



Constructing the Financial Conditions Index for Iran's Economy and Assessing its Effects on Stock Returns by FAVAR and TVP-FAVAR Models

Samere Raki Kianpour^{a,*} , Seyed Aziz Arman^a , and Hassan Farazmand^a 

a. Department of Economics / Faculty of Economics and Social Sciences, Shahid Chamran University of Ahvaz, Ahvaz, Iran.

* Corresponding author.

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Abstract

In this study, the financial conditions index (FCI) for Iran's economy was reviewed. The factor-augmented vector autoregressive model and the factor-augmented vector autoregressive model with time-varying coefficients are used to construct FCI. The ability of the constructed index to predict various variables is also evaluated. The construction of the index and estimation of the models are based on the quarterly data for the period 1989 to 2019. The variables used included interest rate and inflation, exchange rate, consumption, banking facility, total stock market index, money supply, oil revenue, and GDP growth. The findings indicated significant volatilities in the model parameters. According to the findings, under the restriction that model parameters are time-invariant, the shock from the improvement of the financial conditions index led to a negative response to the stock market index and this effect remained for eight periods; However, with time-varying coefficients, the stock market index has responded positively to a shock in FCI, and this effect remained for 10 periods and then disappeared. Furthermore, according to the results of the in-sample prediction error, the Root Mean Square Error (RMSE) represents the high power of model prediction.

Keywords: factor augmented vector autoregressive model, financial condition index, Iran, stock returns, time-varying parameter model.

JEL Classification: C32, E44, G17.

Introduction

A financial condition index (FCI) combines at least four financial prices: a short interest rate, a bond rate, the exchange rate, and a stock price index (Mayes and Viren, 2001). This index may have the ability to summarize financial conditions;

therefore, it can be a valuable tool for policymakers, households, and firms. Monetary policymakers can also employ the financial condition index to investigate the extensive effects of monetary policy on financial markets (Arrigoni and Bobasu, 2020). The construction and use of an FCI involve three issues, including 1- the selection of variables to enter into the FCI, 2- the method of combining these variables or especially the weights that are used to average these variables, and 3- the relationship between the FCI and the macroeconomy and also assessing the predictive power of this index for economic variables.

In the recent literature related to the financial condition index, factor augmented vector autoregressive (FAVAR) models have been significantly considered for structural analysis or forecasting. Specifically, in many FCIs that are the result of estimating a model or equation, there are four problems such as model dependency, ignored dynamics, parameter inconstancy, and non-exogeneity of regressors (Gauthier et al., 2004). Moreover, the requirement to use a small amount of information in the classic approach of the vector autoregressive (VAR) model will lead to possible problems including bias caused by omitted variables (Bernanke et al., 2005). Therefore, one of the methods used in this study to construct the financial condition index is the factor augmented vector autoregressive (FAVAR) model.

Several reasons lead to changes in the range of variables included in the index, changes in the importance of variables to enter the index, or changes in the impact of the index on the economy over time. For instance, the change in the structure of the financial industry (e.g. the growth of the shadow banking system), changes in the response of financial variables to changes in monetary policy (which can include the attention of central banks to the strategy of inflation targeting instead of the strategy of money supply targeting), or the changing impact of financial variables and markets on real activity (e.g. the role of financial variables in the economic recession of 2008 has been more obvious than other recessions). Therefore, considering that macroeconomic time series have cyclical changes or structural breaks over time, the use of time-varying coefficients leads to more accurate results (Del Negro and Otrok, 2008, Eickmeier et al., 2016). In addition, many researchers have found it important to extend factor models to allow for time-variation in coefficients (Del Negro and Otrok, 2008; Meligotsidou and Vrontos, 2008; Eickmeier et al., 2011; Felices and Wieladek, 2012; Korobilis, 2013; Koop and Koroblis, 2014). Therefore, the main question of this study is the effect of the financial conditions index on stock returns in the state of variation over time compared to ignoring the dynamics

across time and the state of constant coefficients. For this purpose, the financial conditions index (FCI) for Iran's economy was reviewed, and then its effects on stock returns were assessed by FAVAR and TVP-FAVAR Models. The remaining sections are as follows. Section 2 reviews the literature on financial conditions indices, including the literature on the selection of variables used in the index, and the techniques used in various studies to construct the index. Section 3 describes the methodology and data collection. Sections 4 and 5 report the results and conclusions, respectively.

Literature Review

FCIs can be thought of as an extension of the monetary condition index (MCI). The MCIs were developed to better understand the effectiveness of the monetary transmission mechanism. The monetary conditions index, in the late 1980s, was provided as a weighted average of short-term interest rates and exchange rates to evaluate monetary policy. The Bank of Canada expanded the use of the MCI by including it in Taylor-rule type equations which were used for policy implementation (Manning and Shamloo, 2015). The index proved to better represent monetary conditions in a flexible exchange rate regime, compared to an index based only on interest rates (Memona and Jabeen, 2018). The global financial crisis of 2008 sparked an interest in and demonstrated the need for better measurement of financial shocks and their impact on macroeconomics. Therefore, recent literature has explored the development of financial conditions indices. The literature has developed various empirical econometric methods for constructing FCIs (Balcilar et al., 2018; Koop and Korobilis, 2014). The extensive literature on money transmission mechanisms is a natural starting place for understanding financial conditions. According to this literature, the range of potential financial measures to include in an FCI is quite vast (Hatzius et al., 2010).

The traditional channels of monetary policy transmission are built upon the core models of investment, consumption, and international trade behavior that was developed. For investment, the key channels are the direct interest rate channel and the closely related Tobin's q channel; and for consumption, the channels operate through wealth effects and intertemporal substitution effects. For trade, the direct channel operates through the exchange rate. The second category –or non-neoclassical set – of transmission channels involves market imperfections in credit markets. There are two basic non-neoclassical channels including lending and balance sheet channels (Boivin et al., 2010).

