, inflation rate, economic growth and the COVID-19 pandemic crisis tend to increase the level of bank risk taking. Findings from subsamples of listed, non-listed, domestic and foreign banks indicate that bank size, bank capital and net interest margin tend to reduce the level of bank risk taking, which supports the findings from the main sample. Finally, the results of this article have important implications for bank management, regulatory mechanisms and policy makers in terms of controlling the risk-taking behavior of banks, ensuring stability in the banking sector and building a sustainable banking sector.

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[**] Lecturer Dr., Van Yüzüncü Yıl University, Gevaş Vocational School, Finance-Banking and Insurance Department, Türkiye, erdaldemir58@hotmail.com.tr

[***] Assoc. Prof., Sivas Cu5mhuriyet University, Faculty of Economics and Administrator Sciences, Türkiye, yaydin@cumhuriyet.edu.tr

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1. Introduction

The banking industry is of pivotal importance to the economy, as it performs several key functions. Firstly, banks accept deposits from individuals and businesses, safeguarding these assets while paying interest to depositors. They then use these deposits to provide loans and advances, facilitating economic activities such as business expansion, construction, and consumer spending (Işık et al., 2025). Additionally, banks create credit, which increases the money supply and supports economic growth. They also offer payment and settlement systems, enabling smooth financial transactions.

Banking is an industry that is inherently associated with risk. Financial institutions are susceptible to a multitude of risks in the course of their operations (Isik and Bolat, 2016; Chen et al., 2018). These risks encompass credit risk, characterized by the potential for borrowers to default on their loan obligations; market risk, stemming from volatility in interest rates, exchange rates, and asset prices; liquidity risk, which pertains to the inability to meet short-term financial obligations; operational risk, arising from internal process failures or external events; reputational risk, which can damage a bank's public image and customer trust; compliance risk, related to violations of laws and regulations; and systemic risk, where the failure of one institution can trigger a broader financial crisis (Adhikari and Agrawal, 2016; Erdinç and Gurov, 2016).

Understanding and managing these risks is crucial for banks to ensure their stability and profitability (Işık and Belke, 2017). By effectively identifying, assessing, and mitigating risks such as credit, market, liquidity, operational, reputational, compliance, and systemic risks, banks can safeguard their financial health and maintain customer trust (Danisman and Demirel, 2019; Nur, 2022). Robust risk management practices enable banks to navigate economic uncertainties, capitalize on growth opportunities, and avoid significant losses. This proactive approach not only enhances the bank's resilience but also contributes to the overall stability of the financial system, fostering sustainable economic development (Martínez-Malvar and Baselga-Pascual, 2020; Mercan, 2021).

Banks' risk-taking tendencies can also drive innovation and economic growth by providing essential funding and credit, but excessive risk-taking can lead to financial instability, negatively impacting banking activities, various economic sectors, and overall economic sustainability (Diaconu and Oanea, 2014; Danisman and Demirel, 2019). When banks engage in high-risk activities without adequate safeguards, they expose themselves to potential defaults, market volatility, and liquidity crises. This can result in significant financial losses, reduced lending capacity, and operational disruptions (Baselga-Pascual et al., 2015; Albaity et al., 2019). The ripple effects of such instability can spread to businesses that rely on bank financing, leading to reduced investments, job losses, and economic downturns. Furthermore, the broader economy can suffer from decreased consumer confidence and spending, ultimately hindering sustainable growth and development. Therefore, maintaining a balanced approach to risk-taking is essential for the long-term health of both the banking sector and the economy as a whole. Understanding these dynamics is crucial for policymakers and financial institutions aiming to create a resilient banking system. Therefore, effective risk management practices are essential to balance the benefits of risk-taking with the need to maintain financial stability (Akbar et al., 2017; Ashraf, 2017).

The aim of the present research is to determine the variables affecting the risk-taking behaviour of banks through panel data regression analysis. For this objective, the annual data of

22 commercial banks operating in the Turkish banking system for the period 2010-2023 were analysed with the Fixed Effects regression model proposed by Driscoll-Kraay (1998).

The existing research makes three contributions to the extant bank literature. Firstly, it is the first study, to the best of the researchers' knowledge, to explore the factors influencing the risk-taking behaviour of Turkish commercial banks. Secondly, for methodological reasons, bank-level and macro-level factors affecting banks' risk-taking propensity were modelled together in the analysis of Turkish banks using a panel fixed-effect estimation model. Furthermore, the employed estimation methodology minimizes bank-specific effects. Thirdly, the risk-taking model was estimated separately for both the main sample including all banks and the sub-samples created to investigate whether there were differences in risk-taking among banks. Lastly, the influence of the COVID-19 pandemic crisis on the risk-taking level of Turkish banks has also been investigated in the current study.

The remainder of this research is divided into a further 5 sections. Section 2 reviews the literature on bank risk taking and explains the research gap. Section 3 presents the data and the research methodology. Section 4 presents the empirical findings and finally, Section 5 concludes the manuscript.

2. Literature Review

This section is divided into two subsections. The first subsection examines the articles in the literature to date that examine banks' risk-taking behavior. The second subsection then assesses the critical research gaps in the banking literature.

