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Investigating the Factors Affecting Banks' Resilience with an Emphasis on FinTech Companies*

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Abstract

Banks have a decisive role in governing the country and are considered as institutions that are effective in the growth and development of countries. Today, the emergence of FinTech companies, which have expanded their field of activity by entering the banking activities, has forced the banking industry to think of solutions and reactions. Hence, in this study, the effects of FinTech companies along with macroeconomic and domestic factors on the resilience of 19 Iranian banks during the period 2013-2019 have been investigated using the panel vector autoregression model. The results of this study show that there is generally a negative relationship between the shokes of FinTechs and the resilience of the banks, the intensity of which will gradually decrease, and a shocks on FinTechs will reduce the resilience index of the banks; and based on the results of the variance analysis, this effect is relatively higher compared to other variables. There is also a positive relationship between the loan loss provision and the banks' resilience in the short term but a negative one in the long term. Generally, there is a positive relationship between the inflation and the banks' resilience, and the inflation shocks can improve the resilience of the banking system. The reason seams to be that due to the inflation, the banks' revenues will rise faster than their expenses, leading to an increase in the net profit margins.

Keywords

Resilience, FinTech, capital adequacy, PVAR model.

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1. Introduction

The global banking industry, under the influence of various digital revolutions, is undergoing fundamental changes throughout its history (Chishti and Barberis, 2016). The modern age of this industry brings traditional business models and existing institutions to fundamental challenges (Bharadawaj et al., 2013; Chalons and Duft, 2017). In addition to the technology pressure and the demand-induced strain, the digital transformation affects the IT management and IT strategy of the banks and changes the processes and even the entire business model of the banks (Veit et al., 2014).

With the advent of financial technology startups (FinTech) in the last decade, a new source of innovation in the field of financial services has emerged. These new businesses, which operate much faster than banks do using digital technologies, provide financial services in a more user-friendly and cheaper way. However, traditional actors (banks and financial institutions) in the financial sector have slowly begun to become involved in new technological innovations. Although tech companies have recently been acquired by banks, most FinTech companies are bank-independent startups. Because many banks, except the well-known large banks, still provide old, costly, and difficult financial services, FinTech companies have taken the opportunity to perform several key tasks of traditional banks (Li, Spigt, and Swinkels, 2017). In other words, FinTech companies are replacing banks, and banks are abdicating some business activities. Banking experts have found that banks face many challenges, including short-term concentration and internal inability to innovate, which prolong the innovation cycle and the time for entring the market (Tornjanski et al., 2015). The answer to the question of how much banks will be affected and to what extent tech companies will replace the current activities of banks, as well as the resilience level of banks to the advent of FinTech, is an empirical issue.

The impact of FinTech companies on banks can be explained by the consumer theory and the distruptive innovation theory (Aaker and Keller, 1990; Christensen, 1997). The consumer theory shows that new services (such as services provided by FinTech companies) can replace old services (such as services provided by traditional banks) by satisfying consumer's similar demand. According to the destruptive innovation theory, start-ups that use innovative technology to provide more accessible and cost-effective goods and services can bring in the marketplace into competition. These theories relate to our study of how the impact of FinTech companies on banks' resilience against them is measured.

One of the key features of FinTech companies is that they use innovative technology to perform the current tasks of banks, such as lending, payments, or investments (Brandl and Hornuf, 2017; Puschmann, 2017). Recently, developing FinTech companies have developed practical applications for improving the productivity of financial services in a wide range of services, including instant and contactless payments, asset management services, investment and financial services advisory, and information storage and data management. (Villeroy and Galhau, 2016). In this regard, Jagtiani and Lemieux (2018) argue that non-bank lenders can guarantee credit information. This service is equally valuable for consumers and small businesses, especially those with poor credit history. In contrast, banks operate on the old information technology system and are slow to adopt new technology (Hannan and McDowell, 1984; Laven and Bruggink, 2016).