The interest rate channel involves the impact of interest rates on the cost of capital and hence on business and household investment spending. Tobin's q channel contains the impact of asset prices on the demand for new physical capital and provides a mechanism through which monetary policy affects the economy by affecting market value. The wealth effects channel operates through asset prices. In the intertemporal substitution effects channel, changes in short-term interest rates alter the slope of the consumption profile, so that lower interest rates induce higher consumption today. The exchange rate channel captures the impact of the real exchange rate on net exports. In addition, the sensitivity of the exchange rate to interest rate movements is important. According to the bank lending channel, an expansionary monetary policy, which increases bank reserves and bank deposits, increases the quantity of bank loans available. Because many borrowers are dependent on bank loans to finance their activities, this increase in loans will cause investment and consumer spending to rise. According to the balance sheet channel, lower net worth means the agent has less collateral, increasing adverse selection and increasing the incentive to boost risk-taking. As a result, lenders will be more reluctant to make loans, leading to a decline in spending and aggregate demand (Boivin et al., 2010; Hatzius et al., 2010).

Therefore, indicators for structuring the FCI are mainly selected from the five categories mentioned above. There are several financial prices that influence the user cost of capital, including the interest rates that firms pay to borrow (both short- and long-term). Similarly, prices that affect household wealth, including equity prices, or consumer interest rates that affect the tradeoff between consumption today and consumption tomorrow would be natural candidates for an FCI. The non-neoclassical or credit channels point to an even broader array of possible FCI components, including measures of liquidity and of borrower risk, and factors affecting the capacity and willingness to lend (Hatzius et al., 2010).

Among the earliest studies to construct FCIs are those of Goodhart and Hofmann (2001) and Mayes and Viren (2001), which emphasize that stock prices, housing, and oil prices are important drivers of financial conditions in the Group of Seven (G7) and Finland, and provide a financial conditions index for these countries. After this research, the use of the FCI index was expanded to other economies. The most recent research and brief descriptions of the variables are as follows. Kapetanios et al. (2018), after constructing the financial condition index for the UK, investigated its effect on the capital market. The variables include different substitutes for interest rate and effective real exchange rate,

Financials market cap, Asset prices such as house price indices, price of gold, and price of crude oil, various indicators of borrowing and lending such as Stock of bank lending and Stock of M0, various indicators of Broad money and debt such as Stock of broad money, and various indicators for Surveys of credit constraints such as factors that may limit production such as credit/finance. Balcilar et al. (2018) estimated the FCI index for South Africa, and tested the forecasting ability of the estimated financial conditions index concerning macroeconomic variables of output growth, inflation, and interest rates. The variables used in the model consist of six variables, including the state of international financial markets, asset prices, interest rate spreads, stock market yields, bond market volatility, and monetary aggregates. Juhro and Iyke (2019) developed a financial condition index and examined the effects of monetary policy on financial conditions in Indonesia. To construct the FCI, they use Bank Indonesia's rate for the interest rate channel, the nominal effective exchange rate for the exchange rate channel, banking system claims on private enterprise for the credit channel, the Share Price Index for the equity channel, and the business confidence index and the consumer confidence index for the expectation or perception channel. Hartigan and Wright (2021) developed a new financial conditions index for Australia by applying the growth-at-risk framework. The variables included asset prices, interest rates and spreads, credit and money, debt securities outstanding, leverage, banking sector risk, financial system complexity, financial market risk, and survey measures of businesses' and consumers' views on financial conditions.

After detecting the variables, the second problem for constructing FCI is to determine the weights and combine the variables. In the literature, a variety of methodologies for constructing FCIs have been developed, but there are two prominent approaches including a weighted-sum approach and a principal-components approach or, more generally, the factor analysis approach. In the weighted-sum approach, each variable in the index is assigned a weight that reflects an estimate of its impacts on the medium-run policy goal. These estimates are obtained through simulations of large-scale macroeconomic models or the estimation of reduced-form demand equations or vector auto-regression (VAR) models. The second approach is based on the principal component analysis, whereby a common factor is estimated from a group of several variables and interpreted as the unobserved common variable of all the variables included in the index. Extracting this factor helps to detect the common structure in these variables and remove noise created by irregular movements of certain variables at

certain times. In this study, the index is constructed using the principal component analysis approach. The approach provides a means to exploit a large information set and handle the omitted-variable problem often encountered in standard vector autoregressive (VAR) models (Eickmeier et al., 2011). In particular, many FCIs based on a weighted-sum approach and derived from a model or equation fail to address the four technical issues including model dependency, ignored dynamics, parameter inconstancy and nonexogeneity of regressors (Gauthier et al., 2004).

Therefore, in different studies, different methods have been used to construct and evaluate the financial conditions index. Beaton et al. (2009) constructed the FCI index for the United States using the vector error correction model (VECM) and the large-scale macroeconomic model (MUSE). Koop and Korobilis (2014), to construct the financial condition index for America, used the TVP-FAVAR model with random fluctuations. Then, they used the root mean square error (RMSE) to check the predictive power of the constructed index for inflation, production growth and unemployment rate. Opschoor et al. (2014), using the GARCH model, investigated the effect of the FCI (Bloomberg Financial Conditions Index) on stock market volatility (daily stock returns) for the United States. Vonen (2011) has used the principal component analysis approach to construct the financial conditions index for Norway, and then the power of the index in predicting economic growth has been evaluated using the root mean square error (RMSE). Gomez et al. (2011) used the principal component analysis approach to construct the index for Colombia. Then, using vector auto regression (VAR) model, the ability of this index to improve economic growth forecasting power has been evaluated. Kapetanios et al. (2018), used principal component analysis approach and Multivariate Partial Least Squares (MPLS) approach to construct the FCI index for England. Then, using a SVAR model, the effect of FCIs on inflation, economic growth, and the capital market (credit supply shocks such as bank loans) has been evaluated. Balcilar et al. (2018), constructed the index for South Africa using principal component analysis approach and TVP-FAVAR and TVP-VAR models. Then, using the BVAR method, the ability of this index to predict production growth, inflation and interest rates has been evaluated. Juhro and Iyke (2019) used the dynamic factor analysis approach to construct an index for Indonesia. Then, the vector auto regression (VAR) model has been used to evaluate the effects of monetary policy on financial conditions. Hartigan and Wright (2021) constructed the financial conditions index for Australia using a dynamic factor model. Then,

using Granger causality, the predictive power of this index has been evaluated for macroeconomic variables including consumption, investment, economic growth, employment growth rate, and unemployment.

