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Research Article

Estimation of Turkish Banking Sector Financial Fragility Index and Determination of the Factors Effecting the Index

Türk Bankacılık Sektörü Finansal Kırılganlık Endeksinin Tahmini ve Endeksi Etkileyen Faktörlerin Belirlenmesi

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ÖZ

Finansal kırılganlık kavramı, finansal krizin henüz meydana gelmediği ancak belirtilerinin gözlemlendiği evrenin erken uyarı göstergesi olarak tanımlamaktadır. Türkiye'deki 15 mevduat bankasının, yabancı sermayeli bankalar dahil, 2006Q1:2022Q2 dönemini kapsayan çalışmada, her banka için bankacılık sektörü finansal endeksi hesaplanmış, bankalara göre değişmeyen makro ekonomik göstergeler ile bankalara özgü oransal göstergelerin endeks üzerindeki etkisi incelenmiştir. Statik panel modellere dayanan sonuçlar, bankaların kırılgan olma olasılığının aktif karlılık oranı ve özkaynak karlılık oranı, enflasyon oranı, kredi risk pirimi, korku endeksi ve ticari kredi faiz oranı tarafından anlamlı bir şekilde belirlendiğini ortaya koymaktadır. Takipteki krediler değişkeninin endekse dahil edilmesiyle literatüre özgün bir katkı yapılması amaçlanmış, endeksi belirleyen faktörlerin ortaya çıkarılması hedeflenmiş ve böylece endeksin bankacılık sektörü risk durumu için güvenilir bir gösterge olduğu sonucuna varılmıştır.

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A B S T R A C T

The concept of financial fragility is defined as an early warning indicator in which a financial crisis has not yet occurred but symptoms are observed. Banking sector fragility index was calculated for 15 deposit banks in Turkey and the impact of macroeconomic and bank-specific proportional indicators was examined for 2006Q1:2022Q2. Results based on static panel models inferred that the likelihood of banks to be fragile is significantly determined by ROA, ROE, inflation rate, CDS, fear index and commercial loan interest rate. Including NPL in the index, it was both intended to make an original contribution to the literature and aimed to reveal the factors determining the index. Thus, BSF index is a reliable proxy for banking sector risk status.

1. Introduction

The stability of banking systems is vital for the overall health of both financial markets and economies. Banking fragility more often characterized by liquidity and solvency

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problems might create systemic risks and lead to financial crises. Although there is no single definition in the literature, financial fragility is often referred to as the inability to withstand adverse shocks which can manifest itself with disruptions and failures. Minsky (1982) in his pioneering work argued that unsustainable levels of debt driven by excessive risk taking and speculative behavior amplified by overconfidence and unrealistic optimism onsets financial crises which are procyclical in nature. Moreover, the collapse of asset prices and widespread panic makes financial institutions such as banks more vulnerable to failures. Therefore, banking fragility and financial fragility are interconnected (Kaminsky and Reinhart, 1999) as adverse developments in financial markets can weaken banks (Claessens et al., 2010) while instable banks with their deteriorated balance sheets might exacerbate financial risks through complicated transmission mechanisms (Gerali et al., 2010).

Bank failures with devastating consequences result from bank fragility, which is often associated with liquidity risk and asymmetric information (Diamond and Dybvig, 1983), excessive leverage and maturity mismatch (Mishkin, 1991), weak regulatory oversight and poor corporate governance (Barth et al., 2001). Therefore, measuring the degree of fragility is crucial for the early detection of potential future financial disruptions and crises and is recognized as an early warning indicator (Minsky, 1977).

In that respect Banking Sector Fragility Index (BSF) developed by Kibritçioğlu (2003) where changes in deposits, loans and foreign liabilities were considered has been used in numerous amount papers as a proxy for banking sector resilience.