The main result is that the instability and the lack of resilience to the shock of the presence of FinTech companies will eventually lead to the replacement of FinTech companies with traditional banks in providing cheaper and more efficient services, or given that banks are a major part of any financial system and the resilience of the banking system is the main part of the resilience of the financial system, they will have the ability to recover quickly to adapt and develop their performance. So our question is how the growth of FinTech companies will affect banks' resilience. Despite the advent of digital innovation and its perceived impact on the financial industry, the impact of digital innovation and the growth of information technology on the financial system has been less

studied. The studies conducted in this field are as follows.

In an article entitled "The Centennial Resilience Index: Measuring Countries' Resilience to Shock", Boorman et al. (2013) designed the Resilience Index to measure the ability of developing countries and emerging markets to withstand shocks. The whole economic system; Cumming and Schwienbacher (2016) examine the pattern of venture capital investment in financial technology using a global sample of companies; Brandl and Hornuf (2017) follow the evolution of the financial industry after digitalization; Li, Spigt, and Swinkels (2017) focus on how retail banks' stock prices react to tech startups; Haddad and Hornuf (2018) test the determinants of the global financial technology market; Jagtiani and John (2018) measure the effects of FinTech on user behavior; Ryu (2018) examines the reasons for users' desire and avoidance of Fintech; Sepehrdoost and Aieni (2013) examined the factors affecting the capital adequacy ratio in Iranian banks; Jahangard, Sohrabivafa and Keramatfar (2017) in their article examine the effects of macroeconomic variables on bank resilience with an emphasis on the concept of capital adequacy.

The word resilience has the Latin root Resilio meaning state, and in Oxford culture it also means the ability of a substance or object to return to its original state and individuals' ability to recover quickly in the face of difficulties (Ghiasvand and Abdolshah, 2015). After many countries faced severe banking crises in the last two decades of the twentieth century, the banking officials gradually applied capital adequacy, which depends on the composition and size of the bank's asset portfolio, as one of the major risks (Freixas, Xavier and Jean, 2008). Currently, this issue has led to the adequacy of capital to be considered as one of the main indicators of the resilience of the banking system. This is widely accepted in the academic and policy-making literature, with the Bank of England, for example, citing capital adequacy as a major factor in financial instability (the Bank of England, 2014).

We test our hypothesis using the data of Iranian stock exchange banks. In general, there are no studies available on how financial technology affects the banking sector. Using the data of 19 banks, we seek to estimate the impact of FinTech companies on the resilience of the banking sector and also to predict the resilience of the banks with the entry of each new FinTech company into the market.

We test the sensitivity of the relationship between FinTech and bank's resilience using the capital adequacy ratio. The main purpose of our paper is to show how Fintech affects bank's resilience and to make the results more realistic, we included the inflation rate and the loan loss ratio provision in our model as representatives of the macroeconomic factors and the internal factors managed by banks. At the present, no studies have been conducted in this field, so our paper is the first experimental study to examine this hypothesis.

The present study has been organized into five sections: In section 2, the methodologies are described along with descriptions of the input-output characteristics and the data used. Section 3 discusses the hypotheses and section 4 explains the research findings. Finally, section 5 is devoted to concluding and providing suggestions.

2. Research Methodology

This research is of applied type in terms of purpose. The method of data collection is post-event (through past information), and in terms of nature and method, the study is of correlation type. In this paper, the effect of the emergence shock of Fintech companies on the bank's resilience is tested and the estimation of the bank's resilience is obtained with STATA software. The data required for the research on the performance of the bank have been extracted via the information of the annual financial statements reports along with the explanatory notes and Rahavard Novin software as well as the website of the Central Bank; also the data related to Fintech companies have been obtained through rah pardakht site.

The spatial scope of the research is Tehran Stock Exchange and the statistical population of the banks

listed on the Tehran Stock Exchange over a period of 7 years (2013-2019). To select the statistical population, due to the non-publication of financial statements of some banks at the end of the fiscal year, the sampling method called filtering has been used to estimate the sample size. In this method, the following items are used as filters to select the banks with special features:

- The financial statements and their accompanying explanatory notes are available;
- In order to select an active bank, the 12-month financial statements of these companies during the years under review in the stock exchange must be published along with their notes.

After applying the above restrictions, 19 banks were selected.