2.1. Past Papers Examining the Factors Influencing Banks' Risk-Taking

In this subsection, as seen in Table 1, earlier studies investigating the factors affecting banks' risk-taking behavior are briefly summarized.

Table 1. Past Studies Examining the Factors Influencing Banks' Risk-Taking Behavior

Study	Analysis Period	Scope	Methodology	Risk Measure	Result
Chaibi and Ftiti (2015)	2005–2011	280 commercial banks in France and Germany	Two-step system GMM	Credit risk (non-performing loan ratio)	Results show that both micro and macro variables have significant effects on banks' credit risk.
Isik and Bolat (2016)	2006-2012	20 commercial banks in Turkey	Pooled OLS, Random Effects, and Fixed Effects panel data regression estimators	Credit risk (non-performing loan ratio)	Credit risk is influenced more by bank-level variables and the 2008 global financial crisis than by macro variables.
Adhikari and Agrawal (2016)	1994-2010	1459 banks in the USA	Fixed Effects panel data regression analysis	-Standard deviation of stock returns - Bankruptcy risk measured by Z-score	Findings indicate that local religiosity reduces banks' risk-taking tendencies.
Işık and Belke (2017)	13 commercial banks in Turkey	2006-2015	Arellano-Froot-Rogers panel data estimator	Liquidity risk	According to the findings, liquidity risk is significantly affected by both macro and micro level variables.
Ahamed (2021)	2005-2018	23 banks in Bangladesh	Pooled OLS and Random Effects panel data estimators	Liquidity risk	Liquidity risk is negatively related to bank size but positively related to capital adequacy and return on assets.
Akbar et al. (2017)	2003−2012	276 financial sector firms including FTSE-listed banks	System GMM	-Standard deviation of stock returns - Bankruptcy risk measured by Z-score	The study reports that board independence and CEO duality reduce bank risk.
Albaity et al. (2019)	2006–2015	276 banks in MENA countries	Two-step system GMM	-Non-performing loans -Bankruptcy risk measured by Z-score	Results show that banks facing lower competition tend to take less credit and bankruptcy risk.

Tablo 1. Continue

Study	Analysis Period	Scope	Methodology	Risk Measure	Result
Ashraf (2017)	1998–2007	34021 observations from banks operating in 98 countries	Pooled panel OLS estimator	-Operational risk based on deviations in interest income -Bankruptcy risk measured by Z-score	Results indicate that political institutions encourage higher risk-taking in banks.
Baselga-Pascual et al. (2015)	2001-2012	204 commercial banks operating in 14 European countries	Two-step system GMM	-Non performing loans -Bankruptcy risk measured by Z-score	The study finds that less concentrated markets, lower interest rates, higher inflation rates, and economic crises increase bank risk.
Chen et al. (2018)	2005-2016	31 commercial banks in China	Fixed Effects panel data regression analysis	Credit risk	Findings indicate that financial inclusion increases the ratio of non-performing loans.
Diaconu and Oanea (2014)	2008-2012	13 commercial banks in Romania	Pooled panel OLS estimator	Bankruptcy risk measured by Z-score	Findings indicate that economic growth and interest rates reduce bank bankruptcy risk.
Dias (2020)	2011-2015	Over 1,800 banks from 135 countries	Cross-sectional regression analysis	Bankruptcy risk measured by Z-score	The study reports an inverse U-shaped relationship between capital adequacy and bank risk-taking (measured by Z-score).
Erdinç and Gurov (2016)	2000–2011	35 European countries	Difference and system GMM	Credit risk measured by non-performing loans	Findings confirm that the intensive use of internal ratings in the post-crisis period leads to a statistically significant decrease in total non-performing loans.
Danisman and Demirel (2019)	2007-2015	25 developed countries	Fixed Effects estimator	-Bankruptcy risk -Operational risk -Liquidity risk	The study finds that capital requirements are the most effective regulatory tool in reducing bank risk and that these requirements are more effective in reducing risk for banks with greater market power. It also finds that higher operating restrictions in developed markets significantly increase bank risk, but this risk increase is mitigated for banks with greater market power.

Tablo 1. Continue

Study	**Analysis Period**	**Scope**	**Methodology**	**Risk Measure**	**Result**
Ghenimi et al. (2020)	2005–2015	49 commercial and 27 participation banks in MENA countries	Two-step system GMM	Liquidity risk	Results show that bank-specific variables affect liquidity risk in both banking systems, while macroeconomic factors determine liquidity risk for conventional banks. Additionally, liquidity risk for Islamic banks is not affected by macroeconomic variables.
Martínez-Malvar and Baselga-Pascual (2020)	1999-2013	Latin American banks	Two-step system GMM	Bankruptcy risk measured by Z-score	Results show that commercial banks with strong capital structures and high liquidity are less risky.
Mercan (2021)	2006-2014	Georgian banks	Pooled panel OLS, Random Effects, and Fixed Effects estimators	-Bankruptcy risk measured based on Z score -Credit risk	According to the findings, bank capital increases bank risk while bank profitability decreases bank risk.
Mohamad and Jenkins (2020)	2011–2019	197 banks from 16 MENA countries	Fixed Effects estimator	Credit risk	Results indicate a positive relationship between corruption and non-performing loans.
Nur (2022)	2000-2020	7 banks listed on the Borsa Istanbul Bank Index	Panel cointegration and causality analysis	Bankruptcy risk measured by Z-score	The findings of the study indicated the presence of a long-term cointegration relationship between the variables. Furthermore, the study concluded that there exists a unidirectional causality relationship from risk-taking tendency to profitability and from liquidity deficiency to risk-taking tendency.

