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An Investigation of Co-Movement of Financial Stability Index with Macro-Prudential Indicator through Wavelet Analysis

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The present study aims at developing an aggregate financial stability index by using banking sector indices to assess financial stability and examine if the variable of credit-to-GDP gap corresponds to its long-term trend which represents the macro-prudential indicator has co-movement with the built financial stability index? To this end, monthly banking balance sheet data were collected from the Central Bank of the Islamic Republic of Iran from March 2007 to March 2017. Co-movement of two time series was assessed at two dimensions of time and frequency through wavelet analysis. It can be observed that there is a greater relationship between the two variables at short-term and medium-term. In the short-term, there is a negative correlation between financial stability and the representative of the macro-prudential variable. The increase of the credit-to-GDP gap results in a decrease in financial stability while these variables are positively correlated at medium-term. An increase in the credit-to-GDP gap increases financial stability, whereas such a relationship cannot be observed for the long-term. Thus, it seems necessary to adopt a macro-prudential policy more at medium term.

Keywords: Financial Economics, Financial Stability, Micro/Macro-Prudential Policies, Principal Component Analysis, Wavelet.
JEL Classification: B26, E23, G17, G21

1 Introduction

In recent years, extensive research has been conducted on financial stability by the banks and financial institutions. Some international institutions, such as the international monetary fund (IMF) and central banks, publish annual financial stability reports. Financial stability is an extensive concept and a challenging topic in the literature in recent years.

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Historically, the central banks have played the dual role of stabilizing the general price level, economic growth stability, or full employment (Goodhart, (1988)). Before the Global Financial Crisis in 2008, the central banks had achieved noticeable measures in stabilizing the general price level. The Global Financial Crisis was, indeed, a warning for the central banks against ignoring financial stability and targeting price stability and economic growth.

By now, several frameworks have been proposed for the development of financial stability. However, there is still a long way to achieve a coherent structure. Such a structure is underway while no financial model has been proposed yet for the missions required of the central bank. Besides, the monetary authorities of countries have not reached a consensus on macro-prudential and micro-prudential tools to help the financial system during a crisis (Kremers, J., Schoenmaker, D., (2009)).

The outbreak of the Global Financial Crisis in 2008 uncovered the undesired effects of financial fluctuation in the real sector of the economy more and revealed the inadequacy of macroeconomic and macro-prudential policies to achieve financial stability. In other words, an absence of financial rules is felt due to the inconsideration of the financial sector, systematic risk, and the soundness of regulations in a bank.

In the modern view, the macro and prudential policies are interacting with each other to create new policies, namely, macro-prudential policies, with a focus on systematic risk in developing financial stability in the overall financial system (Hadian, (2018)).

Financial stability in developed countries is regulated by the conditions of non-bank financial institutions that have a major role in such economies (Investment funds, retirement, and private funds, brokerage, etc.). However, in countries where these institutions are not well developed, and financing depends mainly on banks, banks are the main origins of financial stability and overall stability of the economy.

The legislators - mainly the central banks and international financial institutions - consider a significant role for the banking sector in the monetary and financial stability of the economy. They believe that banking stability - defined by the international monetary fund for the first time and is used by central banks - is determined by financial indices and its elements. These prudential indices should be consistent with accumulated micro-prudential indices in a financial institution and the macroeconomic variables of financial system soundness. They are related to the whole of the banking sector and are known as macro-prudential indices.

Monitoring the micro-prudential rules focuses on the idiosyncratic risk by the implementation of a set of unique banking standards on a bank. On the contrary, monitoring the macro-prudential rules focuses on the threats to the systematic bank stability resulting from the bankruptcy of a bank (due to the depreciation of the national currency or delinquency of the government) on the other parts of the system. The main challenge of the supervisor when pursuing both micro and macro goals is to manage micro-level standards in a way that fulfills the macro-regulatory objectives in the long-run.

The policy supervisors sometimes have to take both micro-prudential and macro-prudential dimensions for bank stability. The goal of the micro-prudential policy is to avoid the institution failure while the macro-prudential policy aims at limiting the likelihood of failure and the costs it may impose on the significant portion of the financial system.

Current indices for financial system soundness are obtained by aggregating the soundness indices of an institution. CAMELS[1] framework is often used to analyze the financial soundness of institutions. The framework includes six sets of indices which reflect the financial soundness in institutions. They are capital adequacy, assets quality, management quality (performance), profitability, liquidity and interest rates, and market sensitivity.

The shock of the 2007-2009 financial crisis has not been seen in the world since the Great Depression of 1930. Therefore, it seems necessary to develop an index to show financial improvement and provide an overall picture of the banking sector. The present article aims to provide a simple index for financial stability in Iran with a focus on the banking sector, being appropriate to reflect the financial crisis.

The existing literature is mostly on macro-prudential indices concerning of Countercyclical Capital Buffer – the macro-prudential tools which are based on the capital in the banks and financial institutions. These indices can account for the unexpected losses in high-stress financial periods while credit is still provided for the economy at the recession condition. The development of such a buffer requires certain indices for assessing the vulnerability accumulation and the imbalances in the financial market before a crisis occurs. The existing literature shows that the credit-to-GDP gap and its long-term trend can be an acceptable index. In other words, this index can be an indicator of the financial crisis (Hadian, 2018).

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

The index of financial stability is an aggregate of financial market variables which are needed to build a single index through which an overall picture of the instability in the financial system can be obtained. The single index can be used to detect a disruption in the financial market over time. It is an important index for adopting appropriate response policies.

A branch of literature on financial stability focuses on the relationship between financial stress and the real sector of the economy.[1] Financial stress can influence economic activities through different transfer channels. First, it can increase financial stress in the households and firms, and make them more risk-averse, which, can result in the postponement of their decisions on investment and consumption until the insecurity is eliminated. Therefore, economic activities decrease (Real Options channel).