In the next step, using the collected data and the vector autoregression models, the effects of the shocks on the banks' resilience are estimated. Since many macroeconomic topics and issues, such as the shock effect of macroeconomic variables, financial variables, and other variables, are presented in such a way that the data needed over a long period of time cannot be found to analyze those shocks in time series models, analysis of these issues is possible in the form of panel vector autoregression models (especially with the Bayesian econometric approach). Vector regression time series (VAR) models have been used in the macroeconomic literature as an alternative to the multivariate simultaneous equation model. All variables in a VAR system are usually examined endogenously; however, the identification of constraints based on theoretical models or statistical methods may impose the effect of exogenous shocks on the system. By the introduction of VAR settings in the panel data, the VAR Panel model has been used in many applications. The methods for estimating the panel vector autoregression model change according to the composition of the data. Therefore, these methods can be divided into two general categories: 1. Microeconomic data (panel data with large N and small T) and 2. Financial and macroeconomic data (panel data with large N and T), in which T represents the time series size and N represents the number of sections (Canova and Ciccarelli, 2013).

Panel data with large N and small T: A lot of data can be found in economics, especially in the review of new policy-makings or in emerging economies, that their time series size is small – about 10 or less. In most studies, the emphasis has often been on single equation estimation methods, while many applied studies require the use of equation systems, or in particular the vector autoregression model. Holtz, Newey, and Rosen (1988) investigated the panel vector autoregression model under conditions where the time series size is small. Although the time series size of these models is small, it does not mean that the data can not be non-stationary or cointegrated. In order to overcome the problems, the Generalized Method of Moments (GMM) is proposed (Arellano and Bond, 1991). Applying the GMM has advantages such as taking into account individual heterogeneity, solving the problem of endogenous variables, increasing the temporal dimension of variables, and eliminating biases in cross-sectional regressions, resulting in more accurate estimates, higher efficiency, and less linearity in the model setimation. Will be less in model estimation. As a result, using the ordinary least squares method will show biased and inconsistent results, which can be solved by the Generalized Method of Moments using instrumental variables. This method is used when the number of cross-sectional variables, N, is greater than the number of time periods, T (Baltagi, 2008; Bond, 2002).

According to the topics of the theoretical literature section that was already studied, for the present study, the following model with regard to the theoretical and experimental literature is introduced:

$$lca_{it} = \beta_1 + \beta_2 lfin_{it} + \beta_3 llp_{it} + \beta_4 linf_{it} + \varepsilon_{it}$$

In this model, the intended variables are as follows:

Table 1. Model variables.

Definition	Variables	Type of variables
Log of capital adequacy ratio	lca	Dependent
Log of number of financial technology (FinTech) companies established each year	lfin	Independent
Log of loan loss provision	lllp	Independent
Log of annual inflation rate	linf	Independent

Capital adequacy ratio: This ratio is the result of dividing the base capital by the total risk-weighted assets in percentage. The sensitivity threshold specified for the capital adequacy ratio in the Basel Committee, which was also approved in the Central Bank's Capital Adequacy Regulation (2003), is 8%. Higher rates often lead to a decrease in financial risk and consequently lower borrowing costs for the bank. In other words, it helps control the cost side of the profitability equation. Thus, similarly, there is a positive relationship between profitability efficiency and capital adequacy ratio. Capital adequacy ratio is a goal that is often explained by the board in response to legal requirements and organizational risk tolerance (in other words, this is an important issue in understanding the reliability of the bank, and to some extent, it is based on discretion). Capital adequacy ratio index is one of the most important criteria for the banking system (Borman et al., 2013). Therefore, in this study, the effects of the shocks of the establishment of Fintech companies on the capital adequacy index have been investigated to be considered as a measure of the resilience of the banking system.

FinTech Companies: The number of FinTech Companies established each year in the banking sector in the field of lending, international money transfer, banking, money management and payment. In Iran, most of FinTech's activities are focused on payments, followed by money management and lending.

Loan loss provision: The variable that is considered for provision in order to cover any type of non-repayment of potential loans; it protects the bank's position in terms of profitability and capital (Betty and Liu, 2011). The level of loan loss provision reflects the quality of the bank's assets and can be used to judge changes in future performance (Thakor, 1987). Dietrich and Wanzenried (2014) suggest that increasing loan loss provision is associated with reduced bank profitability, as bad loans are expected to reduce profitability. Therefore, we expect loan loss provision to have a negative effect on bank's resilience.