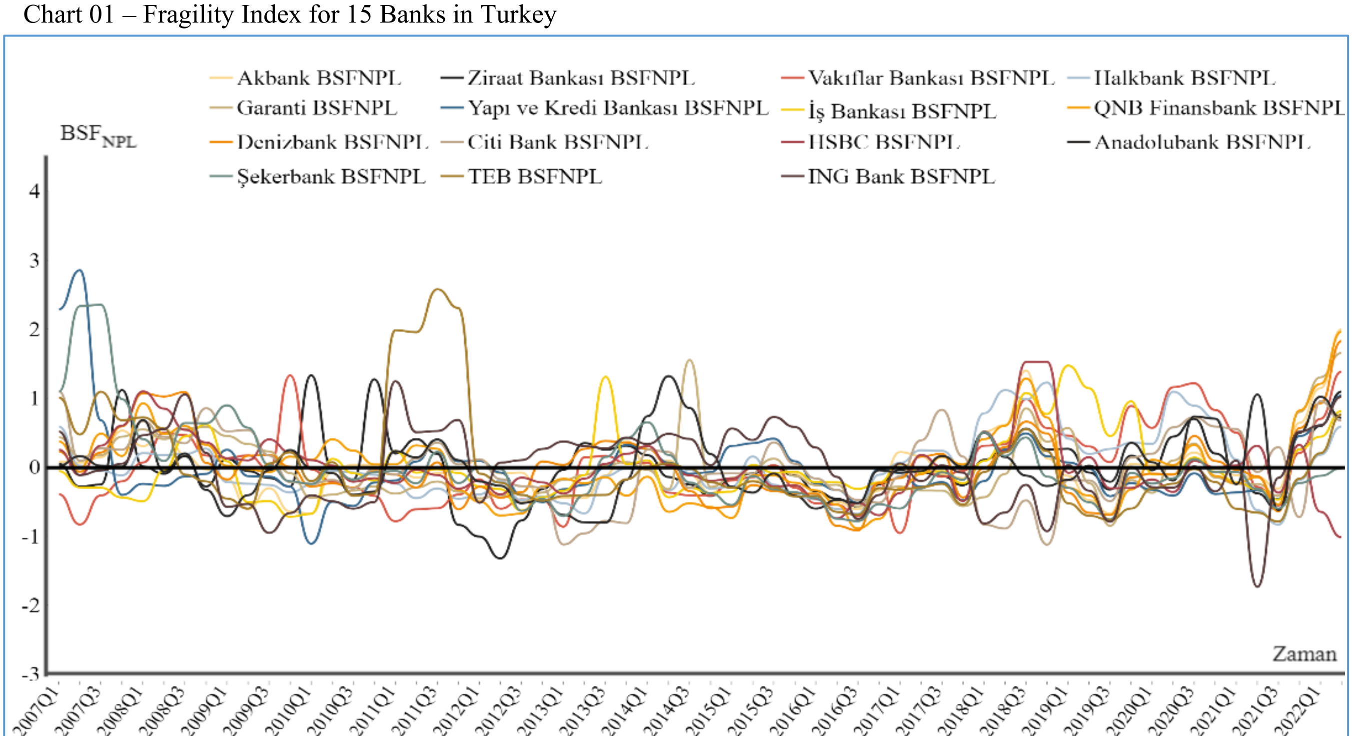
In this study it was intended to extend fragility index by adding nonperforming loans which is an important sign of fragility, as an independent variable to the index.

Moreover, it was aimed to reveal the determinants of extended BSF by using quarterly data for 15 deposit banks operating in Turkish banking sector including foreign-owned banks covering 2006-2022 period. Moreover, Turkey is considered to be an exciting case for research as an example of an emerging market economy, having experienced serious banking crises in the past.

Financial fragility is a stage in which the financial crisis has not yet been occurred, but early warning signals of the crisis are observed. Thus, the concept of financial fragility should be emphasized before the crisis occurs in order to anticipate the danger of crisis and to take precautions. In this study, banking sector fragility index was calculated with the quarterly data of 15 deposit banks including foreign-owned banks operating in the Turkish Banking Sector in the period 2006: Q1-2022: Q2.