Second, under uncertainty condition and asymmetric information, the lower net worth of firms and households reduces their capacity to attract financial resources as they have less collateral for their loans. Under these conditions, the lenders limit granting loans and require higher compensation. Hence the lenders restrict credit availability, which, in turn, results in limited economic activities (financial acceleration mechanism).

Third, the banks lose their capital by the less profit or loss on their non-performing loan and other assets in their balance sheet and as a result, are less willing to lend. Therefore, firms reduce their capital expenditure, and households reduce their spending. It will result in a severe economic recession (bank capital channel).

These three channels show a noticeable relationship between financial stress and reduced economic activities. Earlier research focused mostly on the standard time-domain methods to study the financial index and real sector of the economy. Most of these studies used different versions of the VAR model (Vector Autoregressive), focusing less on the time-varying relationship between the financial stress and real sector economy at different time horizons or frequencies. Here, the wavelet analysis is a suitable technique for signal processing, which appears in the mid-80, with both time and frequency domain at the same time. The distinctive feature of the wavelet analysis is its ability to convert the signal to its time scale components. The wavelet analysis can provide a more vivid picture as compared to other common methods by creating a suitable opportunity for computing the dynamics between financial

[1] Given that the representative of macro-prudential variables (the credit-to-GDP gap) can be considered as a variable of the real sector of the economy.

stress and real sector of the economy through time at time scales or frameworks.

The purpose of this article is to examine the relationship between financial stability and the indicator that represents macro-prudential variables in Iran through the use of wavelet analysis and continuous cross wavelet transform. This approach provides an integrated framework for the evaluation of the type of relationship between the financial stress and the macro-prudential environment in different time horizons, which has made it possible to investigate how this relationship can be deduced over time.

To achieve these goals, first, the financial stability Index is prepared through conventional methods consistent with the available literature. Then, it was studied if the representative of macro-prudential variables can provide signals to the financial crises so that a suitable policy can be taken to be compatible with the financial stability index that is made from micro-prudential variables.

The originality of this study lies in its use of wavelet analysis in examining the relationship between financial stability and the indicator that has a common goal with macro-prudential policy, through time and different frequencies.

In section two, we describe the theoretical framework of the research and explain the place of the present study in the existing literature. Reviewing the related literature, we, then, explain the significance of the present study. In section three, we first introduce the financial stability indices, and then describe and compare the most conventional methods of building financial stability index. In section four, we introduce the wavelet analysis and examine the outputs for R software for synchronization with the financial stability index. The conclusion appears in section six.

2 Theoretical Framework

2.1 Literature Review

There are several studies on financial stability which rely on simple hypotheses in CAMELS indices, emphasizing its applicability. On the other hand, there are several other studies which question the applicability of this method. Regardless of the dispute over it, this method is still used significantly by the central banks and financial institutions, and its use in assessing the financial stability in banks and, in general, the banking system cannot be ignored.

The main components of financial stability are the local macro environment, the international environment, and the bank sector. Financial crises influence the identification of these components. They can cause changes in the existing effective components, or change their structures.

In this paper, financial stability is considered a continuous and measurable criterion that is used to assess the level of bank stress. After the financial crisis from 2007 to 2009, most researchers focused more on financial stability. Since there was a consensus that the main reason for the crisis was the establishment of mortgages and inefficiency in the housing market, they focused more on the bank sector and its role in financial stability.

Financial stability is a broad concept. The European Central Bank considers financial stability in terms of the financial system to withstand macroeconomic shocks. This process leads to less impairment in financial mediation and plays a role in the optimal allocation of profitable investment opportunities (ECB (2013)).

Schinasi (2004) defines financial stability as an ability to facilitate and enhance the financial mediation process, manage risk, and attract shocks. Mishkin (1999) states that the shocks to the financial system disrupt the flow of information so that the financial system can no longer direct the funds to profitable investment opportunities. In other words, financial stability can be interpreted as the impairment of the natural function of financial markets.

Financial stability, along with increased uncertainty about financial assets and investors' behaviors, can result in substantial financial losses and high-risk avoidance of players. Generally, financial stability is not easily detected, but it can be reflected by a wide range of financial variables (Dovern and Van Roye (2014)).

After determining the importance of financial variables in the studies of the monetary transfer mechanism, the theoretical foundations of financial Stability Index were proposed in 2000 (Angelopoulou et al., 2014). Three general axes were detected for the relationship between financial variables and the mechanism (Montagnoli & Napolitano, 2005). First, the central bank should employ financial variables, such as the price of financial assets, only to predict inflation. Next, the central bank should determine an index which the price of financial assets would be part of it. Finally, the central bank should not only target the control of inflation, the stability of the general price level and stability of economic growth or full employment but also aim at the stability of the price of financial assets (Taheri Bazkhaneh, 2018).

Two general strategies can be used to set the representatives of the financial sector. One way is to consider a representative of the financial variables. The other way is that due to bank-based financing in the Iranian economy, an index is determined, which is an aggregate of variables of the banking sector and considering the financial sector information.

If we choose one variable, we have waived the other important financial variables. For example, if we consider only the ratio of non-performing loans to the total loans, as the representative of financial variables, we have then ignored the other variables than include profitability information of banks and other financial institutions. On the other hand, if we choose a statistical index for the financial variable, then we will be able to provide a true picture of the financial sector.

Monetary condition index was the first index made from variables such as currency rate and interest rate that was used to examine the function of transfer of monetary policy in the economy. Later in the studies by Goodhart and Hofmann (2001), this index was employed to identify the channels of monetary policy transfer, and the price of financial assets, as the representative of the financial sector, was then added to it. Following it, financial institutions such as Bloomberg and Goldman Sachs introduced the financial conditions index for monitoring the financial sector conditions.