2.2. Research Gap

A detailed examination of previous studies on bank risk-taking behavior in the literature indicates two important research gaps. The first research gap is related to previous studies conducted in the Turkish banking sector. In two of these studies, credit and liquidity risks were used as dependent variables. The other study, which used bankruptcy risk as dependent variable, focused on cointegration and causality relationship using a sample of only 7 banks. To fill this gap, we used a balanced panel of 22 commercial banks operating in the Turkish banking sector for the period 2010-2023. This is of great importance for generalizing the obtained results to the banking sector. The second critical research gap is related to the methodology used in previous studies. Previous articles have examined the factors affecting the risk-taking behaviour of banks using pooled OLS, Random Effects and Fixed Effects, difference GMM, system GMM or 2SLS panel data regression estimators. To fill this heading, we used the Fixed Effects regression model proposed by Driscoll-Kraay (1998) estimator. As is known, this estimator produces robust and reliable estimation results in cases where there is heterogeneity, autocorrelation, heteroscedasticity and cross-sectional dependence. Besides, the up-to-date nature of the data employed in this research is of critical importance for stakeholders and practitioners in the banking sector in determining the factors affecting risk-taking behaviour in the developing and transforming banking sector.

3. Methodology

3.1. Dataset

The present research aims to estimate the effects of micro and macro factors on the risk-taking behaviour of commercial banks. To this end, an annual data from 22 commercial banks operating in the Turkish banking sector during the period 2010-2023 is examined. The data is in the form of a balanced panel, thus commercial banks with missing data during the research period and other banks (participation banks and investment and development banks) are excluded from the study's scope. Table 2 presents details on used sample. Additionally, Table 3 gives the detailed definitions of the variables used in the analyses.

Table 2. Commercial Banks Included in the Research

No.	Commercial Bank	No.	Commercial Bank
1	Türkiye Cumhuriyeti Ziraat Bankası A.Ş.	15	Citibank A.Ş.
2	Türkiye Halk Bankası A.Ş.	16	Denizbank A.Ş.
3	Türkiye Vakıflar Bankası T.A.O.	17	HSBC Bank A.Ş.
4	Akbank T.A.Ş.	18	ICBC Turkey Bank A.Ş. (Tekstilbank)
5	Anadolubank A.Ş.	19	ING Bank A.Ş.
6	Fibabanka A.Ş. (millenium) eurobanka	20	QNB Finansbank A.Ş.
7	Şekerbank T.A.Ş.	21	Turkland Bank A.Ş. (mng)
8	Turkish Bank A.Ş.	22	Türkiye Garanti Bankası A.Ş.
9	Türk Ekonomi Bankası A.Ş.		
10	Türkiye İş Bankası A.Ş.		
11	Yapı ve Kredi Bankası A.Ş.		
12	Alternatifbank A.Ş.		
13	Arap Türk Bankası A.Ş.		
14	Burgan Bank A.Ş. (Eurobank tekfen)		

Table 3. Definitions of the Variables

Variables	Symbol	Calculation	Expected sign
Panel A: Dependent Variable			
Bankruptcy Risk	BR	1/Z-score=1/((ROAA +BE)/SD of ROAA) ROAA= return on average assets BE=Bank equity to total assets ratio SD=Standard deviation	
Panel B: Bank Level Independent Variables			
Bank size	Ln(assets)	Natural logarithm of total assets	+/-
Bank age	Ln(age)	Bank age Ln(age) Natural logarithm of bank age	-
Bank capital	CAR	Capital adequacy ratio	-
Bank deposit	BD	Bank deposit to total assets ratio	-
Credit risk	CR	Ratio of non-performing loans to total gross loans	+
Liquidity risk	LR	1/ratio of liquid assets to total assets	+
Interest margin	NIM	(Interest income-interest expenses)/total assets	-
Panel C: Macro Level Independent Variables			
Inflation rate	INF	Consumer Price Index (% change)	+/-
Economic growth	EG	Gross Domestic Product (% change)	+/-
Panel D: Crisis Variable			
COVID-19	CVD	Dummy variable that takes the value 1 for 2020 and 2021 and 0 for other years	+

3.2. Empirical Models

The aim of the current research is to determine the variables that affect the risk-taking behaviour of banks. The panel data model developed for this purpose is given below:

$$(\mathrm{BR})_{\mathrm{it}} = \alpha + \sum_{j=1}^{7} (BLIV)_{\mathrm{it}}\,\varsigma_{\mathrm{j}} + \sum_{j=1}^{2} (MLIV)_{\mathrm{t}}\,\delta_{\mathrm{j}} + \psi(\mathrm{CVD})_{t} + \varepsilon_{\mathrm{it}} \qquad (1)$$

