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Assessment of Financial Stability in the Banking Sector in Iran

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The aims of the present study are developing a financial stability index (FSI) using banking indices to measure financial stability in Iran, and examining the relationship between financial stability and macroeconomic variables for policymaking. To these ends, we have employed principal-component analysis, out of sample forecasting, Autoregressive Integrated Moving Average (ARIMA) method, and Vector Error Correction Model (VECM). The monthly data period is spanning 2007:3 through 2017:2. We find evidence of one cointegrating vector. According to the cointegration test, there is a long-run relationship running from inflation, Gross Domestic Product (GDP) growth rate, and unemployment to FSI. Also, the results of the Engle-Granger test indicate bidirectional causality between FSI and unemployment. Forecast evaluation shows that VECM-based FSI prediction is more accurate than the ARIMA model.

Keywords: Financial Stability Index, Principal-Component Analysis, Out of Sample Forecasting, ARIMA, VECM, Macroeconomic Variables.
JEL Classification*:* B22, C53, G17, G21.

1 Introduction

A good deal of research has recently been carried out on financial stability by banks and financial institutions, and even central banks and some institutions such as international monetary fund (IMF) have released annual financial stability reports in recent years.

The financial crisis in 2008, which originated in the United States as a result of the collapse of the U.S. housing market and real estate mortgage crisis, was enough to motivate the academics to begin research in this area, concentrating more on the banking sector influences on the financial stability.

There are two objectives to this study. The first objective is to build a composite financial stability index (FSI) and then forecast the future behavior

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of this index and make a judgment about its performance. The other objective is to unravel the relationship between the FIS and macroeconomic variables. In particular, the paper examines whether any short-run and long-run relationships exist between the FSI and some selected macroeconomic variables. Also, the present study makes a comparison between the forecasting of the FSI in the ARIMA model and the VECM model.

The paper is structured as follows. Section 2 reviews the empirical literature on the Financial Stability Index. Section 3 presents the data and methodology. Section 4 describes the relationship between the FSI and macroeconomic variables. Section 5 deals with forecasting. The final section offers a conclusion.

2 A survey of the literature

Financial Stability Index (FSI) is a continuous and quantifiable measure that is used to gauge the stability level of the banking sector. Financial Stability is a broad concept. European Central Bank gives the following definition for it:

It is a condition that the financial system can resist against macroeconomic shocks. This process may lead to less interruption in financial intermediation and make a role in the optimum devoting of savings to profitable investment opportunities (ECB, 2009).

Schinasi defines it as ‘the ability to facilitate and enhance economic processes, manage risk, and absorb shocks.” (Schinasi, 2007) Mishkin states that “financial stability occurs when shocks to the financial system interfere with information flow so that the financial system can no longer do its role of channeling funds to those with productive investment opportunities.” (Mishkin,1999).

According to these definitions, the index for financial stability should represent macroeconomic elements, and the banking sector’s state at the same time. It should reflect the imbalances of the whole economy and show the effects of shocks on the financial system and welfare, and the growth of the economy.

Some studies in measuring financial stability, have concentrated on the construction of a financial stability index for a specific country. Illing and Liu (2003) introduced a metric of stress in the Canadian financial system aiming to quantify the results of the macro-financial stress test. This index included criteria for possible losses, risk, uncertainty in banks, the exchange rate, debt, and capital markets. The proposed index provides a single measure of macroeconomic stress that changes with successive fluctuations in the values of other variables in such a way that abnormal amounts are reflected in the form of a crisis. Factor analysis, economic standardization, and GARCH[1] econometric modeling were used to provide information on financial stress through changing financial variables. The significant point in the study is that the variables which contribute to building the index are not extracted from any structural model.

Hanschel and Monin (2005) employed an indicator to measures the stress level of the banking sector in Switzerland at a specified time (1987-2002) using balance sheet data. They used raw stress indicators with variance equal-weighted method to create a seasonal stress indicator for the Swiss banking sector. Macroeconomic disequilibria were used for rapid warning signs of bank stress. It evaluates the recognition of critical periods based on the available information (events) and compares stressful periods.

Papuska (2014) presented a simple index of the banking sector in Macedonia to address the effects of the banking crisis in 2008. The index is built on the main elements of CAMELS[2] financial stability indicators.

Brave and Butter (2011) used several econometric criteria, such as the Kalman Filter technique, to construct and forecast the Financial Stress Index. Indices were based on US interbank monthly data from 1970-2010. They used this indicator to predict financial stress and then evaluated the other indicators. In the end, they tried to test the performance of the index with some techniques such as the Markov-switching model.

Morales and Estrada (2010) made a composite financial index, which included profitability, liquidity, and the probability of default of banks and financial institutions variables in Colombia during 1995-2008. They weighted the variables in three major ways: principal component analysis, Variance Equal-weight, and count data approach. In the next step, they built the FSI index in terms of the type of institution. In the last step, they forecasted the index for policymaking objects with a Vector Error Correction Model (VECM) and Autoregressive Integrated Moving Average (ARIMA) model, and tested it with forward and backward-looking approaches. It is consistent with historic economic events and captures the main events in the Colombian economy.

