Peer behaviors in bank lending decisions using panel-data and convolutional neural network method

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ABSTRACT

Economic growth is strongly dependent on financial institutions and many economic activities are in need of lending from banking system, so one of the challenges of managers in banking is making proper lending decisions. this study investigates the effect of peer-banks behavior on lending decisions. We consider both characteristics (size, liquidity, profit, growth, credit risk) and lending behaviors on bank`s loan lending decisions. Data from 19 banks and financial institutions accepted in Tehran Stock Exchange during 2015 to 2020 has been applied with both panel-data method and convolutional neural network(CNN) to find out if there is any convergent behavior.

According to results, the bank`s characteristic (size, profitability, liquidity and risk) have a significant impact on loan lending decisions; also the average lending rate of other banks and financial institutions has a negative impact on bank loan lending behavior. So according to panel-data model lending decisions in banks are not convergent, and banks do not imitate their counterparts in making their lending decisions; but average liquidity in the industry and the average credit risk of rivals have a positive and significant impact on loan lending decisions. Examining hypotheses by the convolutional neural network method also showed a divergent relationship between lending decisions of similar banks by considering all the features. In fact, banks do not imitate lending decisions in the same way, but they consider the information of industry and similar banks in their decisions. Therefore, banks should be aware of the psychological impact of competitors' decisions and the characteristics of similar.

Keywords:

Peer-behavior, convergence, banking behavior, lending, convolutional neural network

1. Introduction

Banks are one of the most important economic entities, so the efficiency of banking decisions plays a very important role in bank performance as well as in the economy. the process of financial stability or instability in the banking sector affects the borrowers and borrowers, the volume of saving, costs, profitability, efficiency, performance and financial ratios of the country. Thus today the fundamental role of banks in the economy has been accepted in the form of financial intermediaries and facilitators of credit payments system.

one of the challenges of managers in banking is making proper lending decisions, which is influenced by internal and external factors. among the interior factors affecting on lending decisions is bank characteristics (liquidity, size, profitability, credit risk and income growth), also external factors include macroeconomic conditions, government regulations, and peer effects of rival banks decisions. (Margaretic et al ,2021)

therefore, it is important to recognize these factors to make efficient lending decisions. among the mentioned factors, convergence and peer behavior play an important role, meaning that peer banks decision is a key role in shaping corporate politics. Of course, knowing of the confidential decisions of similar companies in the industry and the ability to rely on information about it is one of the most doubtful issues that depend on the various factors. For example, firms with logical managers and low information, in a healthy economic system, will have herd behaviors, also studies have shown that convergent behavior happens more in firms with low ability to obtain symmetric information, firms which their managers have more job concerns and firms with low-investment (Joong Im et al,2021).

This paper is linked to the growing literature showing that peers have a significant role on banks' decision-making. thus, we aim to investigate the effect of bank's characteristics on lending decisions and the effect of rival banks' lending and characteristics on bank lending decisions.

Empirical evidence shows that peers can affect banks' funding liquidity policies (Bonfim and Kim, 2019; Silva, 2019), banks' credit policies (Uchida and Nakagawa, 2007), banks' risk management policies (Liedorp et al., 2010; Craig et al., 2014; Tonzer, 2015), group lending (Li et al., 2013), trading decisions (Ng and Wu, 2010), online lending markets (Iyer et al., 2016) and etc.

Due to the study of peer effects in banking markets, the literature has shown that the reasons for peer effects can be various. For instance, a bank may choose to free ride on its peers' market research and follow their lending and/or borrowing decisions, if those peer banks are perceived as having greater expertise (Bikhchandani et al., 1998; Banerjee, 1992). Or banks may find optimal to mimic each other and invest in the same type of assets, in the expectation of collective bailouts were things to turn sour (Acharya and Yorulmazer, 2007; Ratnovski, 2009; Farhi and Tirole, 2012). Alternatively, banks may be sensitive to the decisions of their peers, with which they have agreements of reciprocity and/or long-term lending relations (Cocco et al., 2009), with these relations providing them some cross-insurance (Blasques et al., 2018). An additional possibility is that peer effects can be such that a bank (or group of banks) may reduce its (their) exposure to a given bank in response to (risky) financial decisions of the latter (Caballero and Simsek, 2013). A further reason for peer effects may be reputational concerns (Scharfstein and Stein, 1990). In this study we focus on peer effects on lending decisions of banks and financial institutions.