The latest research on Iran's economy are Taghizade et al. (2016) and Mohseni et al. (2019). In the research of Taghizade et al. (2016), the variables used to construct the financial conditions index include real interest rate, real exchange rate, land price index, the credits to the private sector, the stock price index, and the net foreign assets of the banking system. The principal-components approach was used to construct the index, and then using correlation analysis, the strength of this index in predicting inflation and domestic production was evaluated. In the research of Mohseni et al. (2019), the financial index consists of seven variables, real interbank rate, real exchange rate, house price index, real credit aggregates, the real debt of the banking system to the central bank, the real value of production, and net exports. The principal-components approach was used to construct the index. Then, the effect of a shock in the constructed index on the variance of GDP growth, private sector investment, real exchange rate and unemployment has been evaluated. According to the studies conducted for Iran's economy, the evaluation of the index is based on linear models and the effect of financial conditions on macroeconomic variables including inflation rate, gross domestic product and economic growth, and investment has been evaluated. Table 1 summarizes the studies conducted on the construction and evaluation of financial conditions for Iran's economy.

Table 1. Methods of Contracting and Evaluating the Fci Index for Iran

Author, Year	Methods of Contracting	Predicted Variables	Method of Evaluating
Khorsandi et al. (2012)	weighted-sum approach	inflation rate	Non-nesting Test and RMSE Criteria
Hematy and Boostani (2014)	weighted-sum approach	inflation rate, monetary policy	Cross Correlation
Atrkar and Mahbobi (2016)	weighted-sum approach	inflation rate	Non-nesting Test and RMSE Criteria
Taghizadeh et al. (2016)	principal-components approach	inflation rate, GDP	Correlation Analysis
Taheri et al. (2019)	principal-components approach	Growth rate of GDP	Causality Test and Wavelet Analysis
Mohseni et al. (2019)	principal-components approach	GDP, Investment	Bayesian Vector Autoregression (BVAR)

Methodology

Method

TVP-FAVAR Model

As discussed above, this study uses a factor augmented vector autoregressive model and a factor augmented vector autoregressive model with time-varying coefficients to construct a financial conditions index. The expansion of VAR models and the formation of factor augmented vector autoregressive (FAVAR) models are done through the extraction and inclusion of latent factors (Bernanke et al., 2005). Let Y_t be an $M \times 1$ vector of observable economic variables assumed to have pervasive effects throughout the economy. In the standard approach, a VAR model uses data for the Y_t alone. However, additional economic information may not be fully captured by the Y_t . This additional information can be summarized by a $K \times 1$ vector of unobserved factors. Latent factors include economic activities or credit conditions that cannot easily be represented by one or two series but rather are reflected in a wide range of economic variables (Bernanke et al., 2005). Therefore, for the development of FCI, the factor model is based on two connecting equations. Equation 1 helps in extracting FCI from financial and economic variables X_t and the second equation deals with the interconnectivity of FCI and macroeconomic variables y . In particular, the TVP-FAVAR model with the intercept p consists of two equations as follows:

$$x_t = \Lambda_t^y y_t + \lambda_t^f f_t + u_t \quad (1)$$

$$\begin{pmatrix} y_t \\ f_t \end{pmatrix} = c_t + B_{t-1,1} \begin{pmatrix} y_{t-1} \\ f_{t-1} \end{pmatrix} + \dots + B_{t-p,p} \begin{pmatrix} y_{t-p} \\ f_{t-p} \end{pmatrix} + \varepsilon_t \quad (2)$$

where x_t is an $(n \times 1)$ vector of financial and economic variables for the construction of FCI, y_t is an $(s \times 1)$ vector of macroeconomic variables, Λ_t^y is a matrix of regression coefficients, λ_t^f is a matrix of Factor loadings, f_t is latent factor interpreted as FCI, c_t is a vector of intercept, $(B_{t,1} \dots B_{t,p})$ is a matrix of VAR coefficients, u_t and ε_t are zero-mean Gaussian disturbances with time-varying covariance. The FAVAR model is obtained from the TVP-FAVAR model under the restriction that Λ_t^y and λ_t^f are time-invariant.

This study uses the two-stage principal components approach to estimate the FAVAR model. In the first stage, principal component analysis is used to estimate common factors using all the variables in a large dataset, x_t . In particular, factors are estimated by principal components prior to the estimation of the FAVAR. The second stage consists of estimating a VAR in F_t and y_t . The

FAVAR model is estimated using the EViews 12¹. The TVP-FAVAR model is estimated using the Bayesian approach and the Markov chain Monte Carlo (MCMC) method and Gibbs sampling. The TVP-FAVAR model is estimated using MATLAB (Bainter, 2017).

Data

In this study, variables covering major financial and economic variables are employed to form the index. Therefore, based on the literature of monetary transmission mechanism and also the different researches on Financial condition index, which was described in the previous sections, Non-official exchange rate growth, interest rate (weighted interest rate), consumption growth (private consumption expenditures growth), banking facility growth (facilities extended by banks and credit institutions), money supply growth, oil revenue growth, producer price index growth, industrial production index growth (production index of large manufacturing establishments with 100 employees or more), and market capitalization growth were selected as the model variables to construct FCI. The weighted interest rate is obtained from the weighted average of the expected rates of return on facilities to manufacturing and mining, agriculture, construction and housing, and trade, in such a way that the weights are derived from the division of the Outstanding facilities extended by banks and credit institutions to non-public various economic sectors on the total banks' facilities. The Y vector includes macro-economic variables namely inflation rate (percentage of changes in the consumer price index), total stock market index growth (Tehran stock exchange growth), GDP growth, and effective exchange rate growth.

Model estimation was made using quarterly data from 1989 to 2019. The data related to the variables of non-official exchange rate, lending rate of banks' facilities to different sectors, facilities extended by banks and credit institutions to various economic sectors, money supply, total banks' facilities, oil revenue, production index of large manufacturing establishments with 100 employees or more, and market capitalization have been extracted from the Economic Time series Database of the Central Bank of Iran. The data related to the private consumption expenditures and gross domestic product have been extracted from the national accounts published on the website of the Central Bank of Iran. The data related to producer price index has been extracted from the Economic Time

¹. For more information, see Blake et al. (2015).

series Database and the Statistical Center of Iran. The data related to consumer price index has been extracted from the Economic Time series Database and Economic indicator published on the website of the Central Bank of Iran. The data related to total stock market index has been extracted from Economic and Financial Databank of the Ministry of Economic Affairs and Finance and Economic indicator. The data related to effective exchange rate has been extracted from International Financial Statistics (IFS). All the series were seasonally adjusted using the X-12 procedure.