Financial conditions indices are developed according to the goals of inquiries. Some indices are designed to predict the macroeconomic variables (e.g., Brave and Butters, 2011). Others were made to examine the relationship between the monetary policy and the financial sector (e.g., Goodhart and Hofmann, 2001). Still, some other studies used the financial stability index to design an early warning system (e.g., Ma and Chen, 2014). Finally, there are also some financial stability indices which are employed to discover the relationships between the business cycles and the financial cycles. Concerning the goal of the present research, the desired financial stability index belongs to the last category (Taheri Bazkhaneh, 2018).

Many studies have already been carried out on financial stability index in a particular country (Hakkio & Keeton, 2009; Louzis & Vouldis, 2012; Oet et al., 2011; Van Roye, 2014), or groups of countries variables could be reported as a (Cardarelli et al., 2011; Cevik et al., 2013; Hollo et al., 2012; Vermeulen et al., 2015). The financial stability index for the existing condition of the financial stability in a monetary system is integrated with single asset indices to show the main monetary market sectors in a single index (e.g., the market for money, bond, stocks, and the markets for foreign and banking transactions).

Illing and Liu (2003) introduced an index of financial system stress for Canada. They designed the index by aggregating single indices including indicators for possible loss, risk, and uncertainty in banks, currency rate, and the indices of debt and capital markets. The index could offer a single continuous indicator for macro-financial stress. A change in the units would result in changes in the other variables so that unusual variables could be reported as the crisis. Illing and Liu used techniques such as factor analysis, economic benchmarking, and Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) modeling to obtain information about the financial stress where financial variables change. Since the model employs financial stability index to monitor financial stability and evaluate the intensity of the financial crisis, it is very popular among central banks, international organizations, and economic research institutions. For example, the IMF has proposed this indicator for many emerging and advanced economies.

Hanschel and Monnin (2005) designed an index for assessing the financial stress in Switzerland. Using bank balance sheets, the index measures, and forecasts the stress in the banking sector at one point in time. The indices for raw stress were integrated through the Variance-Equal Weighted method to develop an index for seasonal stress in the Swiss banking sector. Macroeconomic imbalances were used as warning signals to early warning stress. The assessment of critical courses detection was done according to available information (events) and the comparison with stressful periods.

Van den End (2006) developed an index of financial stability for the Netherlands, including interest rate, currency rate, housing price, and stock price index of financial institutions. These indices were used to forecast the crises and test stress, including both micro-prudential indices for the banking sector and macro indicators and indices for other financial markets. Due to the absence of a developed stock market and the dominance of the banking sector over other financial sectors in the financial system in some countries, these indices are employed more than micro-prudential indices by the IMF. The authors proposed a financial stability conditional index (FSCI) which is a modified macro index of Monetary Conditions Index (MCI) and Financial Conditions Index (FCI). The lower limit of the index indicates the stress situation, and the upper limit of the index shows the optimal situation along with changes in market prices. It can be the result of integrated financial imbalances. So, the cyclical measures between these two limits can show the situation in the financial system.

Albulescu (2010) offered an integrative index of financial stability in point. In his study, he employed the macro-financial stability index for Romania between the years 1996 and 2008.[1] He selected 20 indicators, each of which could indicate a dimension of the financial system such as the development of the banking sector, soundness, the vulnerability of the banking system, etc. The sub-indices were all standardized so that the quantities would change between zero and one. Zero was the worst, and one was the best quantity during the period of research. Such standardization could eliminate the difference between measurement units and help aggregation. The researcher also used the same weight for the indices in designing the general index. Besides, the resistance of the index to macro stability factors was examined. He used a Stochastic Simulation model to forecast an index for the Romanian banking system. Based on this index, the periods of crises are shown by the impairment in the index, and the improvement of the financial stability in the Romanian banking system can be observed to have started in 2000, and more improvement was expected to occur in 2010.

Gersl and Hermanek (2007) computed a macro index of financial stability for Czech. Based on financial stability indices provided by IMF, it was noticed that based on financial soundness, the indicators which form the index of financial stability could also be used for comparison and gradation with other European counties.

Evans et al. (2000) emphasized the concept of financial indices in assessing and monitoring the financial stability of a financial institution, and the financial system, in general, as well as forecasting the future activities. They divided the macro-prudential indices into two categories of indices: macro variables relevant to financial system stability, and integrated micro-prudential indices that summarize the financial data reports of financial institutions. They thought that a financial crisis occurs when these two categories show vulnerability in the financial institution at macroeconomic shock occurrence.[2]

Another group of studies has focused on the relationship between financial stability and the real sector's actions (mostly in the US, European countries, and new economies). These studies have inquired into the use of various VAR models of macro-finance.

For example, Cevik et al., (2013) and Hakkio and Keeton (2009) studied the relationship between financial stress and real economy sector through linear standard VAR approach. Afonso et al. (2011), Hollo et al., (2012) and van Roye (2014) employed threshold models to examine the same

[1] Forecasting the Romanian Financial System Stability Using A Stochastic Simulation Model
[2] Macro-prudential Indicators of Financial System Soundness

relationship. Mallick and Sousa (2013), Magkonis and Tsopanakis (2014), and Tng and Kwek (2015) studied the impact of financial stress on macro-economy within a structural VAR framework. In a similar vein, Dovern and van Roye (2014) analyzed the world business cycle and the international transfer of financial stress through a general VAR model. Markov Switching VAR models are employed to examine the relationship between the real economy sector and financial market stress (Aboura & van Roye, 2017; Davig & Hakkio, 2010; Hartmann et al., 2015; Hubrich & Tetlow, 2015).

Most of these studies have indicated that the increase in financial stress results in significantly reduced economic activities, especially during high financial stress conditions. Most of these studies take into consideration the time domain of the data and ignore the frequency domain. However, since the interaction between financial and economic processes is the result of the interaction of various factors in different time horizons from several minutes to several years, it seems logical to think that the relationship between financial stability and economic activity changes during different time scales.

In such a case, the wavelet transform seems to be an attractive way because it allows for the decomposition of each signal into time scale components, taking into consideration both time and frequency domains. It then checks the relationship between the two time series based on the scale-by-scale method.