The banking sector fragility index, calculated by adding the non-performing loans variable to the index, constructed by Kibritçioğlu (2003), was tested with a static panel data model by using sector-specific financial ratios (internal indicators) and external macroeconomic data varying across banks, and statistically significant results are obtained in line with the expectations. After calculating the BSF index to be used as the dependent variable in the model, dependent variables were classified into two categories as bank-specific proportional indicators and macroeconomic indicators that do not change according to banks.

Chart 01 – Fragility Index for 15 Banks in Turkey



Capital Adequacy Ratio (SYO), Return on Assets (ROA) and Return on Equity (ROE) were used as bank-specific proportional indicators and commercial loan interest rate (TKF), GDP growth (GR), inflation rate (ENF), real exchange rate (REK), credit default swap (CDS) and fear index (VIX) were used as macroeconomic indicators for independent variables.

Chart 01 shows the time path graph of the BSF_{NPL} series of 15 deposit banks analyzed within the scope of the research on a common baseline. The existence of correlation and cross-sectional dependence is clearly visible and Breusch ve Pagan (1980) LM horizontal cross-sectional dependence test has also formally determined that the slopes and quantitative values of the financial fragility index series of banks are synchronized with each other.

2. Literature Review

The financial fragility index constructed by Kibritçioğlu (2003) for the banking sector aims to identify and monitor the adversities in the banking sector. Obtaining data for 22 countries and analyzing them in monthly periods until 2022, his study revealed that the banking sector fragility index reflects sectoral climate changes more precisely in a timely manner and was able to predict significant crisis or high vulnerability events. On the other hand, the BSF index could indicate crisis phases, reflect sectoral changes more precisely in a timely manner and predict significant crisis or high vulnerability events.

Karanfil (2014), who created a new fragility index by adding CDS variable to the index constructed by Kibritçioğlu (2003), found that there is a strong short-term positive relationship between the deposit interest rate, exchange rate and foreign trade shocks. He also found that FED policy interest rate, which is considered as an external factor, has a strong indirect effect on the index.

Singh (2010) constructed the fragility index of the Indian banking sector for the period 2000-2009 to identify and date crises and divided the index into 3 phases as non-fragile, medium fragile and high fragile. In his study, various phases of banking crises were modelled the relationship between macroeconomic indicators and fragility was investigated. It was concluded that an increase in the ratio of foreign exchange assets to foreign exchange liabilities, imports, M3 multiplier, overnight interest rate, real interest rate, stock price index and inflation rate increases the fragility of the banking sector, while a decrease in the ratio of money supply (M3) to foreign exchange reserves, industrial production index, exports, foreign exchange reserves and loan-deposit ratio increases the probability of high fragility in the banking sector.

In order to examine the relationship between banking sector fragility and foreign exchange vulnerability, Shen and Chen (2008) constructed two dynamic panel models with and without thresholds. Banking sector fragility (BSF) index is composed of real deposits, loan demand and real foreign liabilities of banks, while foreign exchange market pressure (FEMP) is composed of the weighted average of exchange rate changes and foreign exchange reserves. Using data for 51 countries, this study found out a bidirectional causality relationship between BSF and FEMP, contrary to the stronger and generally thought to be unidirectional interaction between the variables in the model constructed using the threshold value.

Demirel, Barışık and Karanfil (2016), (utilizing Kibritçioğlu 2003) included CDS as an independent variable to the fragility index, they concluded that the real exchange rate, inflation, non-performing loans, policy interest rate, volatility index, US 2-year treasury bill have a positive, while the industrial production index has a negative effect on the index. In the literature, the increase in CDS, which reflect the level of riskiness of treasury bonds, has a significant impact on fragility and has been accepted as a direct determinant of financial fragility.

Bhattacharya and Roy (2012) developed an early warning model to predict the fragility of the banking sector in India and used the banking sector fragility index constructed by Kibritçioğlu (2003). Deposits, loans and investments of commercial banks are involved as the independent variables of the fragility index, while liquidity risk, credit risk and interest rate risk were the indicators, which are the three main risks faced by the sector.