In equation (1), the subscripts "i" and "t" represent individual banks and years, respectively; α is the constant term of the regression model; $(\mathrm{BR})_{\mathrm{it}}$_it is the dependent variable of the model and represents the risk-taking tendency of banks (bankruptcy risk). This variable is measured as the inverse of the Z score variable (1/Z score), in line with previous literature. Therefore, high values of this variable indicate that the bank's risk increases or its stability decreases; $(BLIV)_{\mathrm{it}}$ and $(MLIV)_{\mathrm{t}}$ represent the bank-level and macroeconomic-level control variables, respectively. The bank-level variables are bank size, bank age, bank capital, bank deposits, credit risk, liquidity risk, and interest margin, respectively. The macroeconomic variables are inflation rate and economic growth. In addition, the COVID-19 pandemic crisis is added to Eq. (1) through a dummy variable. This dummy variable takes the value of "1" for 2020 and 2021 and the value of "0" for other years. The parameters α, ς, δ and ψ are the coefficients to be estimated. $\varepsilon_{\mathrm{it}}=\lambda_t + \eta_i + \mu_{it}$ are the error terms of the models. In this equation, η_i represents the fixed effects specific to banks that are unobserved and do not change over time, λ_t represents the time effects, and μ_{it} represents the random error term with a mean of zero (E(μ_{it})=0) and a variance that does not change (Var(μ_{it})=σ2). The panel data regression model expressed in Eq. (1) has been estimated and reported separately for both the main sample including all banks and the subsamples created.

Following the estimation results for the main sample, two sub-samples are created for various criteria (i.e., being registered in BIST and capital structure) and it is checked whether the effects in the main sample changed when the sub-samples were taken into account. First, the banks in the main sample are divided into two groups as listed and unlisted banks. Second, the banks in the main sample are divided into two groups as domestic and foreign banks by taking into account their capital structures.

3.3. Estimation Procedure

The slope coefficients (α, ς, δ and ψ) of the panel data regression model expressed in Equation 1 can be estimated employing panel data estimators such as Ordinary Least Squares (OLS), Random Effects (RE), and Fixed Effects (FE). However, OLS does not take into account the bank-specific fixed effects (η_i), making it a weak estimator. In this study, the Hausman Specification test was used to select the most appropriate estimator between RE and FE. In the Hausman Specification test, the null hypothesis states that the RE estimator is valid, while the alternative hypothesis states that the FE estimator is valid. Since the null hypothesis of the Hausman Specification test was rejected at the 5% or 1% significance levels in the estimated main and sub-regression equations, the FE estimator was preferred for all model estimations. Following this step, autocorrelation, heteroskedasticity, and cross-sectional dependence tests were conducted to examine the assumptions related to errors in the FE models. The Wooldridge test, which tests the null hypothesis that there is no first-order autocorrelation in the model errors, was used to check for autocorrelation. The Modified Wald test, which tests the null hypothesis that the variance of the errors is constant, was utilized to check for heteroskedasticity. To test for cross-sectional dependence, the Pesaran CD test, which tests the null hypothesis that there is no cross-sectional dependence in the model errors, was applied. In the final stage of the estimation strategy, if autocorrelation and heteroskedasticity problems were detected in the error terms of the models, the classical FE estimator was used to address these issues. However, if autocorrelation, heteroskedasticity, and cross-sectional dependence problems were detected in the error terms of the models, the FE estimator proposed by Driscoll-Kraay (1998) was implemented to solve these issues. The Driscoll-Kraay FE estimator can be applied to both balanced and unbalanced panels. Additionally, this estimator provides reliable, efficient, and consistent estimation results in cases where N > T.

4. Empirical Findings

4.1. Summary Statistics

In Table 4, the mean, median, standard deviation, minimum and maximum values, skewness coefficient, kurtosis coefficient, and the number of observations for each variable are presented. The dependent variable of this research, bankruptcy risk (BR), has an average value of approximately 0.31. This variable ranges between 0.147 and 3.479 and has a standard deviation of 0.282. The bank-level variables included in the analysis—Ln(assets), Ln(age), CAR, BD, CR, LR, and NIM—have mean values of 10.777, 3.802, 11.082, 63.541, 4.383, 0.044, and 2.826, respectively. At the macroeconomic level, the variables INF and EG have mean values of 18.316 and 5.852, respectively.