Annual Inflation Rate: Out of macroeconomic indicators, we use inflation rate as an independent variable. How inflation rates affect banks' profits depends on how inflation rates increase compared to wages and other operating expenses. Some studies express this relationship positively (Pasiouras and Kosmidou, 2007; Athanasoglou, Brissimis and Delis, 2008; Talavera, Yin and Zhang, 2018). However, if inflation is unpredictable and banks are unable to adjust their interest rates, costs may rise faster than revenues do, thus negatively affecting bank profits. These debates show that there is an unpredictable relationship between inflation and profit.

3. Research hypotheses or questions

According to the theoretical foundations and the research background, the following have been stated:

- Does the emergence of FinTech companies have a negative effect on banks' resilience?
- Does increasing banks' loan loss ratio have a negative effect on their resilience?
- Does rising inflation have a negative effect on banks' resilience?

4. Findings

Based on the information and the quarterly statistics related to 19 private banks in the country during 2013-2019, the indicators of the descriptive statistics of the research variables are presented according to Table 2.

Table 2. Descriptive statistics of variables.

Descriptive indicators	Capital adequacy	FinTech	Inflation	Loan loss provision
Mean	5.05	67	20.36	6.35
Median	6.28	53	15.6	4.91
Maximum	30.53	182	34.8	51.24
Minimum	-57.5	8	9	0.05
Standard deviation (SD)	9.83	58.51	10.70	6.59
Kurtosis	19.07	2.54	1.36	28.06
Skewness	-3.22	0.87	0.33	4.57

Source: Research findings.

As the calculations of the indicators of the descriptive statistics of the research variables show (Table 2), the average fintech companies, inflation and loan loss provision are 67%, 20.36%, and 6.35%, respectively. Also, the average capital adequacy ratio, which according to the principles of the Basel Committee should be at least 8%, in the private banks studied in the present study, has been obtained 5.05%.

2.4. Unit Root Test for Panel Data

Before estimating the research model in studies that have panel data, it is necessary to test the the stationary (constant distribution of the variable over time) of the all variables used in the estimates. Because if the variables are not stationary, they cause false regression. According Lin and Levin' (2002) study, common unit root tests in panel data such as the Dickey Fuller test, the generalized Dickey Fuller test, and the Phillips-Perron test have lower statistical power than the root unit test for panel data does. Therefore, in order to investigate the stationary of the variables, the Levin-Lin-Chu test, which is one of the most valid unit root tests for panel data, and its basic assumption is that cross-sectional units are independent of each other, has been used. The results of this test are shown in the following table. The results in this table show that the all variables based on the Levin-Lin-Chou test are stationary at level 5% and with confidence 95%. Therefore, all the estimates that will be made in this research are sufficiently valid.

Table 3. Results of the unit root test (LLS) for the panel data of the research variables.

Variable	Symbol	Statistic	Probability	Result
stationary at level 1%	logca	-4.8614	0.0000	Log of capital adequecy
stationary at level 1%	logfin	-17.2167	0.0000	Log of FinTech
stationary at level 1%	logllp	-9.9965	0.0000	Log of loan loss provision
stationary at level 1%	loginf	-5.64	0.0000	Log of inflation

Source: research variables.

3.4. Determining the Optimal Lag in the VAR Model

After examining the statics of the model variables, the first problem in vector autoregression models is to determine the optimal lag length. There are two ways for the researcher to choose the optimal interval. First, diagnosis based on available historical evidence and facts and inference from experiences based on data access and possibilities, and second, the use of one or more information criteria such as Akaike Information Criterion (AIC), Likelihood Ratio (LR), Schwarz Bayesian Criterion (SBC), Hannan-Quinn (HQ), and Final Forecast error (FPE). In this study, due to the limited data available and the length of the period under study, it is not possible to use the second solution and calculate the information criteria correctly, and therefore, based on the empirical evidence, optimal lag *one* has been adopted.