3. Data

In this study quarterly data of 15 deposit banks operating in the Turkish banking sector was used (representing 89.4% of the sector in terms of asset holdings) that covers 2006Q1 – 2022Q2 period. The data was gathered from Turkish Banking Association (TBB) for bank specific variables and from The Central Bank of the Republic of Türkiye (EVDS) for macro-economic variables. Within that scope the first step of the analysis was to calculate BSF_{NPL} index for each bank for the specified period.

$$BSF_{i,t}^{NPL} = \frac{\frac{LKRD_{i,t} - \mu_{KRDi}}{\sigma_{KRDi}} + \frac{LMVD_{i,t} - \mu_{MVDi}}{\sigma_{MVDi}} + \frac{LDYÜK_{i,t} - \mu_{DYÜKi}}{\sigma_{DYÜKi}} + \frac{LNPL_{i,t} - \mu_{NPLi}}{\sigma_{NPLi}}}{4}$$

i= 1, 2, ...15 (number of banks), t= 1, 2, …62 (number of quarters)

$$LKRD_{i,t} = \frac{KRD_{i,t} - KRD_{i,t-4}}{KRD_{i,t-4}} \qquad LDYÜK_{i,t} = \frac{DYÜK_{i,t} - DYÜK_{i,t-4}}{DYÜK_{i,t-4}}$$

$$LMVD_{i,t} = \frac{MVD_{i,t} - MVD_{i,t-4}}{MVD_{i,t-4}} \qquad LNPL_{i,t} = \frac{NPL_{i,t} - NPL_{i,t-4}}{LNPL_{i,t-4}}$$

As it can be seen from above, $LKRD_{i,t}$, $LMVD_{i,t}$, $LDYÜK_{i,t}$ and $LNPL_{i,t}$ represents quarterly rate of growth of loans, deposits, foreign liabilities and non-performing loans, respectively. Also, the variables are standardized by subtracting them from their mean (μ) values and dividing them by their standard deviations (σ).

Table 1: Definition and Descriptive Statistics of Variables

Variables	Definition	# of obs.	Mean	St. Dev.	Minimum	Maximum
BSF_{NPL}	Fragility Index	930	-0,000000345	0,530439	-1,73924	2,854053
SYO	Capital Adequacy	930	16,61183	3,005282	11,8	41,4
ROA	Return on Assets	930	1,655591	0,941528	-2,2	6,2
ROE	Return on Equity	930	14,57925	8,071594	-32	43,4
TKF	Interest Rate	930	15,79613	4,894992	8,54	30,56
GR	GDP Growth	930	5,199302	11,85376	-18,3289	36,39468
ENF	Inflation	930	12,12579	10,5886	4,344287	74,06995
REK	Real Exchange Rate	930	95,80548	20,83037	47,74	127,71
CDS	CDS Spread	930	334,6728	103,6836	173	636,6133
VIX	Volatility Index	930	0,0102889	0,11814	-0,1847973	0,3509649

4. Method

The relationship between variables was investigated by using a panel model as the data covers both time and cross-sectional dimensions. In order to avoid spurious regression, the appropriate model was chosen by deciding whether the data has unit root or not. In panel data analysis in order to direct the unit root and stationarity analyses of variables, the existence of cross-sectional dependence condition should first be investigated and then decided whether first or second generation panel unit root tests are applied (Mensah et al., 2019, Apergis and Payne, 2014). In case of cross-sectional dependence in the variables, the analyses should be continued with second generation panel unit root tests (Apergis and Payne, 2014, Hurlin and Mignon, 2007). In that respect second generation unit root tests were seem to be more appropriate in case of cross-sectional dependence (Güloğlu and İspir, 2011, Yerdelen Tatoğlu, 2017). Therefore, the first stage the analysis was to determine stationarity by considering the cross-sectional dependence of variables.