Table 4. Summary Statistics Turkish Commercial Banks

	Mean	Median	SD	Minimum	Maximum	Skewness	Kurtosis	Observation
BR	0.314	0.267	0.282	0.147	3.479	7.627	70.419	308
Ln(assets)	10.777	10.855	1.882	6.798	14.844	-0.036	2.245	308
Ln(age)	3.802	3.638	0.545	2.639	5.075	0.375	2.297	308
CAR	11.082	10.783	3.301	3.702	26.819	0.729	4.408	308
BD	63.541	63.049	9.796	26.064	87.534	-0.312	3.833	308
CR	4.383	3.54	4.824	0.088	48.588	5.822	46.36	308
LR	0.044	0.042	0.019	0.014	0.12	1.093	4.79	308
NIM	2.826	2.807	1.486	-6.531	8.024	-0.587	9.914	308
INF	18.316	10.018	18.999	6.472	72.309	2.028	5.618	308
EG	5.852	5.237	3.119	0.819	11.439	0.314	2.203	308
CVD	0.143	0	0.350	0	1	2.041	5.167	308

4.2. Multi-collinearity Analysis

Within the framework of panel data regression analysis, it is first necessary to test whether there is a multi-collinearity problem among the independent variables. This is because high correlations among independent variables can cause the estimators to produce biased and inconsistent coefficient estimates. In this research, Spearman correlation analysis and the Variance Inflation Factor (VIF) analysis were conducted to test for multi-collinearity among independent variables. The findings of the Spearman’s rank correlation coefficients for all pairs of variables are reported in Table 5, while the results of the VIF analysis are presented in Table 6. The results in Table 5 indicate that the highest calculated correlation between any pair of independent variables is 0.74. This finding is important as it suggests that there is no significant multi-collinearity problem in the regression models. As is well known, multi-collinearity is generally considered an issue when the correlation coefficient between variable pairs is 0.80 or higher. Secondly, an examination of the VIF results reported in Table 6 reveals that none of the variables have a VIF value greater than 5. This result supports the findings from the correlation analysis and indicates that multi-collinearity is not a significant issue for the regression models used in this study.

Table 5. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) İR	1.00										
(2) ln(assets)	-0.16*	1.00									
(3) ln(age)	-0.08	0.70*	1.00								
(4) CAR	-0.09	-0.37*	-0.16*	1.00							
(5) BD	0.21*	-0.10	0.10	0.12	1.00						
(6) CR	0.74*	-0.19*	-0.16*	0.04	0.18*	1.00					
(7) LR	0.02	0.40*	0.22*	-0.35*	-0.05	0.08	1.00				
(8) NIM	-0.32*	-0.11	-0.02	0.43*	0.02	-0.26*	-0.27*	1.00			
(9) INF	0.07	0.33*	0.13	-0.14	0.18*	-0.11	0.11	-0.01	1.00		
(10) EG	-0.04	-0.11	-0.07	-0.03	-0.05	-0.15*	-0.33*	0.13	-0.12	1.00	
(11) CVD	0.07	0.14	0.08	-0.19*	0.04	0.14	0.16*	-0.19*	-0.05	0.10	1.00

Note: * p<0.01

Table 6. VIF Coefficients

	VIF	1/VIF
Ln(assets)	3.07	0.325960
Ln(age)	2.23	0.448049
CAR	1.63	0.611839
BD	1.23	0.814194
CR	1.34	0.747322
LR	1.77	0.564988
NIM	1.55	0.643442
INF	3.06	0.327240
EG	2.95	0.339307
CVD	2.74	0.364730
Mean VIF	2.26	

4.3. Cross-Section Dependency Analysis

In the existing work, cross-sectional dependency test was performed on a variable basis. For this purpose, the presence of cross-sectional dependence for each variable are examined employing the CD test proposed by Pesaran (2015, 2021). The results of the Pesaran CD test are presented in Table 7. In the CD test, the null hypothesis states that there is weak cross-sectional dependence. Considering Table 7, it is concluded that the null hypothesis is rejected for all variables. This finding indicates that there is a strong cross-sectional dependence for all variables.

Table 7. Pesaran (2015, 2021) CD Test Findings

	CD Statistics	Probability
BR	2.26**	0.024
Ln(assets)	53.83***	0.000
Ln(age)	56.84***	0.000
CAR	18.21***	0.000
BD	9.91***	0.000
CR	25.94***	0.000
LR	18.82***	0.000
NIM	17.49***	0.000
INF	56.87***	0.000
EG	56.87***	0.000

Note: In the CD test, the null (Ho) hypothesis is established as there is weak cross-sectional dependence, whereas the alternative (H1) hypothesis is established as there is strong cross-sectional dependence. * p<0.1, ** p<0.05, *** p<0.01

4.4. Second Generation Panel Unit Root Test (CIPS)

After conducting the cross-sectional dependence test, the time series properties of the variables included in the regression models Aaare examined. For this purpose, the CIPS (Cross-Sectionally Augmented IPS) panel unit root test, proposed by Pesaran (2007), is employed. As one of the second-generation panel unit root tests, the Pesaran CIPS test differs from first-generation panel unit root tests by accounting for cross-sectional dependence. The results of the CIPS panel unit root test are reported in Table 8. Based on the results presented in Table 8, the null hypothesis, which states that the variables contain a unit root, is rejected for all variables in both models with a constant and models with a constant and trend. This finding indicates that all variables included in the analysis are stationary at their levels and do not contain a unit root.