Therefore, through wavelet analysis one can investigate the relationship between financial stress and the real economy sector at different scales or different time horizons, and determine whether such a link is essentially a long-term phenomenon, or a noticeable short-term or medium-term relationship. Also, wavelet methods are a better alternative than VAR analysis to determine the mutual dependence between the time series for some reasons. First, VAR models do not have a spectral display. Consequently, it is not possible to investigate the links in the economic-financial activities at different frequencies. Second, the VAR models can be applied only to stationary data. So, there is a need for data conversion, which can lead to bias and unreliable findings. In contrast, the wavelet analysis is more flexible to accommodate both stationary and non-stationary data and can preserve the main economic and financial directing forces. Third, unlike the VAR model features, the wavelet approach does not impose parametric constraints on the dynamics of time series fluctuations. In short, these aspects justify choosing a wavelet approach, rather than a VAR approach, in studying the interactions between financial stability index and the real economy sector (Ferrer (2018)).

3 Making Financial Stability Index

The implied research hypothesis in this study is that according to bank-based finance in Iran economy, a banking crisis usually results in financial-economic instability. In general, the methods of identification of banking crises are based on two groups of indicators: the event method and the statistical method. Some weaknesses of the event method (e.g., the market events are not strong enough to occur) can impair the ability to identify the crisis at the right time, resulting in a bias. In contrast, in the statistical method, which relies on quantitative measures, it is possible to identify different levels of bank fragility, and the bias is eliminated. Therefore, a statistical index was used in this study (Poor Abdolhan, 2018).

According to the nature of the economy of the country in this study, the sub-indices were selected from the lower level of the financial stability structure, as shown in Figure 1 (market components) and the medium level (markets, financial intermediaries and infrastructure). After being standardized and properly weighted, the sub-indices were aggregated to build the financial stability index at a high level.

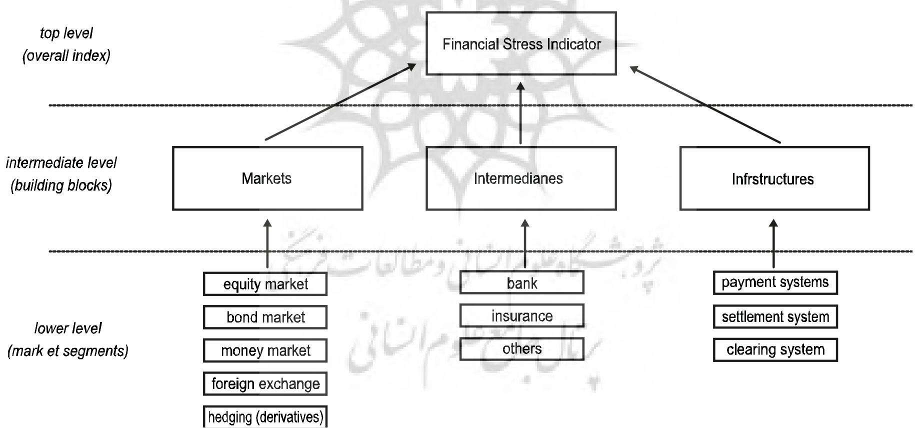

Figure 1. Structure of Financial Stability Index. Source: Kremer and Hollo (2012)

Considering the similar studies, the variables of credit risk, liquidity, and profitability of the Iranian banking sector were used, and the whole sector was considered as a large bank. In previous studies, indices such as the Banking System Fragility Index (BSFI) considered all indices simultaneously (Kibritcioglu, A., 2003). In this study, the aggregate index is designed to measure the financial system at the time of macroeconomic shocks. It considers the financial system as the whole, and the components of the banking system as microelements. The selection of variables is based on the systematic relevance, importance, accessibility, and consistency of the data.

For example, the rate of return on assets and the rate of return on equity was considered as the indicator of profitability, and the ratio of non-performing loans to total loans was considered as an indicator of credit risk. Besides, liquidity risk indicators such as the ratio of liquid liabilities to liquid assets were taken into consideration too. Figure 1 shows how the choices were narrowed down so that the significant variables could be selected in making the financial stability index.

It is better to take other sectors such as infrastructure and other markets into account in making the Financial Stability index. In this study, the focus was on the intermediations (especially banks) among other sectors; the other sectors were ignored for simplicity and limitations in the data from monthly raw balance sheets.

The key point is that the financial stability index must be representative of the profitability and reflects the financial system fragility. In other words, the achievement of this research is the use of sub-indices of the banking sector as a microelement to construct an aggregate index and check the co-movement of the index made with the representative of the macro-prudential variable through wavelet analysis.

3.1 The Data

Monthly balance sheet data are collected from the Central Bank of the Islamic Republic of Iran from March 2007 to February 2017[1]. The data were summarized, cleaned, and aggregated to calculate the financial ratios. The variables which were used in building the index included Return on Assets (ROA), Return on Equity (ROE), Non-Performing Loan (NPL), Liquid Liability to Liquid Assets (LL), The ratio of interbank funds to liquid assets (IF), Uncovered liability ratio (ULR). Table 1 provides a statistical summary of the data.

[1] Data were obtained from 36 banks and financial institutions in different years.

Table 1
Statistical Summary of Research Data

Variable	Mean	Standard Deviation	Minimum	Maximum
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
ULR	0.954097	0.01383	0.916379	0.985376

Source: Research findings

The ROA ratio refers to the profitability of total assets. It focuses on the efficiency of assets for the production of profits. Similarly, the ROE is a ratio that shows the efficiency of stakeholders ' resources. The rest of the variables show the vulnerability of financial institutions: NPL (Non-Performing Loan) is the index of credit risk. The ratio of Liquid Liability to Liquid Assets (LL), the ratio of interbank funds to liquid assets (IF) and Uncovered liability ratio (ULR) are the liquidity risk indicators. According to Aspachs et al., (2006), the criterion for selecting these variables in the index is that the Financial Stability index must take into consideration two key variables: profitability and the likelihood of non-payment of debts. In general, variables that make the index were selected based on the models used in similar studies, the analysis of the financial system of Iran, the systemic relationship between the variables and the accessibility of the data.