Empirical Results

The augmented Dickey-Fuller (ADF) test and the Zivot- Andrews test were used to test for unit root. All the series were stationary at level or in first differences. The results of the augmented Dickey-Fuller and Zivot-Andrews tests are shown in Tables 2 to 4.

Table 2. The Results of Augmented Dickey- Fuller Test (Level)

Variable	t-statistic	P-value
non-official exchange rate growth	-10.28	0.00
weighted interest rate	-1.90	0.64
consumption growth	-15.56	0.00
banking facility growth	-15.56	0.00
money supply growth	-3.73	0.02
oil revenue growth	-11.42	0.00
producer price index growth	-5.69	0.00
industrial production index growth	-11.46	0.00
market capitalization growth	-3.40	0.05
GDP growth	-11.57	0.00
consumer price index growth	-10.76	0.00
total stock market index growth	-6.83	00.0
effective exchange rate growth	-9.10	0.00

Source: Research findings.

Table 3. The Results of Augmented Dickey- Fuller Test (First Difference)

Variable	t-statistic	P-value
weighted interest rate	0.00	-11.11

Source: Research findings.

Table 4. The Results of Zivot-Andrews Test (Level)

Variable	Model A		Model B		Model C	
	Break Date	P-value	Break Date	P-value	Break Date	P-value
non-official exchange rate growth	1378	0.00	1384	0.02	1374	0.00
weighted interest rate	1393	0.00	1387	0.00	1393	0.00
consumption growth	1378	0.00	1385	0.00	1374	0.00
banking facility growth	1386	0.18	1394	0.10	1394	0.00
money supply growth	1392	0.00	1388	0.05	1392	0.06
oil revenue growth	1385	0.06	1385	0.05	1384	0.03
producer price index growth	1375	0.03	1384	0.11	1374	0.00
industrial production index growth	1378	0.02	1382	0.06	-	-
market capitalization growth	1394	0.12	1394	0.00	1392	0.00
GDP growth	1378	0.01	1384	0.08	1386	0.01
consumer price index growth	1375	0.00	-	-	1374	0.06
total stock market index growth	1383	0.03	1387	0.06	-	-
effective exchange rate growth	1380	0.01	1373	0.17	1380	0.05

Source: Research findings.

Further, before extracting factors, to evaluate the sampling adequacy and to examine the strength of the relationship among the variables, the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests have been performed, which are shown in Table 5. From the results, the KMO value is 0.6 (>0.5), and Bartlett's test is 0.000 ($p\text{-value} < 0.001$). Therefore, it is plausible to conduct factor analysis.

Table 5. The Results of the KMO and Bartlett Test

KMO Measure of Sampling Adequacy		0.599
Bartlett's test	Chi-Square	451.224
	P-value	0.000

Source: Research findings.

To determine the number of factors, the eigenvalue and variance of the four first factors are presented in Table 6. From the results, the first three factors have an eigenvalue greater than one and explain 65 percent of the data variance. Therefore, according to Kaiser's eigenvalue rule, the number of three factors can remain in the FAVAR model.

Table 6. Explanatory Power for the Four First Factors

Factor	Eigenvalue	Variance
1	2.70	0.30
2	2.03	0.22
3	1.18	0.13
4	0.91	0.10

Source: Research findings.

Further, the factor loadings were calculated using the principal components approach for the first three factors, which are presented in Table 7. According to the results of the (unrotated) factor loadings, the first factor has the highest correlation with the producer price index, interest rate, and consumption, respectively. The second factor has the highest correlation with the money supply, the banking facilities, and the industrial production index, respectively. Finally, the third factor has the highest correlation with the oil revenue, market capitalization, and exchange rate, respectively.

Table 7. Factor Loadings

Variable	Variable name	Factors		
		1	2	3
non-official exchange rate growth	er	-0.35	-0.05	0.31
weighted interest rate	ir	0.49	-0.13	-0.14
consumption growth	rc	0.36	0.15	-0.19
banking facility growth	loan	-0.16	0.63	-0.20
money supply growth	M1	-0.15	0.64	-0.16
oil revenue growth	roil	0.13	0.15	0.70
producer price index growth	ppi	-0.53	-0.06	0.18
industrial production index growth	pi	0.19	0.25	0.22
market capitalization growth	valut	0.35	0.24	0.44

Source: Research findings.

To evaluate the most important variables affecting the financial condition index, in addition to calculating unrotated factor loadings, rotated factor loadings have also been calculated. Varimax and Oblimin methods were used to rotate the factors. Considering that there is no significant difference between the results of the Orthogonal rotation of the factors and the Oblique rotation of the factors, it can indicate the non-dependence of the factors.

Providing a single index of the above three factors requires combining the factors. There are different ways to combine factors. A way is the implementation of the principal component analysis (PCA) approach for the three extracted factors. For this purpose, the linear combination of each factor has been presented using the calculated factor loadings. Then, the time series of each factor has been extracted using these linear combinations (PC1, PC2, and PC3). The results of the principal component analysis for three factors are presented in the Table 8. The first component (PC) is considered the optimal linear combination of PC1, PC2, and PC3. Therefore, the time series of the financial condition index is extracted according to this linear combination. Before extracting the index, normalization has been done for the time series of the principal components (PC1, PC2, and PC3). The Minimum-Maximum method has been used to normalize the time series of the principal components.

Table 8. Principal Component Analysis for the Three First Factors

Eigenvalues:			
Factors	Value	Variance	Cumulative Variance
PC1	2.19	0.7309	0.7309
PC2	0.80	0.2688	0.9998
PC3	0.00	0.0002	1.000
Factor Loadings:			
Variable	First component	Second component	Third component
PC1	0.6587	-0.2442	0.7116
PC2	-0.6526	0.2849	0.7019
PC3	0.3740	0.9268	-0.0283

Source: Research findings.