Some studies (e.g., Beaudry et al., 2001; Kang et al., 2014; Glover and Levine, 2015) examine the influence of uncertainty on the investment decision of non-financial firms, while some studies (Baum et al., 2009; Quagliariello, 2009; Calmès and Théoret, 2014) focus on banks' lending decision. A similar finding by them is that firms act homogenously (heterogeneously) under high (low) economic uncertainty.

As said before this paper aims to shed light on how financial institutions interact with one another by analyzing bank-specific characteristics and peer bank behavior using both panel-data method and convolutional neural network (CNN). Also we focused on the TSE[1] banks and financial institutions, because we have access to a unique data set with all exposures of financial statements for a long period of time.

[1] Tehran Securities Exchange

Literature review

Economic growth of economies is strongly dependent on soundness of financial institutions. many economic activities are in need of lending from banking system, the distortions in bank lending behavior may lead to economic variables instability and business risk for firms. From the perspective of risk, an increase in loan growth means that a financial institution increases the amount of loan than the previous year. Similarly, an increase in net interest rate margin might represent that a financial institution takes more efforts to either raise the interest rate for lending or decrease the cost of deposit to reach higher net interest rate margin. Both of them would represent financial institutions become riskier than before, which may lead banks to tighten lending standards and decrease leverage. (Lee et al,2017)

Financial integration puts banking sectors on a tendency of convergence. While there is no single measure to account for banking convergence, a relevant series of studies covered topics such as interest rates and profitability. Other studies proposed alternative instruments such as the ratios of deposits and loans to GDP, finding that convergence is higher within the socalled clubs, such as the euro-area (Affinito, 2011).

The credit risks and lending decisions of commercial banks are jointly determined by various internal and external factors. For the internal factors, the share proportions held by heterogeneous shareholders can significantly affect the risk management, lending decisions and operating performance of commercial banks (La Porta et al., 2002; Barry et al., 2011; Zuzana et al., 2011).

For external factors, in countries with better legal protection for creditors, loan sizes increase (La Porta et al., 1998), credit spreads decrease (Laeven and Majnoni, 2005), financial crises are less frequent (Johnson et al., 2000), loan concentrations are higher and loan maturity is longer (Qian and Strahan, 2007).

Also banking decisions of rivals is another affecting factor. Which means an individual firm's decision poses external effects on its rivals, and the rivals can also impact the individual firm's decision making (Leary and Roberts, 2014 and Bernardo and Welch, 2013).

Theory suggests that a more homogeneous banking system is likely to be less stable (Shaffer (1994); Wagner (2008, 2010); Haldane and May (2011)) and it has been proposed that regulators should therefore encourage diversity in the banking system (Goodhart and Wagner (2012)). In a homogeneous banking system, banks hold the same portfolios, e.g., via pursuing similar diversification strategies. On the one hand, diversification reduces the default probability of individual banks as they become less vulnerable to idiosyncratic shocks.

Although there have many studies that explore the determinants of firm lending decision, most of them depict only a part of picture for loan decision of financial institutions. The current study adds to the existing literature with a thorough and complete consideration to the relationship between financial institutions' loan lending decision and the two categories of factors (i.e., firm characteristics, peer effects).

We believe it is necessary to clarify which factors are the most crucial so that decision-makers could appropriately control the risk of the financial system. Note that the influence of the peer effect is less discussed, and it is noteworthy recently because the degree of interdependence or interaction among corporations becomes higher day by day.

Bernardo and Welch (2013) note that a bank's leverage decision can raise negative externalities on peers, and banks can be more aggressive at lending when their rivals are more conservative. Interestingly, Baum et al. (2009) and Calmès and Théoret (2014) find that financial institutions' lending decision become quite homogenous when environmental uncertainty is high. In other words, an economy's uncertainties may dominate the peer effect and then lead to herding behavior in the financial sector. It is noted that shifts in a bank's lending behavior or decision might affect not only its risk, but also the risk of other financial institutions, even the whole risk of financial markets.

Ogura (2006) found that When bankers observe a rival winning in the interbank competition for lending to a firm, they infer that the firm may be more promising than they had thought. From this consideration, they loosen their creditworthiness tests and lower the interest rates they offer in the next lending competition for the firm. Increased interbank competition reduces the impact of this observational learning and decreases the credit risk taken by each bank because of a severe winner's curse, while it increases the aggregate risk taken by the entire banking sector.