Along this strand, we can also mention (Hakkio and Keeton, 2009; Louzis and Vouldis, 2012; Oet et al., 2011; van Roye, 2014). Other studies include making metrics for financial stability for a group of countries. (Cardarelli et

[1] Generalized Autoregressive Conditional Heteroskedasticity

[2] Capital adequacy, Asset quality, Management, Earnings, Liquidity, and the Sensitivity to market risk

al., 2011; Cevik et al., 2013; Hollo et al., 2012; Vermeulen et al., 2015). The difference in these indices includes the selection of variables, frequency of data, and methods of construction. However, they suggest a similar index to measure financial stability.

A new strand of studies deals with the relationship between financial stability and economic activities. (Hakkio and Keeton, 2009; Hollo et al., 2012; van Roye, 2014). They have a similar line of reasoning. More stress leads to more risk-averse behavior in firms and families. Therefore, they postpone the consumption and investment decisions, and as a result, economic activities decrease. (Real Options Channel). In an uncertain situation, economic agents have a lower net worth in their assets and collateral to get a loan. So, their ability to invest decreases significantly. (Financial Accelerator Mechanism).

Moreover, bank income and capital value are at-risk positions, so the banks tend to give fewer loans. This sequence can lead to an economic recession (Ferrer, 2018) (Bank Capital Channel)

Most studies in the field of financial stability have only focused on constructing the FSI index. Previous studies have not much dealt with the relationship between the FSI and macroeconomic variables. Also, researchers have not treated forecasting of the index in much detail. The principal methodology to investigate the co-movement of the time series is more on the application of different VAR models. So far, this method has only been applied to investigate this relationship. However, far too little attention has been paid to long-run and short-run dynamic relationship running from the FSI to macroeconomic variables or vice versa. In this paper, a report on this kind of relationship is presented, setting the VECM model.

Several factors have motivated this study. First, there are very few published studies dealing with the links between financial stability and macroeconomic variables for Iran. Second, it enriches the existing literature on financial stability by forecasting based on ARIMA/VECM approach. Third, there has been little research on constructing the FSI with banking balance sheet data for Iran.

3 Data and Methodology

Monthly data are available from the Central Bank of Iran. The balance sheet data are from 36[1] banks and financial institutions and have a monthly

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[1] The number of banks and financial institutions is not equal during different years. (unbalanced panel)

frequency (120 observations) and the period spanning 2007:3 through 2017:2. The main descriptive statistics of the data are presented in Table 1.

Table 1
Statistical Summary of Research Data

	Mean	Std.Dev.	Min.	Max.
NPL	0.148357	0.038941	0.093191	0.260375
ROE	0.37975	0.162509	-0.00484	0.724043
ROA	0.018796	0.011291	-8.5E-05	0.049565
LL	0.681369	0.115329	0.49237	0.895377
IF	0.008243	0.003477	0.002961	0.019326
TLA	0.954097	0.01383	0.916379	0.985376

Source: Research Findings.

ROA is a return on assets that implies the profitability of banks and financial institutions to total assets. It shows the efficiency of using assets to generate profits. ROE is a return on equity. It shows the effectiveness of the entity when it uses the investor's resources. NPL is total non-performing loans1 (past due 90+ days plus nonaccrual) to total loans. LL is the ratio of liquid liabilities to liquid assets. TL_TAS is the ratio of total liabilities to total assets, and IF is the ratio of interbank funds to liquid assets.

3.1 Methodology

Considering CAMELS indicators and IMF standards, credit risk, liquidity risk, and profitability variables were used to make the FSI. The variables were selected in terms of the systemic relevance, importance, availability, and frequency of the data. For instance, the rate of return on assets and equity was considered as a measure of profitability and nonperforming loans as a measure of credit risk indicators and the ratio of liquid liabilities to liquid assets as a measure of liquidity risk indicators. Figure 1 shows how the study narrowed down the choices to select essential variables.

[1] "A nonperforming loan (NPL) is the sum of borrowed money upon which the debtor has not made his scheduled payments for at least 90 days." (Investopedia)

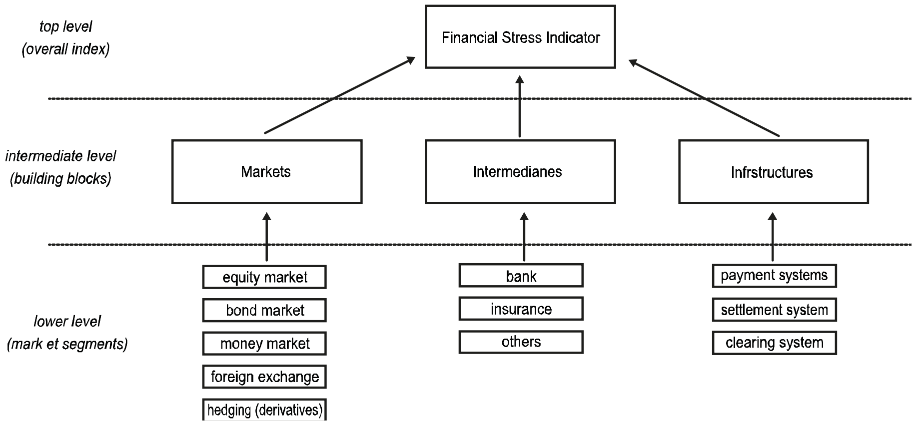

Figure 1. Financial Stability Index Structure. Source: Kremer and Hollo, 2012

To make a comprehensive composite financial stability index, a researcher needs to consider all building blocks such as infrastructures, and all market segments (See Figure 1). This paper just focused on intermediaries and ignored the other parts for simplicity. The key concept is that the FSI should represent profitability and probability of default to reflect the fragility of the financial system (Aspachs et al. 2006). The contribution of the present study is to apply banking sector sub-indices as a microelement, construct a composite indicator out of them, and examines the relationship of the built indicator with macroeconomic variables via ARIMA and VECM approaches to model and forecast the FSI.