In practice when (T>N) cross sectional dependence test as proposed by Breush and Pagan (1980) gives robust results. The null hypothesis of LM Test assumes that the residuals from each cross-sectional unit are not correlated with each other. LM Test statistic $LM_{BP}$is calculated as follows where $\hat{\rho}_{ij}$ represents the correlation coefficient.

$$LM_{BP} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^{2}$$

$$\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T} e_{it}\, e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^{2}\right)^{\frac{1}{2}}\left(\sum_{t=1}^{T} e_{jt}^{2}\right)^{\frac{1}{2}}}$$

The results of the study revealed the existence of cross-sectional dependence therefore CIPS (Pesaran, 2007) and MADF (Sarno and Taylor, 1998) panel unit root tests was used to display robust results in the presence of cross-sectional dependence for the cross-variant variables. The CIPS and MADF test statistics were calculated as follows where the null hypothesis in both assumed the existence of unit root.

$$CIPS(N,T) = N^{-1}\sum_{t=1}^{N} t_i(N,T)$$

$$MADF = \frac{(\iota - \varphi\hat{\beta})\{\varphi[Z'^{(\hat{\Lambda}^{-1}\otimes I_T)}Z]^{-1}\varphi'\}(\iota - \varphi\hat{\beta})N(T-k-1)}{(Y - Z\hat{\beta})'(\hat{\Lambda}^{-1}\otimes\, I_T)(Y - Z\hat{\beta})}$$

On the other hand, for the cross invariant variables ADF (Dickey and Fuller, 1981) and PP (Phillips and Perron, 1988) unit root tests, the theoretical foundations of which are different from each other, were used to analyze unit root. However, it is well documented in the literature that structural breaks should be considered as the series have unit roots although they are stationary. Therefore, Lee and Strazicich (2003) unit root test was used which considers structural breaks in both constant and trend dimensions. As both cross variant and invariant variables were found stationary on I(0), a static panel model was decided to proceed. As is well known there might be unit (period and/or cross) effects in data in which case Fixed (FE) or Random Effect (RE) models are more appropriate. However, if no unit effects are present, then a pooled model would be more efficient. In the literature, F tests are usually performed to reveal the presence of such unit effects. Since unit effects were found to exist, we proceeded by identifying the specific type of effect using a Hausman Test, which tests the null hypothesis of no correlation between unit effects and coefficients. The results show that there are unidirectional (cross) fixed effects, so the static panel model is organized and estimated as follows

$$y_{it} = \beta_{0i} + \sum_{k=1}^{K}\beta_k x_{kit} + u_{it}$$

$i = 1,2, \ldots, 15; \;\; t = 1,2, \ldots, 62; \;\; k = 1, 2, \ldots, 8$

As shown above the slope parameter βk is the same for all horizontal sections ($\beta_k = \beta$), while the constant parameter (β_{oi}) varies from cross section to cross section due to the unit effects it contains. In other words, coefficients of variables are considered to be homogenous while the constants are heterogenous where u_{it} represents the residuals and k the number of dependent variables.

In the last step of the analysis post estimation diagnostic tests are used for autocorrelation and heteroskedasticity by using Breusch and Pagan (1980) LM and modified Wald Tests as proposed by Baum (2000). As the results pointed out autocorrelation, heteroskedasticity and cross-sectional dependence, the model was estimated by using Driscoll and Kraay (1998) fixed effects estimator. Also, logarithms of all variables are used so as to fulfill the desired statistical properties of OLS estimators.

5. Results

In this study, the first stage of econometric analyses started with the Breusch and Pagan (1980) LM Cross Sectional Dependence Test.

Table 2. Breusch and Pagan (1980) LM Cross Sectional Dependence Test

Variables	LM Test Statistic	Probability
BSF_{NPL}	793.538***	(0.0000)
LROA	1774.973***	(0.0000)
LROE	1713.242***	(0.0000)
LSYO	1188.604***	(0.0000)

Note: numbers represent t-statistics and *, ** and *** respectively represent levels of significance at %10, %5 and %1.