Margaretic et al (2021) identified and quantified the importance of endogenous peer effects in the interbank market, based on a unique dataset that includes all interbank loans that have taken place between 15 banks in the Chilean interbank market between 2009 and 2016. They showed evidence consistent with a herding behavior of the lender banks which, according to their model, were peers of the stressed bank. Results showed that peer effects are asymmetric, in the sense that there are many common lenders being sensitive to the decisions of their peers but few common borrowers. Also small and foreign banks are the most sensitive to the lending/borrowing choices of other banks in the same market, possibly because they have long term lending relations with their peers or because they are the more exposed to the risk of not getting funding from other banks.

Chi & Li (2017) Using data for Chinese commercial banks from 2000 to 2014, examined the effects of economic policy uncertainty (EPU) on banks' credit risks and lending decisions. The results revealed significantly positive connections among EPU and non-performing loan ratios, loan concentrations and the normal loan migration rate. This indicates that EPU increases banks' credit risks and negatively influences loan size, especially for joint-equity banks. Given the increasing credit risks generated by EPU, banks can improve operational performance by reducing loan sizes. Further research indicates that the effects of EPU on banks' credit risks and lending decisions are moderated by the marketization level, with financial depth moderating the effect on banks' credit risks and strengthening it on lending decisions.

EPU can directly influence commercial banks in that their behavior can be shocked by macro-policy, not only because banks are important participants in economic activities but also because they often adjust the strategies for lending decisions. Governments also intensively adjust deposit rates and reserve requirement ratios to indirectly achieve economic regulation and control. This suggests that commercial banks are a key loop in the transmission mechanism of official macroeconomic policies. The operating businesses of commercial banks are at enormous risk and inherently possess great influence (Chi & Li,2017)

According to Munteana(2015), Lending convergence is to be expected in developed banking sectors but has the potential to enhance cyclicality. their Results from econometrical convergence models confirm a sudden increase in banking convergence during the financial crisis, followed by a relative moderation after 2012 and Lending convergence is important for macroeconomic policy makers, while also allowing for macroprudential adjustments.

Daniel Fricke(2016) found that banks have in fact become less similar over time. This finding would suggest that concerns over a more homogeneous banking system are not necessarily based on facts. However, He also find that the Japanese banking system has become increasingly concentrated, and that the largest banks in fact have become more similar over time. Interestingly, most indices suggest that banks' portfolios tended to become more similar before the global financial crisis starting in 2007, which then led to an abrupt drop of all similarity measures in 2009.

Agoraki et al (2022) investigated investor sentiment effect on bank lendings and how loan growth may affect bank stability. they used a large panel data set of U.S. commercial banks over the period 1999–2015, using bank-level data. results showed that banks' lending falls when investor sentiment is low, while this effect is more pronounced when banks hold a higher level of credit risk. Also they showed that the Great Financial Crisis leads to a decline in U.S. lending behavior and an increase in the U.S. banking sector instability.

Rezaei & Norouzi in their investigation found that the economic uncertainty variable had a positive and significant effect on the credit risk of banks, Also economic uncertainty has a positive effect on the performance of banks, and finally, in the third model, there was no significant relationship between economic uncertainty and the level of bank lending.

Khodadadi & Mehrara(2018) studied the effect of macroeconomic fluctuation on lending behavior of commercial banks in Iran during 1974-2015, their Empirical results showed that lending to commercial banks (Bank loan to asset ratio) have long run relationship with output changes over the business cycle. In other words, the economic recovery leads to acquiring credit risk and more lending of commercial banks. The increase in commercial banks assets that

approximate the size of the bank, have a significant impact on the behavior of commercial banks lending. The larger banks can afford to higher risks in lending. Monetary base not only increase bank lending (in terms of the ratio of loans to assets), but in the long run, it reduces lending capacity by a negligible size.
According to all these literatures we are investigating the effects of peer behaviors in bank lending decision with both panel-data method and CNN, by which our hypotheses are as follow:

H1: bank characteristics have a significant impact on loan lending decisions of a bank or financial institution.
H2: The average of industry loan lending ratio has a significant impact on banks' or financial institutions' lending.
H3: The average peer characteristics has a significant impact on bank loan lending decisions.
H4: According to the convolutional neural network method(CNN), there is convergence behavior in loan lending and characteristics of banks.