3.1.1 Variance Equal-Weighted Method

The first step is to standardize the variables, which means subtracting the mean of each observation and dividing it by its standard deviation so that they can express in the same unit. In the Variance Equal-Weighted method (VEW), the sample mean can be calculated by:

$$\mathrm{I} = \sum_{i=1}^{k} w_i \frac{X_{i,t} - \bar{X}_i}{\sigma_i} \tag{1}$$

The next step is to combine the variables into a single variable, which calls for the vector of weights and defining the sign for each variable.

$$\mathrm{FSI_t} = w_1\mathrm{ROA} + w_2\mathrm{ROE} - \mathrm{w_3}\mathrm{NP} - w_4\mathrm{LL} - w_5\mathrm{TL\_TAS} - w_6\mathrm{IF} \tag{2}$$

Since six variables have contributed to making the FSI, the weight for each variable would be 0.166. Despite its straightforward estimating and satisfactory goodness of fit, VEW suffers from several significant drawbacks. First, it applies the same weight for all variables. Second, the composite index created by this approach cannot be sufficiently representative.

Contrary to expectations, it is a common approach in the literature. Another critical issue is the sign that each variable would take in the equation. For instance, the sign for ROE and ROA is positive because they are profitability indices and have a positive effect on stability. However, the sign of NP and LL, TLA, and IF are negative due to a negative impact on stability. For the visual inspection purpose, Figures three and four are provided.

3.1.2 Principal Component Analysis

The principal component analysis is a method to reduce the dimension of the data. We look at some patterns in data, identifying their similarities and differences. In other words, PCA compresses big data into something that represents the essence of the original data. It figures out a set of components that summarize the correlation between variables (Morales, 2010). For instance, subjects have a 3-D dimension, but whatever TV shows have a 2-D dimension without losing too much information. PCA gets the data with many dimensions and gives the one that is more important so it can be examined appropriately. "PCA has two general objectives. First, moving from many original variables down to a few composite variables (data reduction) and figuring out which variables play a larger role in the explanation of total variance (interpret)".[1] In another way, we combine variables so that “most of the total variance generated by the variables are taken into account by the combination." (Morales & Estrada, 2010) Considering the drawbacks of the VEW, the PCA is applied in this study.

3.1.2.1 Principal Component Model

Although p components are required to reproduce the total system variability, often, much of this variability can be accounted for by a small number of the k principal components.

Let $x = (x_1. \dots . x_p)'$ be a random vector with the covariance Σ. Geometrically, these linear combinations represent the selection of a new coordinate system obtained by rotating the original system with $x_1. \dots . x_p$ as the coordinate axes. Consider the linear combinations:

[1] https://jonathantemplin.com/files/multivariate/mv05psyc990/psyc990_10.pdf

$$y_1 = a_1'x. \quad (3)$$
$$\vdots$$
$$y_p = a_p'x.$$

With the variance and covariance:

$$var(y_i) = a_i' \sum a_i . \quad i = 1. \dots . p \quad (4)$$
$$cov(y_i . y_j) = a_i' \sum a_k . \quad i.k = 1. \dots . p$$

The principal components are those uncorrelated linear combinations $y_1. \dots . y_p$ whose variance is significant. First principal component = linear combination $y_1 = a_1'x$ that maximize var $(a_1'x)$ subject to $a_1'a_1$ = 1...ith principal component = linear combination $y_i = a_i'x$ that maximize var $(a_i'x)$ subject to $a_1'a_1$ = 1 and cov($a_i'x$, $a_k'x$) = 0 for k < i, i = 1,...,p.

Let λ_1,..., λ_p > 0 be the Eigen-Value of the matrix Σ and let H = (h_1,..., h_p) be an m×m orthogonal matrix such that H′ΣH = diag(λ_1,..., λ_p) = Λ, so that h_i is a eigenvector of Σ corresponding to the eigenvalue λ_i .

Now, the covariance between any linear combination $a'x$ and a linear combination based on an eigenvector $h_i'x$ is given by cov($a'x$, $a_k'x$) = $a'\Sigma h_i$ = $\lambda_i a' h_i$. Hence, cov($a'x$, $a_k'x$) = 0 is the same as a and h_i to be orthogonal.

3.1.2.2 Measures of the Total Variation

In transforming to principal components, the measures trΣ and |Σ| of total variations are unchanged, for

$$\text{tr}\Sigma = \text{tr}H'\Sigma H = \text{tr}\Lambda = \sum_{i=1}^{p} \lambda i \quad (5)$$
$$|\Sigma| = |H'\Sigma H| = |\Lambda| = \prod_{i=1}^{p} \lambda i$$

$\sum_{i=1}^{p} \lambda i$ is the variance of the first k principal components. In the principal component analysis, the hope is that for some small k, this variance is close to trΣ, i.e., the first k principal components explain most of the variation in x, and the remaining p−k principal components contribute little (Martin Singull 2010).