3.2 Aggregation of Variables and Transform into the Financial Stability Index

The hardest aspect of building the financial Stability Index is to determine how the variables are weighted because this determines the impact of each variable on the Financial Stability Index. The problems facing this process are the absence of a reference index to measure the allocated weight accurately. There are several methods to measure the weight of variables.

Due to the weaknesses of the Equal-Weighted Variance method, the principal componential analysis was used. Equation 1 shows the weight each variable has in forming the index. In the end, FSI is aggregated by adding weighted variables.

$$\mathrm{FSI}_t = w_1\mathrm{ROA} + w_2\mathrm{ROE} - w_3\mathrm{IF} - w_4\mathrm{NP} - w_5\mathrm{ULR} - w_6\mathrm{LL} \quad (1)$$

3.2.1 Equal-Weighted Variance Method

For the sake of simplicity, the Equal-Weighted Variance is the most popular method in studying financial system stress. An index is made to give equal weight to each variable. Indicators are standardized assuming normality to reach the unit scale. This technique makes variables standard so that they can be expressed in a unit and then added to each other with the same weight. The general index formula is provided in Equation 2.

$$\mathrm{I} = \sum_{i=1}^{k} w_i \frac{X_{i,t} - \bar{X}_i}{\sigma_i} \qquad (2)$$

In this equation, k is the number of variables which form the index, $\bar{X}_i$ is the mean, σ_i standard deviation and $X_{i,t}$ and w_i the weights for the variables.

Then, we standardize the final index to check it in terms of deviations from the mean. The problem with this approach is that it gives the same weight to all standard variables that make up the index. This hypothesis may be inaccurate depending on system vulnerability and the differences in institutions. Furthermore, through this approach, the variables usually have a normal distribution, which is a strong hypothesis and may cause additional restrictions.

In spite of what was mentioned above, the Equal-Weighted Variance is the most popular method in building financial stress indices because it provides easy calculation, and has better processing as compared to other complex methods. Illing and Liu (2003), Hanschel and Monnin (2005) and Puddu (2008) used this method as the start point for developing their indices.

3.2.2 Principal Component Analysis

In this method, by examining the patterns in the data, the similarities and differences are detected between them. The main idea behind this method is to obtain a series of combinations of selected variables so that more variances, generated by the combined variables, can be taken into account. In other words, large data are compressed to show the nature of the original data. This method is in search of a set of elements to summarize the correlation between variables (Morales and Estrada, 2010). For example, the objects in the real world are 3-dimensional, but what is seen in the display image, without losing much information, has two dimensions. The principal component analysis receives a lot of data and then gives you the most significant dimension to have a better view. This method has two general objectives: first, moving from several main variables to an aggregated variable (data reduction) and then identifying which variables are more important in the explanation of the total variance (interpretation). In other words, variables are combined so that the highest variance generated by the variable is calculated by the aggregate index (Morales & Estrada, 2010). After applying the method and implementing it in the SAS (Statistical Analysis System) software, we reached the following index with relevant weights.

$$\mathbf{IPC} = -0.279331(\mathbf{NPL}) + 0.475068(\mathbf{ROA}) + 0.394296\,(\mathbf{ROE}) - 0.398852(\mathbf{LL}) - 0.345602(\mathbf{IF}) - 0.512144(\mathbf{ULR})$$

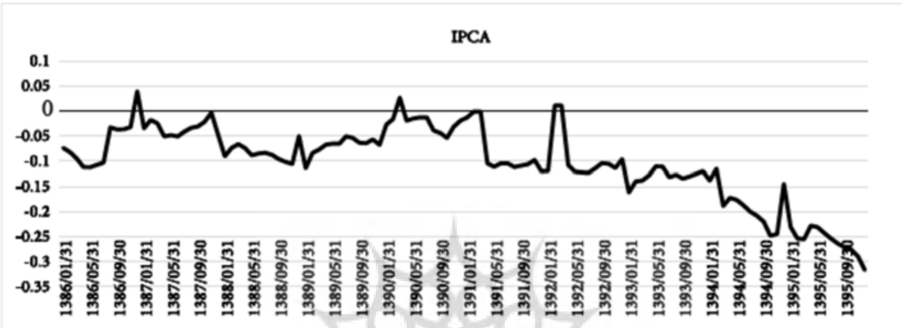

Figure 2. Financial Stability Index after Seasonal Adjustment through Principal Components Analysis. Source: Research findings.

Diagram 1 shows the chart of financial stability index obtained by principal component analysis after seasonal effect adjustment using the STL[1] algorithm.

4 Wavelet Analysis

In this section, Wavelet analysis and Continuous Cross Wavelet Tools (CCWT) are introduced briefly. The CCWT is designed to assess the amount of relationship between time series in a two-variable framework. Wavelet analysis is a mathematical tool for signal processing in a time-frequency domain; it was proposed as an alternative to the Fourier method[2] since the mid-1980. Wavelets combine the data from both time and frequency domain

[1] Seasonal and Trend decomposition using Loess and splits time series into trend, seasonal and remainder component.
[2] The Fourier method allows the study of how the relationships between variables change at different frequencies using spectral variable methods but do not apply time information to the data. Besides, the Fourier transform is only suitable for the Stationary time series. It should be noted that there are some Fourier-based tools such as Window Fourier Transformation that overcome these limitations. However, as Kaiser (2011) puts it, WFT is an inaccurate and inappropriate method for estimating time-frequency location.

to preserve time data. Therefore, it is suitable for describing non-stationary signal behavior. Also, to decompose a signal in its time-scale components, wavelets can be used to identify the relationships between the series based on the scale-to-scale method, and how they evolve. Therefore, Wavelets help discover inter-variable patterns, which is not simply possible through conventional time domain.