Table 2 shows the results of Breusch and Pagan (1980) LM Cross Sectional Dependence Test for the cross-sectional variants (first degree differences were taken which is more reliable when the time dimension T is bigger than the number of groups N). The null hypothesis stating that there is no cross-sectional dependence is rejected at the 0.01 significance level for all variables so second-generation panel unit root tests should be preferred. (Güloğlu and İspir, 2011, Yerdelen Tatoğlu, 2017).

Table 3. Pesaran (2007) CIPS Panel Unit Root Test

Variables	CIPS Test Statistic Constant	CIPS Test Statistic Constant and Trend
BSF_{NPL}	-3.977***	-4.145***
LROA	-2.357***	-2.998***
LROE	-2.636***	-3.358***
LSYO	-3.171***	-3.383***

Note: numbers represent t-statistics and *, ** and *** respectively represent levels of significance at %10, %5 and %1.

Table 3 shows the results of the CIPS panel unit root test. At different significance levels, the null hypothesis stating the existence of a unit root in the variables is rejected for BSF_{NPL}, LROA, LROE and LSYO variables (since |CIPS statistic|>|critical value|) and it is seen that these variables do not contain unit root which means the variables are stationary. However, although it is found that the series do not contain unit root, the MADF panel unit root test was used to see whether they are the stationarity for alternative series other than CIPS panel unit root test.

Table 4. Taylor and Sarno (1998) MADF Panel Unit Root Test

Variables	MADF Test Statistic
BSF_{NPL}	257.420**
LROA	151.779**
LROE	137.278**
LSYO	127.378**

Note: numbers represent t-statistics and *, ** and *** respectively represent levels of significance at %10, %5 and %1.

Table 4 shows the results of MADF panel unit root test. At 5% significance level, the null hypothesis of unit root existence in the variables is rejected as the MADF test statistic is bigger than the critical value. In this case, according to the MADF unit root test all the variables are stationary.

Table 5. ADF Unit Root Test

Variables	Constant	Constant and Trend
LTKF	-2.8719*** (0.0547)	-3.4209*** (0.0581)
LGR	-7.9569* (0.0000)	-7.9140* (0.0000)
LENF	-	-
LREK	-0.4835 (0.9848)	-2.7729 (0.2127)
LCDS	-1.0522 (0.7871)	-2.1512 (0.5721)
LVIX	-10.0790* (0.0000)	-9.9829* (0.0000)
Variables	**Constant**	**Constant and Trend**
ΔLENF	-2.3123 (0.1715)	-2.7836 (0.2089)
ΔLREK	-10.2150* (0.0000)	-10.3859* (0.0000)
ΔLCDS	-6.5126* (0.0000)	-7.5186* (0.0000)
ΔΔLENF	-9.2613* (0.0000)	-9.3912* (0.0000)

Note: numbers represent t-statistics and *, ** and *** respectively represent levels of significance at %10, %5 and %1 where Δ, ΔΔ represent first and second differences respectively. The symbol '-' is not shared since there are values where the test statistic that should be obtained negative is positive.

Table 5 shows the ADF unit root test results of macroeconomic variables. It is observed that the null hypothesis is rejected for LTKF, LGR and LVIX means these three variables are stationary at level. On the other hand, the null hypothesis cannot be rejected for LREK, LCDS and LENF. The null hypothesis is rejected for LREK and LCDS variables only after first degree differences are taken, and the degree of stationarity for LENF variable is '2' according to this test. Although ADF is a reference test, as it does not consider some basic assumptions, alternative unit root tests (PP and LS) were required to reach a conclusion about the final degrees of stationarity (Esenyel, 2017;

Çatalbaş, 2021).