Table 2
Eigen-Values: (Sum = 6, Average = 1)

	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.418634	2.111106	0.5698	3.418634	0.5698
2	1.307529	0.402561	0.2179	4.726163	0.7877
3	0.904967	0.636568	0.1508	5.63113	0.9385
4	0.268399	0.190499	0.0447	5.899529	0.9833
5	0.0779	0.055329	0.013	5.977429	0.9962
6	0.022571	---	0.0038	6	1

Source: Research Findings.

Table 3
Eigen-Vectors (loadings)

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
ROA	0.475068	0.379201	-0.16357	0.086016	-0.118501	0.7631
ROE	0.394296	0.553592	-0.17093	-0.2616	0.485636	-0.4523
LL	0.398852	-0.52591	0.186003	0.344667	0.631174	0.112065
IF	-0.3456	0.514798	0.367096	0.670952	0.174631	-0.01049
TLA	-0.51214	0.058465	0.091277	-0.490557	0.533868	0.447546
NPL	0.279331	0.068715	0.87541	-0.33845	-0.190322	-0.01181

Source: Research Findings.

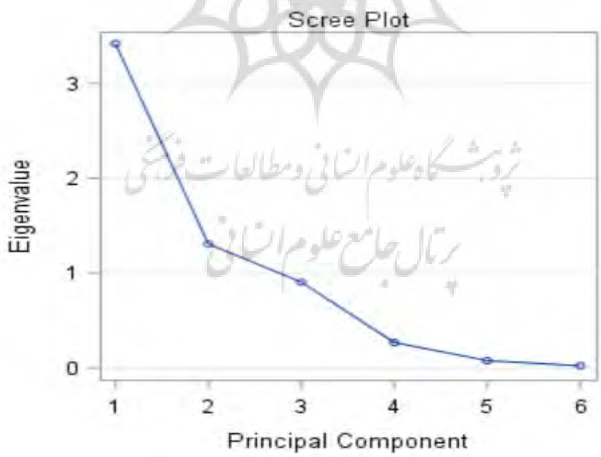

Figure 2. Scree Plot. *Source:* Research Findings.

After applying the PCA approach and running Proc component process in the SAS[1] software, we obtain an underlying index with associated weights:

$$\mathrm{IPC} = 0.475068\ \mathrm{ROA} + 0.394296\ \mathrm{ROE} + 0.279331\ \mathrm{NPL} + 0.398852\ \mathrm{LL} - 0.512144\ \mathrm{TL\_TAS} - 0.345602\ \mathrm{IF} \tag{6}$$

Visual inspection of the data shows that there is one main fracture in the Scree plot in Figure 2. Hence, Principal component 1 (PC1) and associated weights are selected from Table 3 in equation 7.

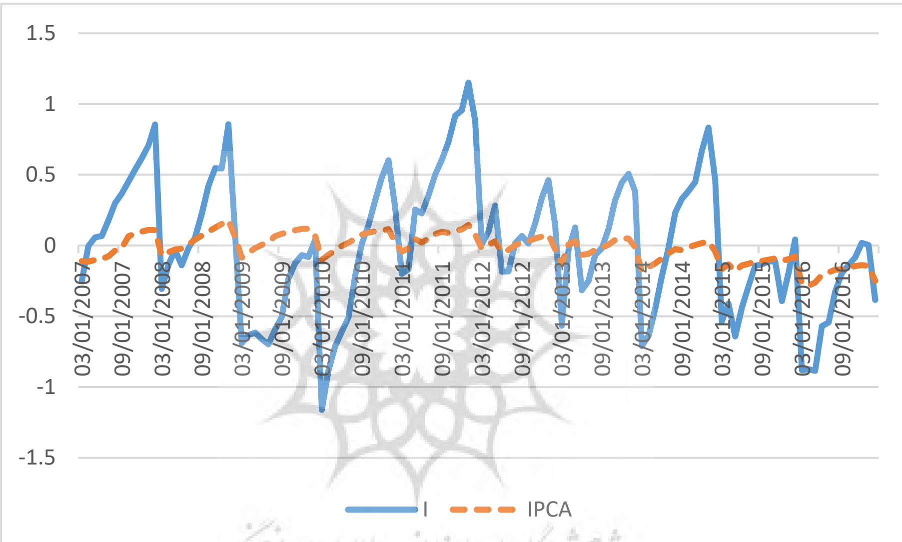

Figure 3. Financial Stability Index Diagram in VEW and PCA Methods. *Source:* Research Findings.

[1] Statistical Analysis System

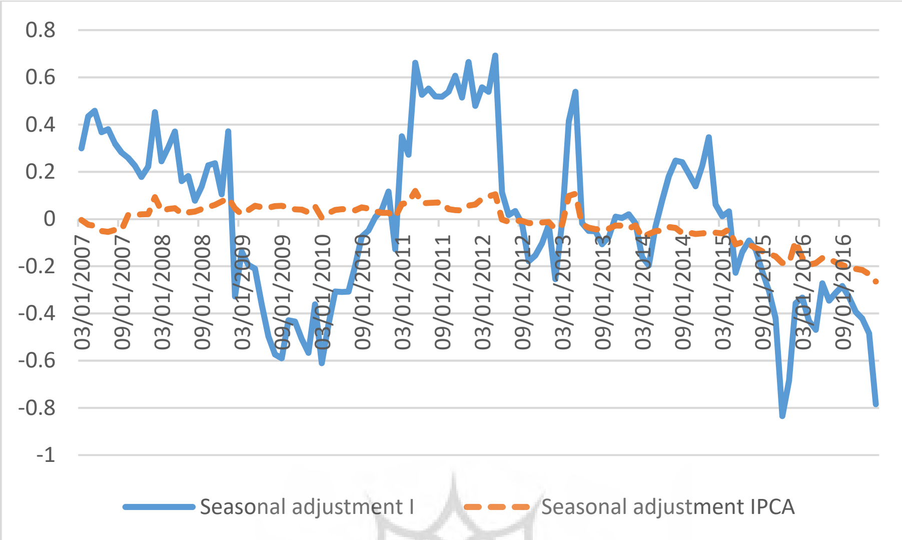

Figure 4. FSI Diagram Using VEW Method and PCA Method after Seasonal Adjustment. *Source:* Research Findings.