A wavelet is a "small wave packet" that grows or disappears in a limited period. This function is displayed with the ψ symbol in the space L^2(R) , and is placed with the average zero and normalized in origin. Based on Mother Wavelet, a wavelet-model family of girls $\psi_{u,s}(t)$ can be easily achieved by scaling and locating the ψ.

$$\psi_{u,s}(t) \coloneqq \frac{1}{\sqrt{s}}\psi(\frac{t-u}{s}) \tag{3}$$

Where S is the scale parameter or delay that controls the wavelet width and u is the location parameter to show where the wavelet center is.

There are two types of wavelet transform: continuous wavelet transform, and discrete wavelet transform. Continuous wavelet transforms operate at every possible scale and condition of the time, while the discrete wavelet transforms use a specific subset of discrete and spatial values. By taking the x (t) signal in the Space L^2(R), the continuous wavelet transforms according to the Ψ wavelet, is a function of two variables, the $W_x(u,s)$, which is obtained by wrapping a signal in the full family of wavelet girls.

$$W_x(u,s) \coloneqq \int_{-\infty}^{+\infty} x(t)\ \psi_{u,s}^{*}(t)dt \tag{4}$$

Where the * symbol shows the complex conjugate. Due to their intrinsic characteristics, continuous wavelet transforms contain additional information on signals, which makes it easier to interpret and provide more tangible visual results. As Grinsted et al. (2004) State, the continuous wavelet transforms are more suitable for the extraction of time series features, while discrete wavelet transforms are more useful for noise reduction and data compression. Due to their simple nature and adaptability, discrete wavelet transforms used more for economic and financial applications. However, the continuous wavelet transforms have gained popularity in recent years in the economy and finance. There are different types of mother wavelets, such as Harr, Morlet, Daubechies, Mexican hats, etc. in the existing literature. Among them, the Morlet wavelet, introduced by Goupillaud et al. (1984), has been used more than others. It is defined as,

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{\frac{-t^2}{2}} \quad (5)$$

Where the positive parameter ω_0 represents the central dimensionless frequency of the wavelet.

Morlet wavelet is a complex wavelet which can be decomposed into real and imaginary parts. This characteristic allows for separating the domain and the signal phase under the study, providing more information about co-movement and latency between the two time series. Therefore, in addition to numerous economic and financial applications, the Morlet wavelet has been used in this study to investigate the interactions between financial stress and macro-prudential indicator.

In a single-variable framework, the wavelet power spectrum X(t) is the wavelet squared coherence of the continuous wavelet transform. This method measures the relative contribution at any time and any scale relative to the variance of the time series. Hence, the wavelet power spectrum can be interpreted as the density of signal energy in the time-frequency space.

To identify the relationships between time series, two well-known cross-wavelet tools namely the square of wavelet squared coherence and wavelet phase difference were proposed by Torrence and Compo (1998) in the framework of continuous wavelet transforms. However, before applying these hybrid tools, it is necessary to introduce the concepts of cross wavelet transform and wavelet power spectrum. Wavelet transform of two time series X (t) and Y (t) is obtained through the following relationship;

$$W_{xy}(u,s) = W_x(u,s)W_y^*(u,s) \quad (6)$$

W_x And W_y are the continuous wavelet transforms for X(t) and Y(t) respectively.

The cross-wavelet power spectrum can be easily obtained from the absolute value of cross wavelet, $W_{xy}(u,s)$, which shows local covariance between two time series at any point of time and frequency. Therefore, the continuous wavelet power spectrum shows the parts in the time-frequency space in which two time series have high joint power. According to Torrence and Webster (1999), it is possible to define the second power of the wavelet coherence in the form of the rectified cross wavelet power spectrum, which is normalized by the multiplication of wavelet power spectrums in every time series. The squared wavelet coefficient is obtained by the following relationship.

$$R^2(u,s) = \frac{\left|S(s^{-1}W_{xy}(u,s)\right|^2}{S(s^{-1}\left|W_{xy}(u,s)\right|^2)S(s^{-1}\left|W_{xy}(u,s)\right|^2)} \quad (7)$$

Where S is the smoothing operator for both time and scale, which ensures that the amount of cohesion in all scales and times is not equal to one. Although the selected operator has important concepts in the analysis results, different types of rectifying operators can be selected (Cohen and Walden, 2010).

In the present study, in line with the study by Torrence and Compo (1998), we used a Gaussian filter, which is the most commonly used operator in experimental applications. The squared wavelet coherence can be thought to be a local linear correlation between the two stationary time series (time and frequency), which is similar to the correlation coefficient of linear regression. Therefore, it can be used to assess the relationship between the changes in the two time series at frequency and time. The range of changes is between zero and one; the values close to zero show a weak correlation at a certain frequency while the values close to one indicate a strong correlation between the two time series. Since the theoretical distribution of squared wavelet coherence is not clear, it is common to use the Monte Carlo method to determine the level of statistical significance. As with other types of wavelet transforms, the continuous wavelet transform that is applied to the time series is affected by boundary disputes.

It is because the wavelet values at the beginning and end of the signal are not usually calculated accurately, i.e., they include the missing values in the time series. In the conversion of time series, due to instant wavelet fluctuations, random values replace the actual derived values of the conversion. It results in a biased error that is known as the edge effect. Although there are different methods for dealing with these edge effects, all of them produce fake coefficients in the boundaries (Mallat, 1998) and the area which is influenced by the edge effects increase as the time scale increases. The area of the time-frequency sheet, where the edge effects are important, is called a cone of influence and is illustrated graphically with a cone that is enclosed with a thin black line. The values of wavelet functions outside the cone-shaped area, due to the presence of edge effects, should be interpreted more accurately.