4.4. Stability Test the VAR Model

The stability test of the model depends on the damping or persistence of the disturbance impulse effect, and indicates that the model is reversible and contains infinite moving-average vectors that can be used to interpret the instantaneous impulse-response functions the variance analysis. If the disturbance impulse effect is damping over time, then the model is stable, and if the impulse effect is persistent, then the model is unstable. If the VAR is not stable, then the results (for example, the standard error of the instantaneous impulse-response function) are not valid. The results of the model stability are shown in Figure 1. Considering that the specific values of this model are less than one and the root of the campanion matrix is located inside the unit circle, so the condition of the stability in the Panel VAR model is satisfied.

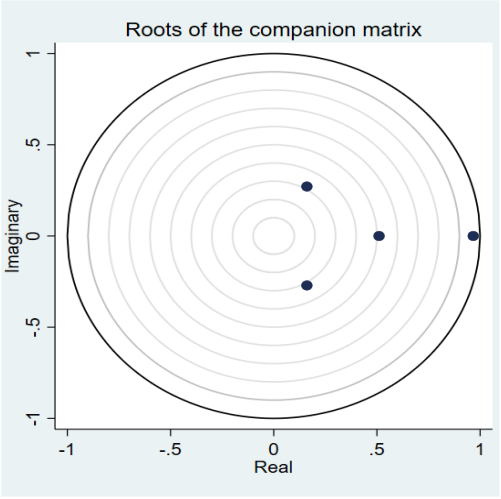

Figure 1. Model stability test.
Source: Research findings.

5.4. Estimation of the Research Model Using Panel Vector Autoregression Method

The Generalized Method of Moments (GMM) has been used to estimate the research model as vector autoregression. In this regard, the software code written by Love and Abrigo (2016) with the aim of estimating the vector autoregression models by the GMM method in the STATA software is used. The results are presented in the following table 4.

Since vector autoregression models, whether time series mode or panel data mode, is based on prediction, the coefficients of this model are not interpreted. Moreover, due to the presence of time-lagged variables, their interpretation is difficult and even impossible. Accordingly, to interpret the outputs of this econometric method, the impulse-response functions and the variance analysis related to the estimation model are analyzed.

Table 4. Results of estimating the capital adequacy model by panel data vector autoregression method.

Symble	z	std	Coef.
Logca L1.	-0.69	0.3134	-0.2173
Logfin L1.	-2.45	0.1878	-0.4601
Loginf L1.	+2.81	0.0970	0.2728
Logllp L1.	+1.33	0.2047	0.2722

Resource: Reseach Findngs

6.4. Impulse-Response Function

The estimated coefficients in the vector autoregression models often do not have a specific economic interpretation directly; however, by-products (such as instantaneous impulse-response functions and variance decomposition of forcast errors) obtained after estimating the vector autoregression model can contain important interpretations. Accordingly, one of the applications of the Panel VAR model is to investigate the reaction of the model variables to the shocks generated in each of the variables. In this section, in order to investigate the relationship between “Fintech companies, inflation, and loan loss provision” and “banks' resilience”, the dynamics of the interaction of the variables is evaluated through the panel data-based vector regression model (PVAR). In fact, the effect of a specific shock on the variable is examined and it is shown that if a sudden change (shock) occurs in a variable, what will be the effect on the variable

itself and other variables during different periods. These impulses are usually selected by the size of a standard deviation, so they are called single impulses or shocks, and the origin of the coordinates or the starting point of the response variable is the values associated with the stable state of the model (without the presence of impulses). Figure 2 shows the instantaneous impulse-response of the resilience to the shocks entered by a deviation from the model variables.

The bold lines in the middle represent the instantaneous impulse-responses of the banks's reseilience, and the upper and lower margins are the positive and negative margins for the standard deviation of the instantaneous impulse-responses at confidence level 95%, calculated using Monte Carlo simulation with 1000 replications. As it can be seen from the diagram, the positive shock effects of the variable "FinTech" have a negative effect on the resilience and reduce it. This decline was more severe in the first years and its effect gradually decreased.

However, the negative effect of the FinTech shock on the resilience has remained stable for more than one year. The emergence of FinTech companies has led to the provision of innovative, high-quality, cheaper, and more convenient financial services that inevitably increases competition for traditional banks; and as a result, their customers are reduced, leading to a loss of part of the market share (especially in payments, credit cards, savings), which in turn causes a decrease in the banks' income from financial services, their accumulated profits and ultimately their capital adequacy ratio.