4 The Relationship between the FSI and Macroeconomic Variables

In the time series method, it is necessary to consider the interactions among variables in the form of a system of simultaneous equations. If the equations have a structural pattern, including lagged variables, it is called the simultaneous dynamic equations system.

In the structural equations, economic theory is used to model the relationships between variables, but economic theory often cannot create a dynamic statement that can explain all of these relationships. Also, when endogenous variables appear on both sides of the equation, estimation, and inference of the results encounter some problems.

Economic theories do not provide information on the parameters of short-term relationships or the dynamics of models. Typically, theories determine long-term or static relationships between variables. Besides, it is not evident that which variable is dependent and which one is an independent variable. This type of link does not include feedback between variables and presents the estimation of coefficients incorrectly. Also, the lack of proper specification of the dynamics of the model in the traditional approach may result in weak predictions and reject economic theories. (Enders, 2008)

These issues led economists to use unstructured methods to model relationships among time series variables. One of these approaches is the vector autoregressive (VAR). Sims adopted this approach between 1972 and 1980 as an alternative to macro-econometric models. The most basic form of a VAR treats all variables symmetrically without referring to the issue of dependence versus independence (Enders, 2008). VAR models are introduced based on the empirical relationship between inputs. These models correspond to a reduced form of simultaneous equations. Each of the variables is allowed to depend on its past realizations and the previous realization of other variables. Therefore, in these models, there is no need to specify short-term structural relations or causal relationships between variables.

The way variables are taken into account is based on the relations between the macroeconomic variables such as inflation, GDP growth rate, unemployment rate, and financial stability index.

Time series must be examined for cointegration. Cointegration analysis helps to specify long-run economic relationships between two or several variables and to avoid the risk of spurious regression. Cointegration analysis is essential because if two non-stationary variables are cointegrated, a Vector autoregression model (VAR) in the first difference is misspecified due to the effect of a common trend. Cointegrated variables have an error correction representation such that each variable responds to the deviation from the long-run equilibrium.

In an error-correction model, the short-term dynamics of the variables in the system are influenced by the deviation from equilibrium. If the variables are cointegrated, the residuals from the equilibrium can be used to estimate the error correction model in a dynamic Vector error-correcting mechanism (VECM) (Georgantopoulos, 2012).

One necessary condition to set VECM is to make sure that there is a long-run relationship among variables. A VECM model is set up using the error term of the long-run relationship. The first condition that must be met is that all variables should be integrated of the same order. If it turns out that there is a long-run relationship, the next step is selecting the optimal number of lags of the VAR model. The last step is to apply the Johansen-Juselius test that allows for the existence of multiple cointegrating relationships.

4.1 Unit Root Test

Cointegration analysis requires determining the features of each series in the model. This study firstly examines the stationary properties of the univariate time series. Augmented Dickey-Fuller (ADF) is employed to test the presence of a unit root. The estimated results of the unit root test are reported in Table 4.

Table 4
Unit Root Test

	t-statistics	probability	Variable	t-statistics	probability
FSI	-.990046	.9329	D(FSI)	-18.42228	0.000
P	-3.3497	.0737	D(P)	-4.6086	0.0039
GDP growth	-1.9282	.6208	D (GDP growth)	-7.7502	0.000
Unemployment rate	-2.3915	.3773	D (Unemployment rate)	-9.4222	0.000

Source: Research Findings.

The Dickey-Fuller (DF) test (1979) is one of the most widely used unit root tests. The ADF test is created by the autocorrelation of the non-systematic component in DF models (Dickey and Fuller, 1981). Compared to DF, the ADF test can be used for time series models that are more extensive and complicated. (Shao et al., 2019) According to ADF test results, the series follows an I (1) process, which means contain a unit root.

The result of the unit root analysis indicates the need for cointegration among these series. We, therefore, proceed to test for cointegration using the Johansen-Juselius test that allows for the existence of multiple cointegrating relationships.

4.2 Selecting the Optimal Number of Lags of the VAR Model

The optimal number of lags of the VAR model was selected based on some model selection criteria such as Akaike Information Criterion (AIC), Schwartz Bayesian Criterion (SBC), Hannan-Queen Information Criterion (HQ) and Likelihood Ratio (LR) and Final Prediction Error (FPE). Table 5 shows the optimal number of lags of the VAR model. All the mentioned measures suggested the inclusion of four lags.