Despite extracting a linear combination with the highest explanatory power of data variance, the previous approach is only able to present the index time series and does not provide the contribution of the main variables in this index. The optimally-weighted linear combination approach is another way of the linear combination of factors that provides the optimal linear combination in terms of variables. In this approach, the weight of each variable is obtained from the factor loading of that variable and is called the factor score. Calculating the linear combination without considering the weights is another alternative approach. In this approach, after calculating the factor loadings (i.e. the results presented in Table 6) for each factor, the variables are combined, and this is done by adding (or averaging) the variables in the factors. If the factors are independent of each other, it is possible to add the factors to provide their linear combination. First, factor loadings have been normalized. For normalization, the absolute values of the coefficients of the variables are added together, then the coefficient of each variable is divided on this sum. In this way, according to the normalized coefficients, the financial condition index vector can be presented as Equation 3:

$$\begin{aligned} \text{FCI} = & -0.03\text{er} + 0.07 \text{ir} + 0.13\text{rc} + 0.13\text{loan} + 0.16\text{m1} + 0.39\text{roil} - 0.15\text{ppi} \\ & + 0.27\text{pi} + 0.41\text{valut} \end{aligned} \quad (3)$$

According to the results, over the study period, market capitalization as an asset channel has the highest weight in the indicators that constitute financial conditions, slightly followed by the oil revenue. The industrial production index is ranked third, which can emphasize the mutual effects of the real sector and the monetary sector on one another and the importance of the role of production

changes and on production-side disturbances on the transmission mechanisms. The money supply and, as narrowly followed, banking facility growth as the lending channels are ranked fourth and fifth, respectively. Accordingly, the results indicate the importance of credit channels in the monetary transmission mechanisms. Ultimately, the interest rate and exchange rate channels have the lowest weights. The interest rate channel's low weight indicates its dispensable role in the monetary transmission mechanism channels, as expected Iran's economy. Similar to the previous approach, normalization has been done with the Minimum-Maximum method for the time series of variables, which is described in Equation 4. Using normalized weights and variables to extract the index leads to the index being in the range of zero and one.

$$X_{it}^{Normal} = \frac{X_{it} - X_i^{min}}{X_{it} - X_{it}^{max}} \quad (4)$$

where X_{it} is the time series of variable X_i at time t , X_i^{min} is the minimum value of the time series of variable X_i , X_{it}^{max} is the maximum value of the time series of X_i .

Figure 1 compares the changes in the GDP to the changes in the financial conditions index derived from the first and second approaches, which FCI1 shows the time series extracted from the first approach (principal component analysis approach for the extracted factors), and FCI2 shows the time series extracted using the second approach (linear combination with equal weights of extracted factors). As demonstrated, for a significant part of the period study, it can be seen changes in the presented financial conditions index (both approaches) is codirectional with the real changes in GDP. Some periods where there was full compliance between RGDP and FCI are shaded. Accordingly, an increase in the financial conditions index can be defined as corresponding to expansionary financial conditions, and a decrease in it can be defined as contractionary financial conditions.

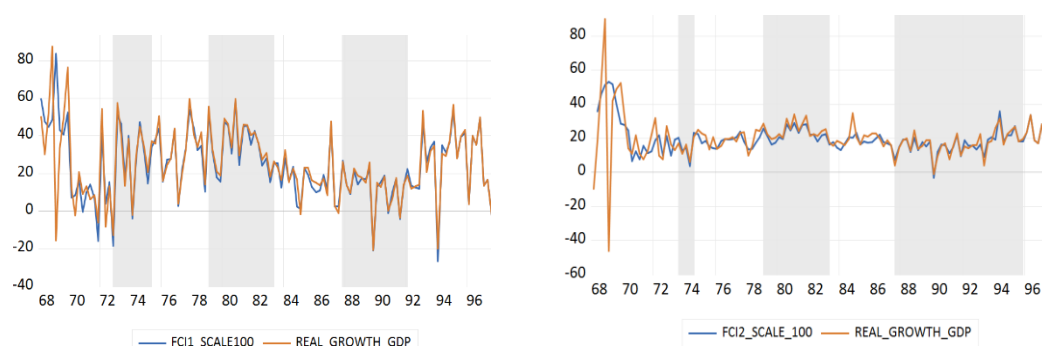


Figure 1. A Comparison between GDP Growth and Financial Condition Index (First Approach and Second Approach)

Source: Research findings.

Figure 2 compares and investigates changes in the real money supply and the extracted FCIs. As demonstrated, the real money supply and the extracted FCIs have not been necessarily codirectional over the study period. Some periods where changes in the real money supply as the conventional index of the monetary policy and FCIs are not codirectional are marked.

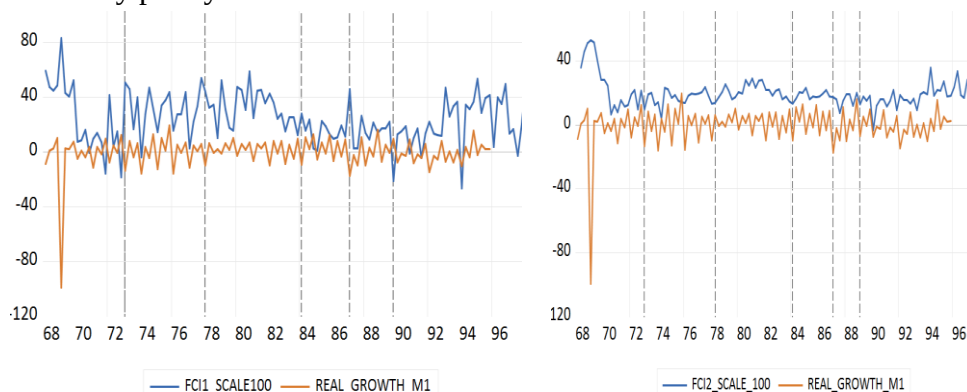


Figure 2. A Comparison between Money Supply Growth and Financial Condition Index (First Approach and Second Approach)

Source: Research findings.

According to the results and graph, there is no significant difference between the extracted time series for the financial condition index. In the following, the models are estimated.

The approach used to estimate the FAVAR model, as stated above, is the two-stage principal components approach, in which the factors are estimated using the principal components approach and before estimating the FAVAR

model. Therefore, while estimating the model, the FCI index is considered a variable in the model, the stationarity of the FCI time series has been evaluated using the augmented Dickey-Fuller (ADF) test. The result is presented in table 9. According to the results, the time series of the financial condition index is stationary at the five percent significance level.

Table 9. The Result of Augmented Dickey- Fuller Test for FCI (Level)

Variable	Augmented Dickey- Fuller	
	t-statistic	P-value
Financial Condition Index (FCI)	-5.26	0.00

Source: Research findings.