Methodology

This research is an applied study in terms of purpose. Also, this research is descriptive-correlational in nature. On the other hand, the present study is post-event (semi-experimental), Which means that this study is based on analyzing past and historical information of banks' financial statements. Also, this is analytical-causal, and the hypotheses are tested with regression models based on composite data using E-views software version 12. Also, to investigate the convergence or non-convergence of the lending behavior of banks and financial institutions, the convolutional neural network has been implemented using Python software (Python 3-10). The statistical population includes all active banks and financial institutions listed on the Tehran Stock Exchange from 2015 to 2020. In the present study, the systematic elimination method has been used to determine the statistical sample; therefore, banks and financial institutions of the statistical community that met the following conditions have been selected as a statistical sample, and the rest have been removed.

- In order to make the information comparable, the company's financial year should end on March 20th.
- The bank or financial institution should be active on the Tehran Stock Exchange from the beginning of 2015 to the end of 2020.
- All data required for the research for the surveyed banks should be available.

After considering all the above criteria, 19 banks and financial institutions remained in the screened community. They have been selected as research samples. Therefore, according to the six years of research and considering that the information model of the previous year is also needed in the implementation, the observations consist of 133 years-company (7 years × 19 banks and financial institutions).

The scope of this research includes the banks and financial institutions listed on the Tehran Stock Exchange; because it is easier to access the financial information of financial institutions listed on the stock exchange, and the information in the financial statements of these companies has better quality. Also, the financial reports of these companies are more homogeneous and more comparable.

The required information in the theoretical foundations of this research has been collected by library method using taking notes in the study of domestic and foreign dissertations, publications, books and articles available in libraries and Internet databases.

Financial data of banks and financial institutions have been collected from reports related to financial statements and attached explanatory notes using the information network of Tehran Stock Exchange (Codal) and Rahavard Novin 3 software.

The following regression according to muntean(2015) and lee et al(2017) have been used to test the hypotheses:

$$loan_{it} = \beta_0 + \beta_1 prft_{it-1} + \beta_2 size_{it-1} + \beta_3 liq_{it-1} + \beta_4 growth_{it-1} + \beta_5 risk_{it-1} + \varepsilon \tag{1}$$

(2)

$$loan_{it} = \beta_0 + \beta_1 \widetilde{loan}_{-it} + \beta_2 \widetilde{prft}_{-it-1} + \beta_3 \widetilde{size}_{-it-1} + \beta_4 \widetilde{liq}_{-it-1} + \beta_5 \widetilde{growth}_{-it-1} + \beta_6 \widetilde{risk}_{-it-1} + \beta_7 prft_{it-1} + \beta_8 size_{it-1} + \beta_9 liq_{it-1} + \beta_{10} growth_{it-1} + \beta_{11} risk_{it-1} + \varepsilon$$

In the mentioned models:

- Loan $_{it}$: the ratio of lending loans (equals the number of facilities granted to individuals to total assets) in bank i and year t.
- $\widetilde{Loan}_{-it}$: the average loan lending ratio of industry other than the bank or institution in year t.
- Size: natural logarithm of the bank's total assets and $\widetilde{size}_{-it-1}$ is the average of other banks size in last year
- Profitability (prft): the ROA criterion (the ratio of net profit to total assets) has been used to calculate it. And $\widetilde{prft}_{-it-1}$ is the Average profitability of other banks(industry) in last year.
- Liquidity (Liq): this variable is calculated from the ratio of current assets to total assets and $\widetilde{liq}_{-it-1}$ is the Average of other banks liquidity in last year.
- Growth: equal to the growth rate of the bank's total income and $\widetilde{growth}_{-it-1}$ is the average of other banks growth in last year.
- Credit risk (Risk): obtained through the ratio of deferred facilities to total receivables and $\widetilde{risk}_{-it-1}$ is the average of other banks credit risk in last year.

In models, dependent variable is loan lending's ratio in each bank. Using 1st model we will be testing first hypothesis, so coefficients of β shows the effect of each variable of banks characteristics.

Also second model is used to test H2 and H3, in H2 we concentrate on coefficients of average of loan ratio in all other banks and financial institution in the industry, which The significant level(β_1) would show that if bank lending decisions is affected by other peer-banks' lending decisions.