Table 5
Selecting the Optimal Number of Lags of the VAR Model

lag	Log L	LR	FPE	AIC	SC	HQ
0	-236.61	NA	16.47889	14.15352	14.33309	14.21476
1	-179.12	98.07121	1.447757	11.71293	12.61079	12.01913
2	-149.97	42.86794	0.69735	10.93939	12.55554	11.49054
3	-123.011	33.30172	0.409401	10.29477	12.6292	11.09088
4	-69.6553	53.35576*	0.057287*	8.097373*	11.15009*	9.138438*
5	-54.3311	11.71852	0.091995	8.137124	11.90813	9.423146
6	-39.8973	7.641444	0.226875	8.229252	12.71855	9.76023

* indicates the optimal number of lags of the model. *Source:* Research Findings.

4.2.1 Testing for Cointegration

If there exists a long-run relationship between the series, one possible approach to model the data is setting a Vector error correction model (VECM). The Johansen cointegration test is used to find out the long-run relations of the series.

Two statistics, namely, maximum Eigen-value and Trace test, in the Johansen-Juselius test, can be used to determine the number of cointegrating vectors. The Eigen-value tests the null hypothesis that the number of the cointegrating vector is r against the alternative of r+1 cointegrating vectors. Trace statistics test the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r against a general alternative.

Table 6
The Johansen-Juselius's Tests Results

Maximum Eigen-value				Trace test			
H0	H1	Test Statistics	Critical value 95%	H0	H1	Test Statistics	Critical value 95%
r=0	r=1	27.21076	27.58434	r=0	r>=1	51.45777	47.85613
r<=1	r=2	11.50615	21.13162	r<=1	r>=2	24.24701	29.79707
r<=2	r=3	6.738247	14.26460	r<=2	r=3	12.74085	15.49471

Source: Research Findings.

Trace test indicates 1 cointegrating equation at the 0.05 significance level, and the Maximum-eigenvalue analysis indicates no cointegration at the 0.05 significance level. According to Granger's representation, the long-run equilibrium relationship requires the structure of the vector error correction model.

4.3 VECM Model Estimation

The vector error correction model aims to make a relationship between the long-run equilibrium of variables and the short-run dynamics of them. In this model, the first difference between series and long-run error term are used.

Table 7

VECM Model Estimation

	Coefficient	Probability
α	0.381382	0
β	-1.380427	0
γ	-1.295481	0
δ	-0.967372	0
ε	-0.006449	0.0012
θ	-0.002548	0.1582
ϑ	-0.000897	0.6152
μ	0.013289	0.1571
ρ	-0.002589	0.7294
σ	-0.010872	0.1046
τ	-0.000573	0.8261
φ	0.003107	0.366
ω	-0.000863	0.7449
ϵ	-0.024542	0.0003

Source: Research Findings.

$$\mathrm{D(IPC)} = \alpha\,(\mathrm{IPC}(-1) + 0.023\mathrm{GR}(-1) - 0.049\mathrm{U}(-1) + 0.0011\mathrm{P}(-1) + 0.51) + \beta\,\mathrm{D(IPC}(-1)) + \gamma\,\mathrm{D(IPC}(-2)) + \delta\,\mathrm{D(IPC}(-3)) + \varepsilon\,\mathrm{D(GR}(-1)) + \theta\,\mathrm{D(GR}(-2)) + \vartheta\,\mathrm{D(GR}(-3)) + \mu\,\mathrm{D(U}(-1)) + \rho\mathrm{D(U}(-2)) + \sigma\,\mathrm{D(U}(-3)) + \tau\mathrm{D(P}(-1)) + \varphi\mathrm{D(P}(-2)) + \omega\mathrm{D(P}(-3)) + \epsilon \tag{7}$$

Table 8

Model Estimation

R-squared	0.922427	Mean dependent var	-0.007868
Adjusted R-squared	0.876588	S.D. dependent var	0.088016
S.E. of regression	0.03092	Sum squared resid	0.021033
Durbin-Watson stat	1.697255		

Source: Research Findings.

α is interpreted as a speed of adjustment parameter. The larger α is, the greater the response to the previous period's deviation from the long-run equilibrium and vice versa.

Since the coefficient of cointegrating relationship, α, is positive and significant, there is a diverging long-run relationship running from growth rate (GR), inflation (P), and unemployment (U) to financial stability (IPC).

4.4 Engle-Granger Test

The Engle-Granger test allows investigating the causality relationship between the FSI and macroeconomic variables. The null hypotheses mentioned in Table 9. Results of the short-run test indicate unidirectional causality running from inflation (P) to GDP growth rate (GR). The results also indicate bidirectional causality between financial stability (IPC) and unemployment (U). Therefore, IPC can be taken into account for the Granger Cause of U.

Table 9

Engle-Granger Test

Null Hypothesis:	F-Statistic	Probability
P does not Granger Cause IPC	0.40392	0.7512
IPC does not Granger Cause P	0.58883	0.6271
GR does not Granger Cause IPC	0.62181	0.6064
IPC does not Granger Cause GR	1.56752	0.2178
U does not Granger Cause IPC	5.62397	0.0035
IPC does not Granger Cause U	4.58775	0.0093
GR does not Granger Cause P	1.37933	0.2681
P does not Granger Cause GR	3.07828	0.0424
U does not Granger Cause P	1.38892	0.2653
P does not Granger Cause U	1.41486	0.2578
U does not Granger Cause GR	0.11703	0.9494
GR does not Granger Cause U	1.082	0.3717

Source: Research Findings.