Finally, according to the Schwarz information criterion, the number of lags is estimated at one. Figure 3 shows the results of the impulse response functions (IRF) extracted from the estimated FAVAR model following a 1 standard deviation shock up to 15 months for the financial conditions index, which, respectively, X10, X11, X12, and X13 show the real growth of non-oil gross domestic product (at constant prices 2005=100, and after seasonal adjustment), inflation rate (percentage of changes in the consumer price index 2005=100), the percentage of changes in the total share price index, and the percentage of changes in the nominal effective exchange rate.

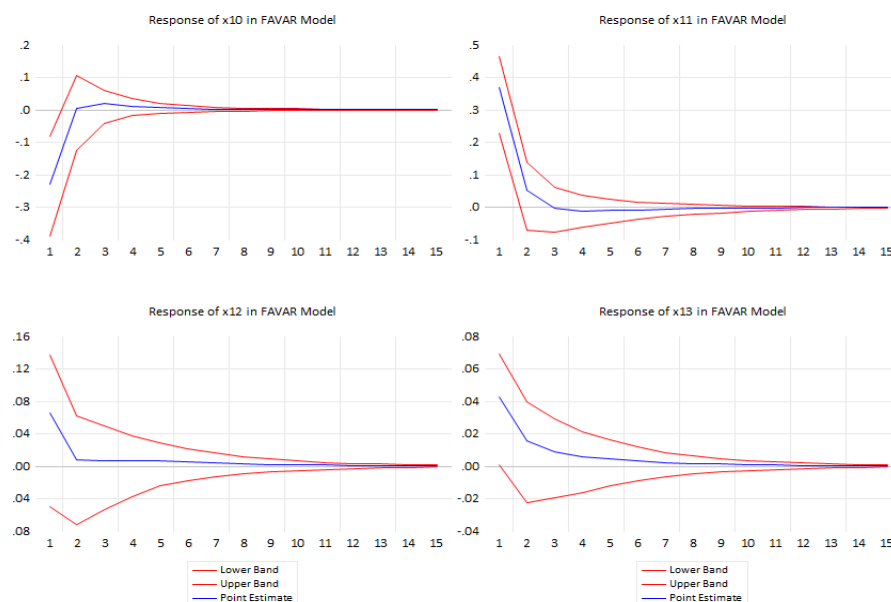


Figure 3. Impulse Response Functions of FAVAR

Source: Research findings.

According to the results of Figure 3, in the framework of the factor augmented vector autoregressive model, a positive shock from FCI has positively affected gross domestic product in the short term, but the effect of this shock has disappeared after seven periods. Furthermore, a positive shock from FCI has negatively affected the inflation rate, however, the effect of this shock remained only for seven periods and then disappeared. Regarding the effect of FCI shock on the total stock market index, a positive shock in FCI has negatively affected the total stock market index growth, but this effect has sustained only for eight periods. Ultimately, a positive shock in FCI has negatively affected the effective exchange rate, but the effect of this shock has sustained maximally up to 12 periods and has disappeared afterward.

In the following, considering the variability over time of all parameters and stochastic volatilities, the TVP-FAVAR model is estimated. As stated above, the parameters are estimated using Monte Carlo and Markov chain (MCMC) methods. For the elements of diagonal of variance-covariance matrix, prior distributions are considered as Equation 5, which is a gamma distribution with a mean of 4 and a variance of 0.02. To calculate posteriors, $M=10000$ samples are drawn. Therefore, the parameters have been calculated according to the estimated prior and posterior functions for the model and using the Gibbs approach based on Bayesian estimates.

$$(\Sigma_{\beta})_i^{-2} \sim \text{Gamma}(4, 0.2) \cdot (\Sigma_{\alpha})_i^{-2} \sim \text{Gamma}(4, 0.2) \cdot (\Sigma_{\eta})_i^{-2} \sim \text{Gamma}(4, 0.2) \quad (5)$$

In Figure 4, the graphs of the first-row show time-varying parameters for the variables, and the graphs of the second row show stochastic volatilities. The results indicate the model's parameters varying over time, and significant volatility for the developed FCI index and its variables. Nevertheless, according to the results of the graphs of the second row, the stochastic volatility or variance of the error terms of the financial condition index decreased.

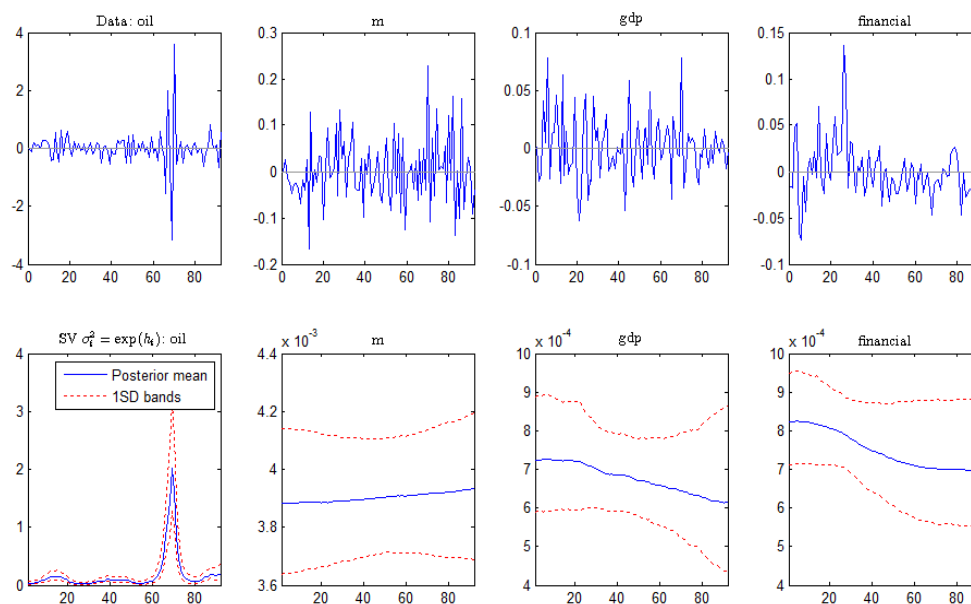


Figure 4. Coefficients (First Row) and Stochastic Volatilities (Second Row)

Source: Research findings.

Figure 5 investigates a shock from variables on FCI (and other variables) using posterior means. According to the results, the effect of oil revenue, compared with other variables, is insignificant and has been descending over time, so it has roughly been positive up to the 30th period and become negative afterward. The money supply effect on FCI has expectedly been positive, and it has followed a descending trend from the 40th onward. Moreover, the $\text{gdp} \rightarrow \text{financial}$ graph shows the coefficient of GDP on the financial condition index and according to the results, it has a negative effect on the financial condition index.