Table 6. Phillips-Perron Unit Root Test

Variables	Constant	Constant and Trend
LTKF	-2.2063 (0.2062)	-2.6224 (0.2722)
LGR	-7.9547* (0.0000)	-8.5391* (0.0000)
LENF	-	-
LREK	-0.7286 (0.9919)	-2.5826 (0.2925)
LCDS	-1.3198 (0.7210)	-1.9447 (0.6684)
LVIX	-17.1341* (0.0000)	-16.6732* (0.0000)
Variables	**Constant**	**Constant and Trend**
ΔLTKF	-4.9591* (0.0001)	-4.9958* (0.0007)
ΔLENF	-2.3123 (0.1715)	-2.8160 (0.1975)
ΔLREK	-10.8876* (0.0000)	-15.0903* (0.0000)
ΔLCDS	-6.5624* (0.0000)	-6.9364* (0.0000)
ΔΔLENF	-9.4409* (0.0000)	-9.7205* (0.0000)

Note: numbers represent t-statistics and *, ** and *** respectively represent levels of significance at %10, %5 and %1where Δ, ΔΔ represent first and second differences respectively. The symbol '-' is not shared since there are values where the test statistic that should be obtained negative is positive.

Table 6 shows the Phillips-Perron (PP) unit root test results of macroeconomic independent variables. The null hypothesis is rejected for LGR and LVIX which means these variables are stationary. On the other hand, LTKF, LREK, LCDS and LENF variables are stationary after first differences are taken. The variables that are found to be non-stationary by ADF Unit Root Test and Phillips-Perron Unit Root Test at the same degree, should be examined whether they follow a stationary process with the unit root test with two structural breaks developed by Lee and Strazicich (2003).

Table 7. Lee and Strazicich (2003) Structural Break Unit Root Test

Variables	Test Statistic Constant	Test Statistic Trend	Break Time Constant	Break Time Trend
LTKF	-3.2072	-5.9654**	-	2012Q2; 2019Q1
LENF	-3.3713**	-8.7728*	2014Q3; 2017Q4	2014Q1; 2019Q3
LREK	-3.9387**	-5.6945	2018Q2; 2019Q4	-
LCDS	-4.7243**	-6.9534***	2012Q2; 2018Q2	2012Q3; 2020Q1

Note: numbers represent t-statistics and *, ** and *** respectively represent levels of significance at %10, %5 and %1.

The results of unit root test are displayed in Tables 5, 6 and 7.TKF, GR and VIX are stationary at I(0) where REK and CDS have unit roots and become stationary at I(1) and ENF becomes stationary at I(2) in both unit root tests where only TKF has unit root according to PP Test. Nevertheless, as data covers a long period time the presence of structural breaks should also be considered. In that manner, as it can be observed from Table 7 that there are structural breaks either in constant or trend and variables are stationary on I(0). As a result we conclude that our variables are stationary on I(0) when different unit root test criteria's are evaluated together.

Table 8. Panel F and Hausman Tests

Cross and/or Time Effects F Test Statistic	Cross Effect F Test Statistic	Time Effect F Test Statistic	Hausman χ^2 Statistic
161.51*** (0.0000)	92.02*** (0.0000)	2.5e-13 (1.000)	67.78*** (0.0000)

Note: numbers represent t-statistics and *, ** and *** respectively represent levels of significance at %10, %5 and %1.

The null hypothesis of no cross and /or time effects has been rejected and the F Test results reveal that there are only cross effects in our model according to Table 8 and the FE model is more appropriate as the null hypothesis of no correlation between unit effects and coefficients is rejected by the Hausman Test.