5 Forecasting

It is necessary to forecast the FSI index to prevent financial system vulnerabilities, to have policy-making hints, and to do banking supervision. One objective of the study is to assess the accuracy of the index. Since financial stability is a broad concept, and stability levels are unknown variables, evaluation of the FSI turns out to be complicated. In some studies, such as those by Popovska (2014), Puddo (2008) and Hanschel and Monin (2005), regression has been run, where the dependent variable is the FSI, and independent variables are macroeconomic variables such as the unemployment rate, inflation rate and the growth rate of the economy. In line with the literature, the stability level is compared with the historical evaluations of the financial crisis. It is expected that when a financial crisis occurs; the index shows low stability levels. It is also expected that the index detects major events. The variables which are considered in the index have a dynamic relationship with the stability level of the financial system, so one can conclude that the behavior of these variables in period t may determine stress events in period t+1. The implicit assumption is that the index includes the necessary information to explain future variations of the stability index1. Therefore, an autoregressive analysis is applied. In this model, FSI is considered as a dependent variable.

5.1 Forecasting Based on the ARIMA Model

According to the Augmented Dicky Fuller test, the FSI index is an integrated series of order one I (1). So, we employ an ARIMA[2](p,r,q) model. Based on some model selection criteria such as Akaike Information Criterion (AIC), Schwartz Bayesian Criterion (SBC), Hannan-Queen Information Criterion, and the correlograms graphs, the most parsimonious[3] model was an ARIMA (3,1,3). See Table 10.

$$(1-L)FSI_t = a_0 + a_1(1-L)FSI_{t-1} + a_2(1-L)FSI_{t-2} + a_3(1-L)FSI_{t-3} + b_0\epsilon_t + b_1\epsilon_{t-1} + b_2\epsilon_{t-2} + b_3\epsilon_{t-3} \quad (8)$$

Where FSI_t is the stability index, L is the lag operator, and ϵ is the error term.

[1] Morales 2010

[2] Autoregressive Integrate Moving Average.

[3] A parsimonious model fits the data well without incorporating any needless coefficients. (Enders, 2008)

Table 10
Model Selection

ARMA order	Akaike	Schwarz	Hannan-Quinn
0,0	-2.007947	-1.965291	-1.992643
0,1	-2.202661	-2.074695	-2.156748
0,2	-2.191993	-2.021372	-2.130776
0,3	-2.390214	-2.176937	-2.313692
1,0	-1.95203	-1.824064	-1.906117
1,1	-2.160053	-1.989431	-2.098835
1,2	-2.149995	-1.936718	-2.073473
1,3	-2.347898	-2.091966	-2.256072
2,0	-2.269735	-2.099113	-2.208517
2,1	-2.428469	-2.215192	-2.351947
2,2	-2.854861	-2.598928	-2.763034
2,3	-3.005266	-2.706678	-2.898135
3,0	-2.951333	-2.738056	-2.874811
3,1	-3.136502	-2.880569	-3.044676
3,2	-3.193114	-2.894526	-3.085984
3,3	*-3.358167	*-3.016924	*-3.235732

note. * indicates the best model. *Source:* Research Findings.

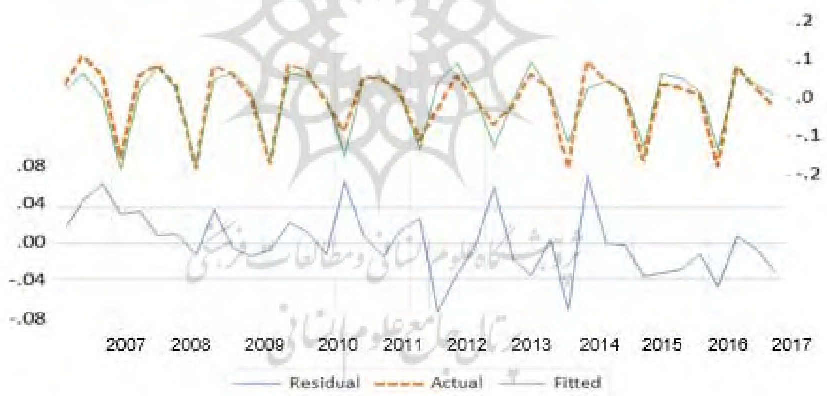

Figure 5. Actual, fitted and residual for IPC in the ARIMA (3,1,3). *Source:* Research Findings.