Therefore, in order to increase financing for new technologies, banks must become expert and innovative market participants, and the potential of FinTech should not be neglected or underestimated.

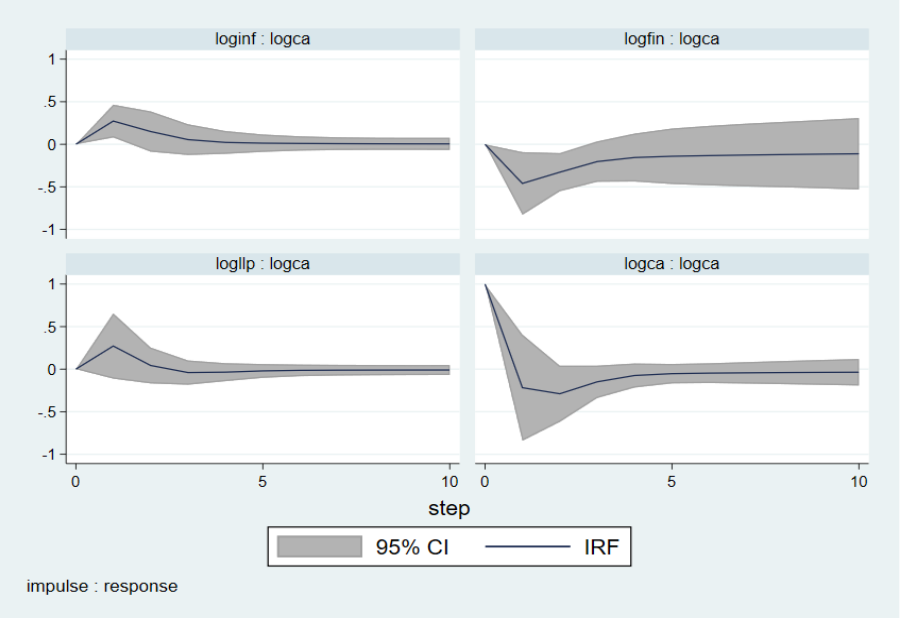

Figure 2. Capital adequacy response to shocks from explanatory variables.
Source: Research findings.

The effect of the shock of the variable "inflation" on the resilience is positive. Some thinkers believe that if inflation is predictable, then it has a positive effect on profit margin and if it is not predictable, then it has a negative effect on profit margin. Of course, it should be noted that although there is no empirical consensus on the effect of inflation on profit margins, it is often expressed that high inflation is generally associated with higher interest rates and consequently higher profit margins. Even if inflation is not forecast by the bank, the bank might not reflect rising inflation in short-term interest rates, but in medium and long term, they will adjust their interest rates to offset the inflation, and the profit margins will increase (Tarus et al., 2012). If inflation is predictable, bank's revenues will rise faster than their expenses will and their net profit margins will increase (Saona, 2016).

The resilience response to shocks from loan loss provision in the first two years, although small, is positive and then negative and gradually decreases in severity. An increase in loan loss provision indicates an increase in the bank's high-risk loans, which will reduce the banks' profitability and accumulated profits and ultimately lead to a decrease in the equity and the resilience.

7.4. Variance Analysis

The variance analysis was used to analyze the effect of the exogenous shocks of each variable on the forecast error variance of the variable "capital". The purpose of calculating the variance analysis index is to determine the relative extent of the contribution and significance of the impulses caused by each variable in its changes compared to the changes of other variables. In other words, in the variance analysis method, the share of shocks applied to different model variables in the forecast error variance of a variable is determined. The results of the variance decomposition of forcast errors for the studied variables over a 10-year period are given in the following table.

In the mentioned periods, in the first stage, the most change in the "resilience" belongs to this variable itself, and in the next stage, the variables "FinTech", "loan loss provision" and "inflation" have the most impact, respectively. The results of estimating the variance analysis function are: approximately 73% of the percentage of the variance changes in the "resilience" go back to the previous periods of this variable; also, 13% of the changes are related to the "FinTech"; 2% are related to the "inflation"; and 12% are related to the "loan loss provision". The results of analysis variance test also confirm that the FinTech shock has the greatest impact on the banks' resilience, therefore, the FinTech shock is a major risk for the banks' resilience, followed by the loan loss provision shock and then the inflation shock.