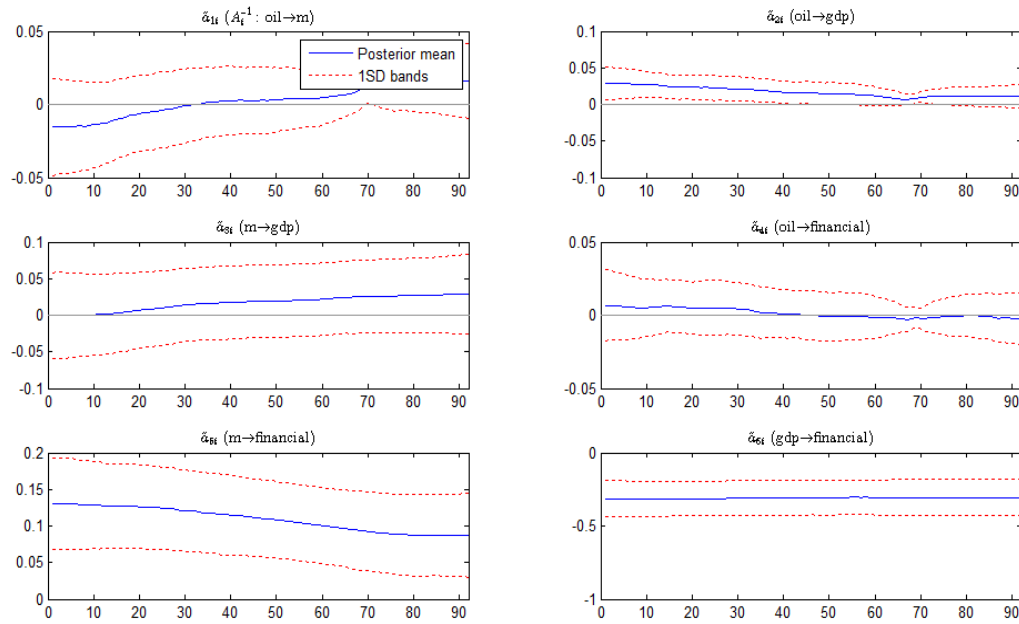


Figure 5. Posterior Mean for Shock of Variables

Source: Research findings.

Figure 6 shows the results of the impulse response functions extracted from the estimated TVP-FAVAR model following a 1 standard deviation shock up to 10 periods for the financial conditions index, and Figure 7 shows how the financial conditions index affects macroeconomics variables and stock market.

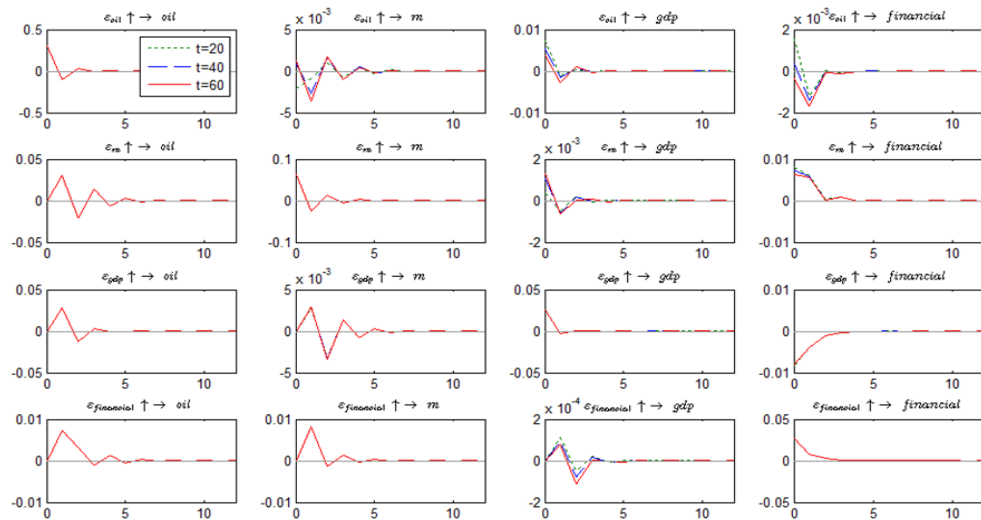


Figure 6. Impulse Responses Function (TVP-FAVAR)

Source: Research findings.

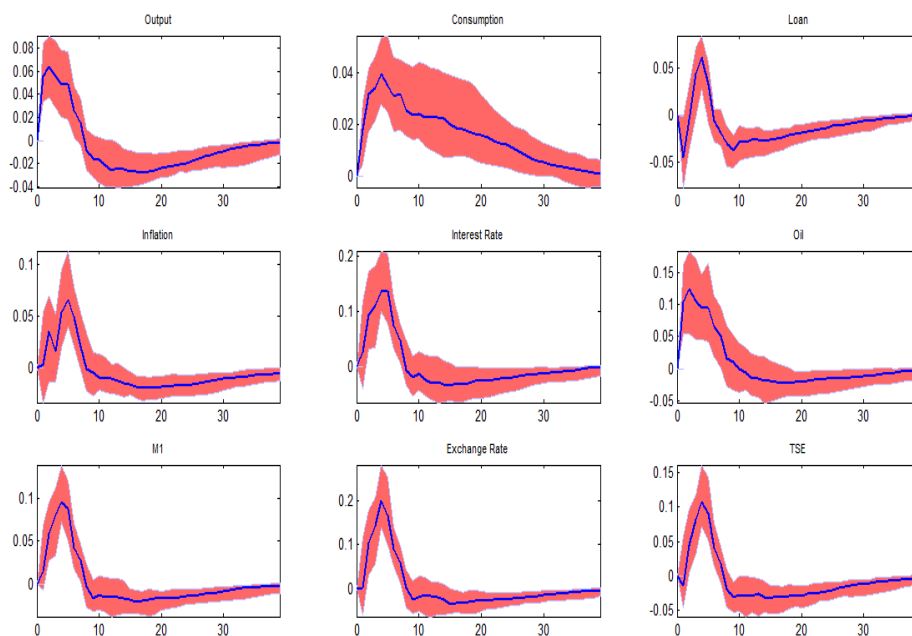


Figure 7. The Responses of Variables to the Shock from the Financial Condition Index
Source: Research findings.