The squared wavelet coherence with the advantage of measuring the relationship power between the two time series in the frequency time-space is not able to distinguish between the positive and negative co-movement and the identification of priority relationships between the time series under the study. It can be solved by using the wavelet phase difference, which offers details of delays in the two-series volatility and thus provides information on the priority of relationships. The phase difference can be computed through cross wavelet transform as follows;

$$\phi_{xy}(u,s) = tan^{-1}(\frac{\Im(S(s^{-1}W_{xy}(u,s)))}{\Re(S(s^{-1}W_{xy}(u,s))})\tag{8}$$

Where $\Im$ and $\Re$ refer to the imaginary and real parts (Ferrer (2018)).

5 Results

This section illustrates the results obtained through the continuous cross wavelet tools, which were used to examine the interactions between the financial stability index extracted from Iran's banking sector and the representative of the macro-prudential variables, the total credit-to-GDP gap, at constant prices in the year 1998 drawn upon Hodrick Prescot's method, between 2007 and 2017.

Seasonal data has been converted to monthly data through Quadratic-Match Average method. Before analysis of the mutual cross-time between the financial stability and the mentioned variable, the wavelet power spectrums for the time series are shown in Figures 1 and 2. This tool is an index of the local variance of the mentioned series to provide an initial assessment of the behavior of each series in the time-frequency domain.

Contour plot diagrams are used to illustrate the wavelet power. They consist of three dimensions: period, time, and power. Period and time are characterized by horizontal and vertical axes; power is characterized by different gray colors. Areas with darker gray color are related to areas of very high power (high variance at the corresponding frequency) while areas with white color show absence of power (low variance at the corresponding frequency).

Color analysis for each of the series shows that wavelet power is not stable over time, nor different frequencies. Figure 2 shows that the highest (darkest) values of the wavelet power range for all the values of financial stability coincide with the onset of financial distress in Iran, according to index obtained through principal component analysis. Also, the highest wavelet power spectrum for Financial Stability Index of 20 to 40 belongs to the years 2008 to 2011, the period of financial instability in Iran's economy, according to principal component analysis.

Most energy of macro-prudential variables indicator is focused on financial distress. In general, evidence from the wavelet power spectrum suggests that financial stress is significantly concurrent with the macro-prudential variable representative in shorter scales with very low power.

Similar to the power spectrum, the squared wavelet coherence is also drawn through a contour plot. Figures 2 and 3 show the period and time on the horizontal and vertical axes, respectively. The squared wavelet coherence is displayed by the grey scale in which the increased amount of coherence is shown by increased darkness.

The straight black line in these figures separates the areas where the coherence of the squared wavelet is statistically significant at a level of 5%. Also, the Monte Carlo simulation method was used to assess statistical significance. In particular, the significance level of 5% using the Monte Carlo simulation of 120 pairs of ordinarily distributed time series with the same length, mean, and variance has been specified as the main series.

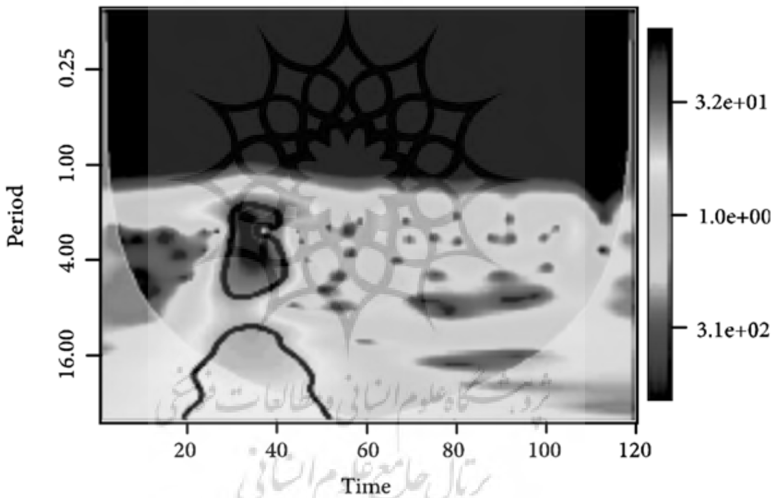

Figure 3. The Energy Power Spectrum for Financial Stability Index. Source: Research findings.

The thin black line specifies the cone of influence. The figures show that the coherence of the squared wavelet allows for the detection of time, the frequency of dependence between the financial stability Index and the representative of the macro variables, and the phase difference is always associated with a financial stress index. The results of wavelet coherence analysis indicate that the financial stress index and the macro-prudential variable have not remained stable during the time and over time scales. In particular, the highest level of coherence between financial stress and the index of the macro-prudential variable representative has been almost at the beginning of financial turmoil.

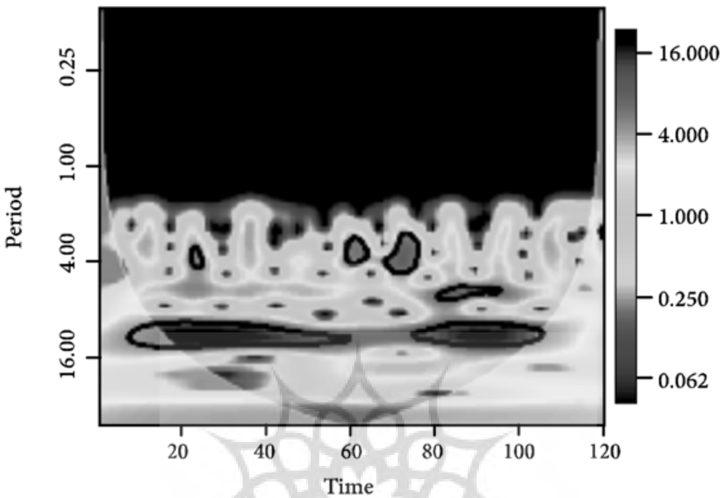

Figure 4. The Energy Power Spectrum for Macro-prudential Representative Variable. Source: Research findings.

Figure 4 shows the important economic and financial relationships are mostly concentrated at time horizons less than one year. In contrast, the relationships have been poor for the horizons of more than one year since the beginning of the year. It indicates that there is a real need for a macro-prudential policy mostly in the medium and short terms.