Table 5: Variance decomposition of forcast errors of the variable "capital adequacy" for a 10-year period

Period	Logca	Logfin	Loginf	Logllp
0	0	0	0	0
1	1	0	0	0
2	+0.7763	+0.0773	+0.0150	+0.1314
3	+0.7485	+0.1086	+0.0215	+0.1214
4	+0.7376	+0.1203	+0.0227	+0.1193
5	+0.7301	+0.1276	+0.0229	+0.1191
6	+0.7245	+0.1343	+0.0228	+0.1185
7	+0.7197	+0.1400	+0.0227	+0.1177
8	+0.7154	+0.1451	+0.0226	+0.1169
9	+0.7116	+0.1497	+0.0224	+0.1162
10	+0.7081	+0.1540	+0.0223	+0.1156

Source: Research findings.

5. Conclusion

In Iran, traditionally and also due to the lack of depth of the capital market, it is the banking system that covers most of the financial system. Therefore, the role and position of the banking system in the economy is very important and its strength and stability against various shocks can help the country to achieve economic growth and development. Accordingly, in the present study, the effect of the emergence of FinTech companies along with domestic and macroeconomic factors on the resilience of the country's banks during 2013-2019 was investigated. In this regard, the panel data autoregression method and the information of 19 banks were used.

In order to evaluate the resilience of the banking system, various quantitative criteria such as capital ratio, liquidity ratio, overdue receivables ratio, and profitability are used. In the present study, the capital adequacy ratio has been used as a proxy for resilience. Also, the number of FinTech companies, the inflation rate and the loan loss provision ratio have been used in order to examine the effect of FinTech companies, the macroeconomic and domestic factors, respectively. In this study, the effects of the FinTech shock, the macroeconomic factor shock, and the internal factor shock were investigated using the panel data autoregression method and the results of the instantaneous impulse-response functions and the variance analysis. The results of the instantaneous impulse-response functions show that there is a negative relationship between the FinTech and the banks' resilience. Therefore, it can be said that the FinTech shock has a negative effect on the banks' resilience and by reducing the financial services income and profitability, reduces the shareholders' equity, leading to a decrease in the banks' resilience index. The results also showed that there is a positive relationship between the inflation and the banks' resilience and the shocks caused by the inflation improve the resilience of the banking system generally. Increased inflation on the one hand due to the devaluation of money leads to the outflow of deposits from the banks towards the parallel markets and on the other hand leads to increased demand for the facilities from the banks. In Iran due to the high risk of competing markets, including the currency market, gold market, etc., these outflows of deposits can be temporary and return to the banking system, and ultimately the positive effect of inflation, i.e. increasing demand for facilities, is bolder than its negative effect, leading to an increase in the banks' profitability and resilience. Also, the result of the instantaneous impulse-response functions shows that there is a negative relationship between the loan loss provision and the banks' resilience, and based on the results of a shock to the loan loss provision, it reduces the banks' resilience index. An increase in the loan loss provision indicates an increase in their risky facilities, which will ultimately reduce the profitability of banks and even their losses, which will ultimately reduce the bank's resilience; this issue is currently one of the biggest problems of the country's banking system.

According to the results of the variance analysis in the long term, about 13% of the changes are related to the FinTech, 12% are related to the loan loss provision, and 2% are related to the inflation. The results of the variance analysis also confirm that Fintech shock has the greatest effect on the banks' resilience.

Based on the results of this study, it is suggested that banks pay special attention to these shocks due to the significant share of the shoke of Fintech companies and loan loss provision on reducing banks' resilience and also due to the fact that these factors are largely within their control. In order to reduce the shock of FinTech companies, banks should take necessary measures to prevent the reduction of their market share by establishing FinTech-based companies or by cooperating with FinTech companies that will be considered as their main competitors in the near future, and by upgrading their credit system, reduce their loan loss provision.

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