Table 8. Pesaran (2007) CIPS Panel Unit Root Test Findings

	Constant Model	Constant &Trend Model
	CIPS Statistics	**CIPS Statistics**
BR	-2.845***	-3.259***
Ln(assets)	-2.331**	-2.762**
Ln(age)	-2.205**	-3.725**
CAR	-2.415***	-2.960***
BD	-2.334**	-2.762**
CR	-2.386***	-3.341***
LR	-3.120***	-3.249***
NIM	2.235**	-2.815**
INF	2.210**	2.761**
EG	2.210**	2.761**
	-2.07 (%10)	-2.60 (%10)
Critical values	-2.17 (%5)	-2.70 (%5)
	-2.34 (%1)	-2.89 (%1)

Note: In the CIPS test, the null hypothesis is "the variable contains a unit root". The critical values given at the bottom of the table for the case of N and T = (22,14) are taken from the study of Pesaran (2007). * p<0.1, ** p<0.05, *** p<0.01.

4.5. Estimation Results

Table 9 reports the estimation results of the panel data model expressed in Eq. (1) for the main sample for all banks included in the analysis. According to the diagnostic test results presented in the lower part of Table 9, it is decided that the SE estimator is the most appropriate estimator in estimating the regression model in Eq. (1) (Hausman test). Then, three tests (autocorrelation, heteroskedasticity and cross-sectional independence) are conducted regarding the errors of the SE model. The findings of all three tests indicate that there are significant deviations from the assumptions regarding the errors of the SE model. Hence, the Driscoll-Kraay SE estimator is used in estimating the coefficients of the model expressed in Eq. (1) to correct the relevant deviations.

As seen in Table 9, a negative and significant relationship at 1% level of significance is reported between the Ln (assets) variable representing bank size and bankruptcy risk (BR). Similarly, Dias (2020), Ashraf (2017), Martínez-Malvar and Baselga-Pascual (2020) reported a negative relationship between bank size and bank risk-taking. Our finding, which is inconsistent with the results reported by Baselga-Pascual et al. (2015) and Mercan (2021), suggests that that bankruptcy risks will decrease as banks grow. A negative and significant relationship at 1% level of significance is observed between the CAR variable representing bank capital and BR. This finding, which is consistent with the results reported by Baselga-Pascual et al. (2015) and Martínez-Malvar and Baselga-Pascual (2020), suggests that banks with higher capital levels have lower bankruptcy risks. Similarly, a negative and significant relationship at 1% level of significance is determined between the NIM variable representing interest margin and BR. The present finding aligns with the conclusions drawn by Dias (2020), which indicate that financial institutions with high interest margins are associated with reduced bankruptcy risks in comparison. The estimated coefficient of liquidity risk was found to be positive and significant. This result, which is similar to the findings of Dias (2020), indicates that banks with higher liquidity risk tend to increase bank risk.

When the estimation results are examined in terms of macroeconomic variables, it is concluded that inflation rate (INF) and economic growth (EG) have a positive effect on bankruptcy risk, that is, they increase the bankruptcy risk. This finding reveals that increasing inflation and economic growth trigger the bankruptcy risk that banks are exposed to. Ashraf (2017), Danisman and Demirel (2019) and Baselga-Pascual et al. (2015) reported in their study that inflation decreases (increases) bank stability (risk), whereas GDP increases (decreases) bank stability (risk). However, Diaconu and Oanea (2014) and Mercan (2021) reported in his study that neither inflation nor GDP had a significant effect on bank risk. Similarly, insignificant coefficients regarding GDP and inflation variables are also found in the study conducted by Martínez-Malvar and Baselga-Pascual (2020).

In addition, a positive and significant relationship was found between the CVD variable representing the COVID-19 pandemic and BR at the 1% significance level. This finding reveals that the pandemic crisis caused an increase in bankruptcy risk. Danisman and Demirel (2019) reported a positive relationship between the crisis dummy variable and bank risk-taking behavior in their study. However, no significant relationship is found between the BM variables representing Ln(age) and bank deposits and BR.

Table 9. Estimation Results (Whole Sample)

	Coefficient	**Standard Error**	***t*-statistic**	**Probability**
Ln(assets)	-0.2366691***	0.0117501	-20.14	0.000
Ln(age)	0.09458	0.1077789	0.88	0.390
CAR	-0.0276***	0.00660	-4.17	0.000
BD	-0.00147	0.000944	-1.56	0.135
CR	0.0370***	0.00742	4.98	0.000
LR	1.285***	0.206	6.23	0.000
NIM	-0.0354***	0.00992	-3.56	0.002
INF	0.0266***	0.00415	6.39	0.000
EG	0.220***	0.0417	5.27	0.000
CVD	2.022***	0.395	5.12	0.000
Constant term	0.484***	0.11562	4.19	0.000
Hausman	54.62***			
Autocorrelation	23.717***			
Heteroskedasticity	8738.98***			
Cross-sectional dependence	9.350***			
Within Group R^2	0.6021			
F-statistic	102.94***			
Number of banks	22			
Number of observations	308			
Panel estimator	Driscoll-Kraay Fixed Effects (DK FE) estimator			