Table 9. FE Model Results

Fixed Effect Driscoll-Kraay Estimator				
Dependent Variable: BSF_{NPL}				
Indep. Var.	**Coefficient**	**Stan. Dev.**	**t Stat.**	**Prob.**
LSYO	-0.80193***	0.135886	-5.90	0.0000
LROA	0.133784***	0.03821	3.50	0.0000
LENF	0.018027***	0.002192	8.22	0.0000
LCDS	0.361816***	0.097935	3.69	0.0000
LGR	-0.62302***	0.077251	-8.06	0.0000
LTKF	0.18403**	0.078598	2.34	0.0190
LREK	-1.5817***	0.248429	-6.37	0.0000
LVIX	0.35085***	0.161458	2.17	0.0300
Fixed Term	21.74524***	2.980589	7.30	0.0000
Diagnostic Tests		**Test Statistic**		**Prob.**
Modified Wald Test / Ki-Square Statistic		5081.26***		0.0000
Breusch-Pagan LM Test / LM Statistic		479.392***		0.0000

Note: numbers represent t-statistics and *, ** and *** respectively represent levels of significance at %10, %5 and %1.

Table 9 shows the results of our FE panel model where the coefficients are predicted by using Heteroskedasticity and Autocorrelation robust Driscoll-Kraay estimators. As it can be seen all of the coefficients are significant at 0.01 level where only TKF is significant at 0.05 level. Moreover, SYO, GR and REK have negative signs which represents banks' cautious behaviour in that specific period. The other coefficients are positive signs means a period of increased risk appetite of banks.

6. Conclusion

In this study it was aimed to contribute to the existing literature by extending the BSF index by adding NPL variable (BSF_{NLP})to the calculations of banking fragility. In the literature review, NPL has not been used in prior studies while calculating BSF which was developed by Kibritçioğlu (2003). Moreover, the data spans a long period time including GFC of 2007-8, COVID and it represents 89% of Turkish banking system. The conclusion of the study has some important implications as both bank specific and macroeconomic variables determine the status bank fragility measured by the BSF_{NPL} index. In that respect risk appetite of banks rise when BSF_{NPL} moves in upward direction especially when index values are positive that is manifested by excessive risk taking which is followed by sudden downward movements representing prudential and contractionary behaviour.

The increase in inflation rate, VIX index and CDS spread represent the periods when the banking sector's risk appetite increases, the index moves upwards in such periods in line with our expectations consistent with the literature (Kibritçioğlu, 2003; Karanfil, 2014; Singh, 2010; Mazlan et al., 2016; Bhattacharya and Roy, 2016, Rejeb and Arfaoui, 2012), Especially the decrease in inflation rate was often seen together after periods of increased fragility indicates that the periods when the sector acts prudentially coincide with the tight monetary policy followed to ensure price stability. The inverse relationship between GDP growth and the index creates the impression that especially an increase in NPL dominate the index in periods of economic stagnation. In other words, the index follows an upward movement due to the increase in the risk of NPL.

Along with these findings, the increase in interest rates also increases BSF_{NPL} index probably as a result of rise in excessive risk taking and expansions in lending. On the other hand, the depreciation of the national currency (downward movement in the real exchange rate) moves the index upwards. This situation represents periods when foreign liabilities are dominant in the index as the rise in demand for foreign currency depreciates domestic currency. In addition, ROE, which is a sector-specific ratio, moves in the same direction as the index, as expected. In other words, the periods when the profitability ratios increase coincide with the periods when the banking sector expands its balance sheet and the indicators that make up the index move upwards. Similarly, in line with our expectations, there is an inverse relationship between SYO and the index. This means that periods in which risk appetite increases and periods in which capital adequacy ratio decreases occur simultaneously.

Since macroeconomic and sector-specific variables have important impact on financial fragility as expected, the results of the study are of great importance for all financial market participants and regulators. Positive or negative deviations of the fragility index from the long-run average value, especially when it goes beyond the threshold limits, indicate periods of increased fragility. Therefore, attention should be paid to risky periods of increased fragility and it should not be overlooked that fragility indices serve as a preliminary warning indicator. While most of the financial sector data are published annually, more frequent publication of data for the banking sector would be important for a clearer and earlier determination of the fragility structure of the banking sector. The inclusion of the fragility index in the financial sector data published by supervisory agencies will serve as an early warning signal, and the index will be analysed by the relevant banks and necessary measures can be taken in a timely manner.

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