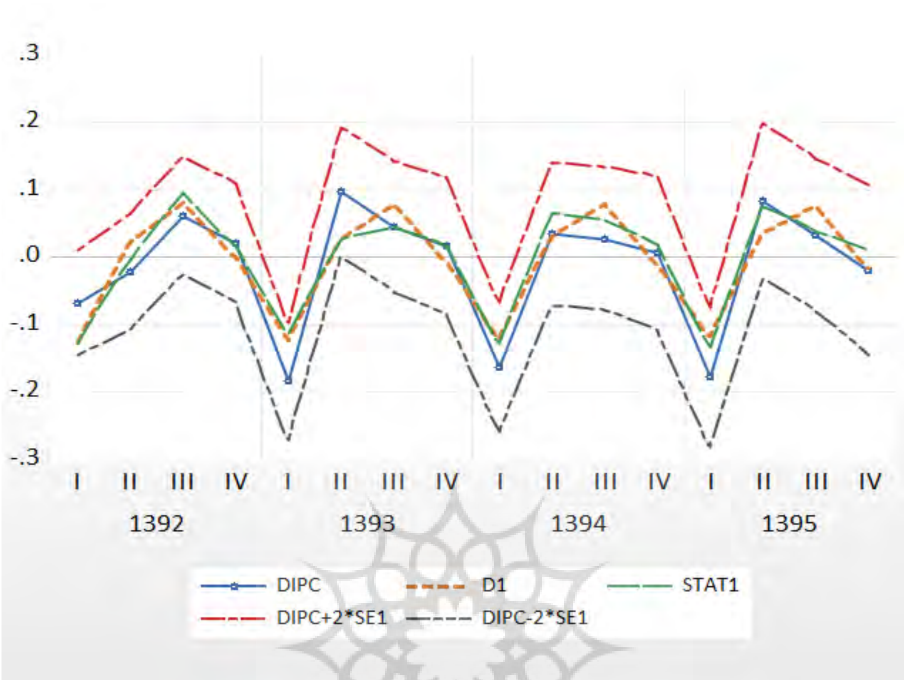

Figure 6. Out of sample forecasting for IPC in the ARIMA (3,1,3). *Source:* Research Findings.

It is possible to perform out of sample forecasting to evaluate the performance of the prediction of the FSI by applying this model. In this method, the in-sample period is between the second quarter of the year 2007 and the last quarter of 2012 and out of sample period starts from the first quarter of 2013 and ends in the first quarter of 2017. Figure 5 shows out of sample forecasting results in dynamic (D1) and static approach (Stat1). The difference level of the FSI in the Principal-component approach denotes DIPC. Visual inspection shows that the forecast can capture the trend of the index. According to forecast evaluation measures (See Table 11), the dynamic forecasting is more accurate than static forecasting.

Table 11
Evaluation of the Static and Dynamic out of Sample Forecasting for IPC in ARIMA (3,1,3) Model

Forecast	RMSE	MAE	MAPE	SMAPE	Theil
D1	0.126743	0.107326	215.5334	157.8796	0.629297
STAT1	0.129498	0.107417	237.3809	150.1041	0.640838

Source: Research Findings.

5.2 Forecasting Based on the Vector Error Correction Model

Similarly, the in-sample period is between the second quarter of the year 2007and the last quarter of 2012 and out of sample period starts from the first quarter of 2013 and in the first quarter of 2017. Figure 6 shows out of sample forecasting results in a dynamic approach. It is possible to make a comparison between the evaluation of forecasting based on VECM and ARIMA methods with some measures such as RMSE. Table 12 shows that all forecast evaluation measures in the VECM model are more accurate than in the ARIMA.

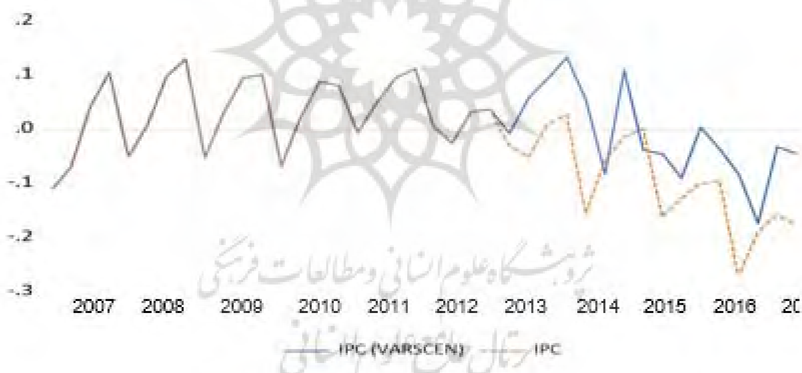

Figure 7. Out of Sample Forecasting for IPC in the VECM Model. *Source:* Research Findings.

Table 12
Forecast Evaluation of IPC in VECM and ARIMA Models

	RMSE	MAE	MAPE	Theil
IPC in ARIMA	0.126743	0.107326	215.5334	0.629297
IPC in VECM	0.109172	0.093852	347.1691	0.524484

RMSE: Root Mean Square Error
MAE: Mean Absolute Error
MAPE: Mean Absolute Percentage Error
Theil: Theil inequality coefficient

Source: Research Findings.

6 Conclusion

According to ECB, financial stability is a condition in which the financial system can resist against macroeconomic shocks. The present study is designed to construct the financial stability index according to the Variance-Equal Weighted method and principal component analysis and then to determine the relationship between the FSI index and macroeconomic variables. The principal component analysis helps us compress the data to retain the majority of variance and show the economic changes in a better way. Considering the drawbacks of the VEW, the PCA is applied in this research. The behavior of macroeconomic and banking variables set in the VECM model shows the evidence of one cointegrating vector. The results indicate that there is a diverging long-run relationship running from inflation, GDP growth rate, and unemployment to FSI. Results of the short-run test indicate bidirectional causality between financial stability (IPC) and unemployment (U). Forecast evaluation shows that VECM-based FSI prediction is more accurate than the ARIMA model.

It is difficult to explain this result, but it might be related to short-run policies with short-run objectives in both the banking sector and the economy of Iran. There are, however, other possible explanations. Further research is needed to examine the links between the FSI and macroeconomic variables more closely, considering data limitations.

Out of sample forecasting was performed in ARIMA, and the VECM model and findings indicate that forecast evaluation measures are more accurate in the VECM model.

Financial Stability is a broad concept. The findings of this study have several important implications for future practice. If we want to have a comprehensive indicator, it is better to include different markets such as stock exchange and world economic indicators to enhance the model and improve the forecasting results. Future studies can be done by developing the index by adding indicators of other related economic sectors.

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