The black arrows indicate the phase difference within the statistically significant range on the wavelet coherence diagrams. The zero-phase difference means that two basic time series are moving together at a specific scale. When the time series are in a phase (positively correlated), the arrows point to the right, but when the series is not in the same phase, the arrows point to the left (negatively correlated).

Besides, once the arrows show an upward direction, it means that if the series are positively correlated, the first time series (here the Financial Stability Index) leads the second series (here the macro-prudential indicator variables), and if they are negatively correlated, the second time series leads the first time series. Conversely, once the arrows show a downward direction, it means that if the series is positively correlated, the second series will lead the first time series. Therefore, the left and downward directions indicate that time series are negatively correlated, and the first time series leads the second time series. Similarly, the left and upward directions indicate that the time series are negatively correlated, and the second time series leads the first time series.

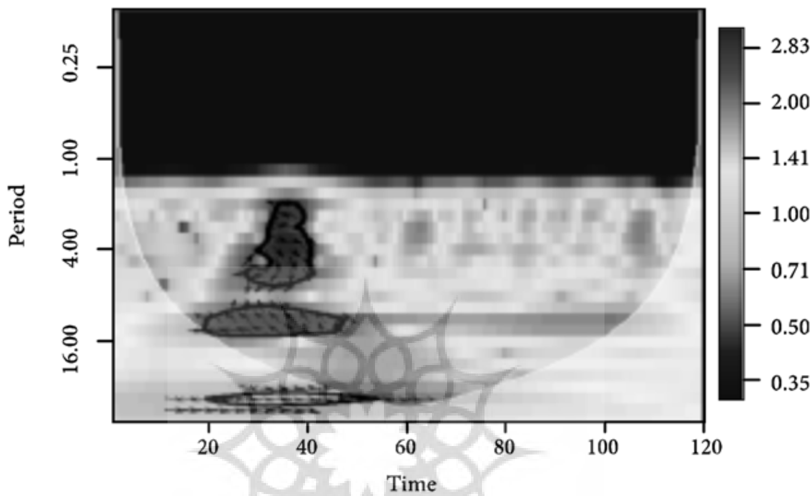

Figure 5. Cross Wavelet for both Financial Stability Index and Macro-prudential Representative Variable.

In the short term, the arrows that point to the left and upward direction indicate that the financial stability and the macro-prudential representative are negatively correlated, and the increased credit-to-GDP gap leads to financial stability. Meanwhile, it is observed that the correlation between the two series is reduced over time.

The outputs of the cross-wavelet method include an infinite number of explanatory indices or the correlation between the two time series at different frequencies, which is not possible to display in the table. Thus, a contour plot analysis method was used. In the medium term, the arrows that point to the right and the downward direction, the financial stability and the macro-prudential representative variables are positively correlated, and the increased credit-to-GDP gap leads to the financial stability. Therefore, the adoption of macro-prudential policy is more suggested in the short term for the Iranian economy.

As it can be seen in Figure 4, the financial stress is not on a long-term co-movement with the macro-prudential representative variable, and in the short term, it has increased along with the reduced ratio of the credit-to-GDP gap as compared to the long-term trend during the financial crisis. It has a negative co-movement, resulting from a combination of factors involving more uncertainty about the price of financial assets and economic prospects, and, in general, higher investment costs, increased harder credit conditions, reduced consumption and investment costs within the existing accelerating options and banking capital channel.

This finding shows that the most relationship between financial stability and the macro-prudential indicator is in the medium-term time horizon, which can be resolved by “wait and see" attitude adopted by households and companies, is in response to uncertainty as suggested by Bloom (2009) and Basu and Bundick (2017).

Higher financial distress generates significant incremental understanding of uncertainty and risk, resulting in reduced consumption and fewer investment decisions as a general behavior and an economic factor. The same argument indicates that the fluctuations in the macro-prudential indicators have an insignificant impact on the long-term economic activities since the economic factors, namely, the firms and households, in the long run, complete their information and adapt themselves to new condition.

6 Conclusion

The recent global financial crisis and the big economic recession have shown that financial turmoil has a detrimental impact on economic activities. This paper examined the relationship between financial stability and the macro-prudential variables indicator in the frequency time-space through a continuous cross Wavelet method to provide an appropriate platform for assessing the interactions. Empirical results show that the interaction and the explanatory power between the macro-prudential variable indicator and financial indices undergo considerable changes through time, and, depending on the time horizon, are different. It can be accounted for by ‘wait and see” attitude of the firms and households at the financial uncertainty.

In particular, these factors tend to postpone consumption and investment decisions until the uncertainty is removed. Thus, the economic consequences of the financial stress are not immediate, but, after a while, the highest co-movement of a medium-term nature occurs. There will be no co-movement, in the long run, when the information is completed, and the economic factors intervene.

After using wavelet analysis to investigate the co-movement of two time series of financial Stability Index and macro-prudential variable indicator in two dimensions of time and frequency, it was observed that the relationship between these two variables was more in the short and medium-term in Iran's economy. The financial stability and the representative of the macro-prudential variables are negatively correlated in the short-term, and the increased credit-to-GDP gap results in decreased financial stability. Besides, it is observed that the correlation between the two series is reduced over time. In the medium-term, the financial stability and the representative of macro-prudential variables are positively correlated, and the increased credit-to-GDP gap results in financial stability. If it is estimated that the representative of macro-prudential variables increases, it seems then necessary to take a macro-prudential policy in the short-term.

The evidence presented in this study may have important practical implications for different economic agents. Timely identification and forecasting of adverse conditions in the financial system must be of high priority for policymakers to enforce efficient, prudent policies and reduce the contradictory effects on real economic activities as much as possible, mainly in the short- term. Finally, under the conditions of high financial stress, policymakers may have to resort to policy procedures that differ from the usual guideline.

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