The results of impulse response functions indicated that the gross domestic product responded positively to shock in the financial condition index only for a short time, but in the second period its effect became negative; moreover, the effect of the shock disappeared and in the long run, did not affect GDP. The money supply responded initially positively to shock in the financial conditions index, though this effect has followed a descending trend from the third period, and in the long run had no effect on the money supply. According to Figure 7, the growth of the gross domestic product responded positively to shock in the financial condition index, but after 10 periods its effect has been negative and then the effect of the shock disappeared and in the long run had no effect on GDP. The inflation rate, exchange rate growth, and interest rate have shown a similar response to the shock from the financial conditions index. Considering the important role of these variables in the financial condition index, these variables responded positively to the shock in FCI, but the effect of the shock decreased and disappeared after 10 periods. The growth in consumption responded positively to the shock in FCI and the effect of the shock has remained for 40 periods. Finally, the stock market index growth responded positively to the shock in FCI at 10 periods.

Finally, to show the predicting power of the estimated model, 4-period ahead forecast (green graph), 8-period ahead forecast (blue graph), and 12-period ahead forecast (red graph) are shown in Figure 8. In addition, the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Theil inequality coefficient (TIC) have been calculated to evaluate the in-sample and out-of-sample prediction power of the model. The results of the three criteria to determine the in-sample and out-of-sample prediction error are presented in Table 10.

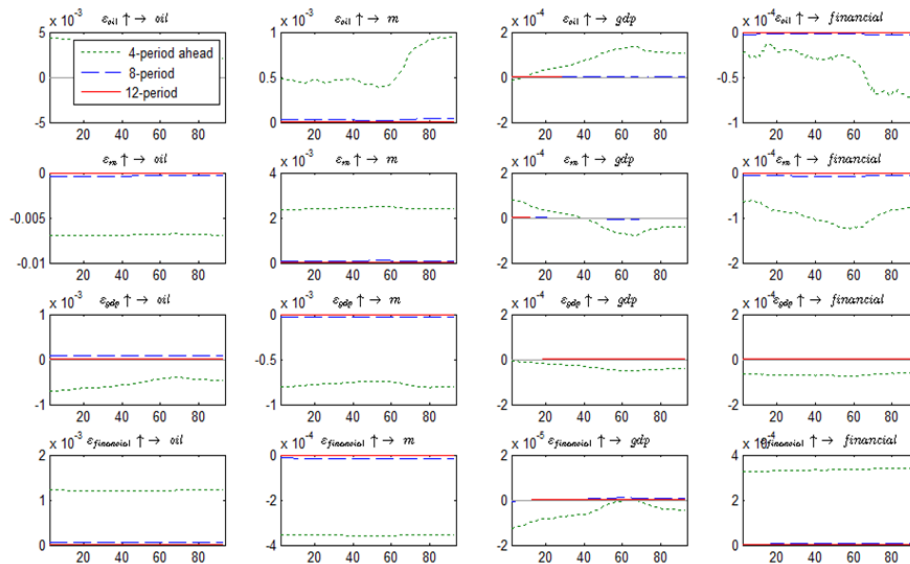


Figure 8. The Response of Variables to the Shock from Financial Condition Index

Source: Research findings.

Table 10. In-Sample and Out-of-Sample Prediction Error

Models	RMSE	MAE	TIC
Result of In-sample prediction error	0.486	0.371	0.032
Result of Out-of-sample prediction error	0.145	0.106	0.006

Source: Research findings.

According to the graphs, Predicting the response of variables to the shock from the financial condition index (4- period ahead, 8- period ahead, and 12-period ahead) indicates the high predictive power of the model. In addition, based on the results of in-sample and out-of-sample prediction error, the Root Mean Square Error (RMSE) and Theil inequality coefficient (TIC) represents the high power of model prediction.

Conclusion

In this study, the financial conditions index (FCI) for Iran's economy was reviewed. Then, the effect of FCI on the macroeconomic variables and its power to predict economic variables such as stock return were investigated. According to the model estimation results, the model parameters are time-varying, so significant volatility exists in FCI and its relevant variables. The results indicated that the primary variable influencing FCI over the study period is market capitalization, narrowly followed by oil revenue, industrial production index, money supply, and banking facility. However, compared to other variables, the effect of oil revenue on FCI was found to follow a descending trend over time and be disappeared nearly after 30 periods. Similarly, the impact of money supply on FCI was found to be gradually reduced over 40 periods. Therefore, according to the findings, the money supply shows the highest and most sustained effect on FCI. Accordingly, monetary policy can be said to play a pivotal role in forming financial conditions in Iran's economy.

According to the results, the shock from FCI has positively affected gross domestic product in the short term, but the effect of this shock has disappeared after seven periods. However, concerning the time variability of parameters, the GDP growth has first positively responded to the shock from FCI, and the effect of this shock has sustained for ten periods. Such a positive response could be due to a rise in consumption or banking facility growth after the shock from FCI. As indicated in the empirical results, the shock from FCI has positively affected consumption and the effect of this shock has sustained for 40 periods. Moreover, a positive shock from FCI has positively affected banking facility and money supply, and the effect of this shock has sustained for 10 periods. However, concerning the time variability of parameters, the positive shock from FCI on GDP has become negative after ten periods. Such a negative effect has sustained up to 30 periods and ultimately disappeared in the long term. Regarding the effect of FCI shock on the inflation rate, a positive shock in FCI has negatively affected the inflation rate for seven periods, however the effect of this shock has disappeared after seven periods. Moreover, concerning the time variability of parameters, a positive shock in FCI has positively affected the inflation rate, however the effect of this shock has been descending and disappeared after 10 periods. Regarding the effect of FCI shock on the total stock market index, when the parameters are constant, a positive shock in FCI has negatively affected the total stock market index growth, and this effect has sustained for eight periods. Nonetheless, when the parameters are time-varying, the total stock market index

growth has positively responded to the shock from FCI, but the effect of this shock has disappeared after ten periods due to the impact of factors included in the model. Therefore, according to the findings, ignoring the variability over time can lead to incorrect results and wrong policies and decisions. Furthermore, predicting the response of variables to the shock from FCI indicates the model's predictive power.

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- Funding: This work does not receive any funding.
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- Consent to Publication: The authors have given their consent for the publication of the manuscript.
- Competing Interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
- Availability of Data and Materials: Data is available on request from the authors.

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