Note: Bank and time effects are included in the regression models through dummy variables. However, the coefficients related to these are not reported. In the Hausman test, the null hypothesis is that the Random Effects estimator is a valid estimator. Autocorrelation was checked with the Wooldridge test. In this test, the null hypothesis is that the errors within units are temporally uncorrelated. Heteroscedasticity is tested with the Modified Wald test. In this test, the null hypothesis is that the error variance does not differ across cross-sectional units. Cross-sectional dependence is tested via Pesaran's CD test. In this test, the null hypothesis is that the errors across cross-sectional units are uncorrelated. In the F test, the null hypothesis is that the model is insignificant. In this test, the null hypothesis is that there is no dependence between cross-sections.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Following the estimation results for the main sample, sub-samples are formed for various criteria (i.e., being registered in BIST and capital structure) and it is checked whether the effects in the main sample changed when the sub-samples were taken into account. The estimation results of the model in Eq. (1) in terms of sub-samples are presented in Table 10.

Table 10. Estimation Results (Sub-Samples)

	Non-listed Banks (Model I)	**Listed Banks (Model II)**	**Domestic Banks (Model III)**	**Foreign Banks (Model IV)**
Ln(assets)	-0.254***	-0.232***	-0.0866***	-0.390***
	(0.0139)	(0.0295)	(0.0149)	(0.0235)
Ln(age)	0.00995	-0.379**	-0.541***	0.115
	(0.161)	(0.136)	(0.122)	(0.376)
CAR	-0.0210*	-0.0344***	-0.0104**	-0.0379**
	(0.00997)	(0.00884)	(0.00391)	(0.0124)
BD	-0.000746	-0.000460	0.00396***	-0.00142
	(0.000967)	(0.00139)	(0.00104)	(0.00117)
CR	0.0376***	0.0179*	0.000148	0.0365***
	(0.00793)	(0.00851)	(0.00771)	(0.00665)
LR	2.419***	0.0530	0.361	0.320
	(0.366)	(0.465)	(0.333)	(0.887)
NIM	-0.0373***	-0.0338**	-0.0329**	-0.0431**
	(0.0121)	(0.0123)	(0.0136)	(0.0141)
INF	0.0283***	0.0437***	0.0278***	0.0423***
	(0.00579)	(0.00554)	(0.00517)	(0.0131)
EG	0.232***	0.402***	0.280***	0.339**
	(0.0564)	(0.0538)	(0.0515)	(0.127)
CVD	-0.0677	3.788***	2.586***	-0.0419
	(0.0531)	(0.496)	(0.446)	(0.0956)
Constant term	0.460**	1.020***	0.666***	0.780*
	(0.153)	(0.141)	(0.130)	(0.353)
Hausman	18.07**	33.95***	31.70***	23.06***
Autocorrelation	20.501***	35.940***	21.371***	30.688***
Heteroskedasticity	1990.98***	210.23***	147.83***	1024.78***
Cross-sectional dependence	4.582***	1.068	2.296**	4.298***
Within Group R^2	0.6233	0.4432	0.4802	0.7056
F-statistic	123.34***	8.52***	103.26***	119.32***
Number of banks	13	9	11	11
Number of observations	182	126	154	154

Note: Bank and time effects are included in the regression models through dummy variables. However, the coefficients related to these are not reported. In the Hausman test, the null hypothesis is that the Random Effects estimator is a valid estimator. Autocorrelation was checked with the Wooldridge test. In this test, the null hypothesis is that the errors within units are temporally uncorrelated. Heteroscedasticity is tested with the Modified Wald test. In this test, the null hypothesis is that the error variance does not differ across cross-sectional units. Cross-sectional dependence is tested via Pesaran's CD test. In this test, the null hypothesis is that the errors across cross-sectional units are uncorrelated. In the F test, the null hypothesis is that the model is insignificant. In this test, the null hypothesis is that there is no dependence between cross-sections.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

According to the estimation results of Models I, II, III and IV from Table 10, there is a negative and significant relationship between bank size and bank risk taking level, which also supports the result in the main sample. Unlike the main sample, Model II and III estimation results show that there is a significant inverse relationship between the age of banks and the risk of bankruptcy. This indicates that as banks age, their tendency to go bankrupt will relatively decrease. However, it should be noted that this finding is valid for listed and domestic banks. The estimation results of all models indicate that there exists a significant inverse relationship between bank capital and bankruptcy risk. This finding is in line with the result obtained from the main sample. The estimated coefficient of bank deposits was found to be significant only in the sample of banks including domestic banks. This finding regarding domestic banks indicates that increasing bank deposits will also increase the risk of bankruptcy. Similar to the result based on the main sample, increases in credit and liquidity risks for non-listed banks increase the risk of bankruptcy. However, this relationship was not observed in other sub-samples. Furthermore, no significant relationship was found between credit risk or liquidity risk and bankruptcy risk in the sample of domestic banks. Additionally, the estimated coefficient of the NIM variable was found to be negative and significant in all subsamples. This finding is similar to the results obtained from the main sample where all banks were included. In other words, increasing interest margins are inversely related to banks' risk-taking tendencies.

The estimated coefficients of the INF and EG variables are positive and statistically significant for all subsamples, which is in the same direction as the result obtained from the main sample where all banks are included. In the main sample, it was reported that the COVID-19 pandemic crisis increased the bankruptcy risk of banks. However, this finding is only valid for the two subsamples including domestic and listed banks. There is no significant relationship between the pandemic crisis and the bankruptcy risk for non-listed banks and foreign banks.

5. Conclusion

In the current work, the impact of micro and macro factors on banks' risk-taking behavior was analyzed utilizing annual data of 22 commercial banks in the Turkish banking sector for the period 2010-2023. The research employed the inverse Z-score as a measure of banks' risk taking. The bank-level variables included in the analysis were bank size, bank age, bank capital, bank deposits, credit risk, liquidity risk and net interest margin, respectively. The independent variables at the macro level are inflation rate and economic growth. In addition to these variables, a dummy variable is added to the regression models to represent the COVID-19 pandemic crisis.

In this study, which analyses the risk-taking behavior of banks, the main sample, which includes all banks, was first used for estimation purposes. Two subsamples were then created. The first sub-sample includes listed and unlisted banks. In the second sub-sample, banks are divided into two groups: domestic and foreign banks. The purpose of creating the sub-samples is to compare the results of the main sample and the sub-sample and to determine whether there is a significant difference between the samples. This is of great importance for the regulatory authorities, policymakers, and other stakeholders related to the banking sector.

Considering the panel data analysis results in terms of the main sample, it has been determined that bank size, bank capital, bank deposits and net interest margin tend to reduce the risk taking levels of banks. However, the variables such as credit risk, liquidity risk, inflation rate, economic growth, and pandemic crisis tend to increase the risk-taking levels of banks.

When the estimation results are examined in terms of sub-samples, the coefficients of bank size, bank capital and net interest margin variables are found to be negative and significant, which are the same as the main sample findings. Considering the sub-samples created, the effect of bank deposits on risk taking was found to be positive and significant only in the local banks sample. It was concluded that credit risk triggered the bankruptcy risk in all samples except the domestic banks sample. As for liquidity risk, the estimated coefficient of this variable was found to be statistically significant only for non-listed banks. The positive relationship observed between the variables representing inflation and economic growth in the sub-samples and the bankruptcy risk is consistent with the main sample. Finally, it was concluded that the COVID-19 pandemic crisis increased the bankruptcy risk only for listed and domestic banks.

The findings of this research have important implications for bank management, regulatory mechanisms and policy makers in terms of controlling the risk-taking behavior of banks, ensuring stability in the banking sector and building a sustainable banking sector.

A strong negative relationship between capital adequacy (CAR) and bankruptcy risk was found across all models. Thus, regulators should enforce higher capital requirements, especially for banks with aggressive risk-taking strategies. In addition, banks should increase retained earnings and reduce excessive dividend payouts to maintain strong capital buffers.

Unlisted banks are more vulnerable to credit and liquidity risks, which increases the risk of bankruptcy. In this case, banks can apply stricter liquidity coverage ratio requirements and encourage stable funding sources rather than relying on short-term deposits. In addition, for unlisted ones, risk assessment models should be well maintained and conservative credit policies should be adopted. Besides, regulators should apply stricter credit classification rules to prevent asset quality deterioration.

The results show a negative and significant relationship between bank size and bankruptcy risk across all models. This suggests that larger banks are generally more stable, likely due to economies of scale, diversified portfolios, and better access to funding. However, bank size alone does not eliminate risk—as seen in past financial crises, large banks can still fail due to excessive risk-taking (e.g., "Too Big to Fail" problem).

Higher deposit levels in domestic banks increase risk, possibly due to asset-liability mismatches. Regulators should evaluate the sufficiency of deposit insurance schemes to prevent deposit-driven instability. Domestic banks should diversify funding sources instead of over-reliance on deposits. Additionally, these banks may use long-term funding mechanisms such as bond issuance or capital market instruments.

The pandemic increased bankruptcy risk only in domestic and listed banks. Given this finding, sector-specific emergency liquidity support mechanisms could be developed for public and local banks. Furthermore, these banks could be allowed to restructure loans for sectors in distress during crises (e.g. tourism, small businesses).

Higher NIM consistently reduces bankruptcy risk in all models, indicating that profitability is crucial for resilience. Banks should optimize operating costs and digital transformation to maintain higher interest margins. Furthermore, policymakers should balance interest rate regulations to prevent excessive pressure on bank profitability.

Inflation and economic growth positively impact bank risk-taking across all models. Regulators should require banks to hold additional capital buffers during economic booms to cushion risks during downturns. Moreover, central banks should closely monitor credit expansion during high-growth periods to prevent excessive risk-taking.

The first limitation of this study is related to the fact that the sample used for the analysis consists of only Turkish banks. Therefore, the findings cannot be generalized for the banking sectors of other countries. Another limitation is related to the time period covered by the study.

In future studies, alternative variables representing the risk-taking behaviors of banks (i.e., leverage risk, portfolio risk, interest income risk, non-interest income risk, operational risk) can be used to add depth to the research topic. In addition, an analysis can be made that includes an international comparison, which can make an important contribution to the literature in terms of generalizing the results.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest
There is no potential conflicts of interest in this study.

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