In H3 we focused on the other coefficients ($\beta_{2\text{-}6}$) which shows that peer`s characteristics affect bank lending decisions.

Also as said before we will be using Convolution neural networks (CNNs) for H4.

convolutional neural network

to examine **H4** we use CNN method to know if banks and financial institutions are acting similarly and there is convergence behavior between them in both aspects of lending decisions and characteristics.

Convolution neural networks (CNNs) are one of the most important deep learning methods in which multiple layers are taught in a powerful way. This method is very efficient and is one of the most common methods in various applications of computer vision and detecting convergence between different features.

the CNN method uses images or figures as the model inputs But the lending ratio data and the data related to the bank's characteristics are in the form of time series.

Therefore, to convert financial data to figures as the model input we will create a 6*6 matrix for each internal variable (bank size, profitability, liquidity ratio, lending and growth ratio). This Matrix will be given to the model as the figure. The following table shows this process better.

Table4. CNN model Inputs

	1394	1395	1396	1397	1398	1399
LOAN						
SIZE						
profit						
LIQ						
RISK						
GROWTH						

After making the figures, they must be prepared to be entered to the model. In most cases, the model had a fitness problem. This happens when few data are available or the available data is complicated. To cope with such problem, the data are divided into training and examining groups.

Our approach for dividing the data into training and examining groups is adopted from the Cross-Validation method. For this purpose, we divide the data into subsets of 250. The first five subsets are considered as the training group, and a subset is considered as the examining group. In the next step, we will run1 the subset forward and then repeat it again. The figure1 below shows the process of training and testing well on Bank Mellat data.

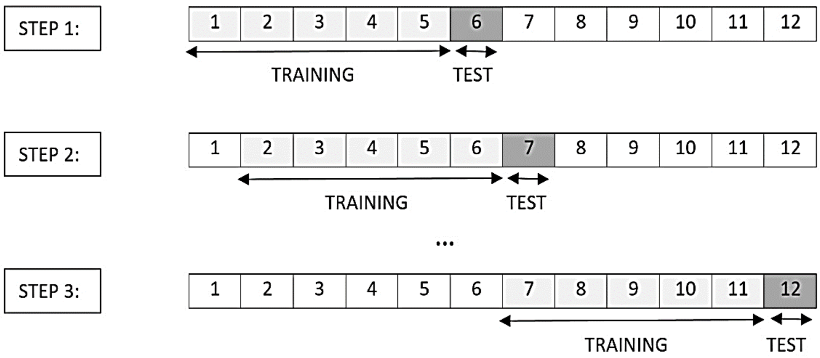

Fig 1. The process of Test and Training

Therefore, we will train the model in 7 levels and enter new data each time. At the end recall, f1score and MSE measures will show the convergent or divergent behavior in features.

Findings & Results:

Descriptive Statistics of variables is shown in table 1:

As shown in table 1 Std. Dev. Of Growth and profit of bank has the highest number, and size which is log af assets has the largest mean and median with maximum of 8.23.

Using regression model number 1 the results of testing **H1** is shown in table (2).

Table1. Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
A_GROWTH	0.502102	-0.2144	3.778025	-1.35782	1.581582	1.009238	2.694507
A_LEV	0.972234	0.978958	1.024779	0.924894	0.030668	0.016756	1.778027
A_LIQ	0.773406	0.77055	0.849521	0.697838	0.043249	0.075795	2.13836
A_LOAN	0.511086	0.514986	0.567914	0.45868	0.025478	-0.24951	2.204079
A_PROFIT	-0.8627	-1.17507	1.042252	-2.63963	1.301915	0.105804	1.340165
A_QTOBIN	1.098006	1.020304	1.457738	1.005361	0.146485	1.758066	4.544459
A_RISK	0.755342	0.778074	0.839175	0.626131	0.063082	-0.76795	2.260173
A_SIZE	8.605571	8.584085	9.023268	8.235659	0.227223	0.278096	2.067375
GROWTH	0.502102	0.130923	60.31169	-14.7943	5.838384	8.262253	85.45804
LEV	0.972234	0.956909	1.450569	0.834434	0.087292	2.56423	11.73948
LOAN	0.511086	0.556155	0.765997	0.065169	0.162747	-0.90473	3.178491
PROFIT	-0.8627	0.196859	7.69959	-19.5036	4.546763	-2.18589	7.918742
RISK	0.755342	0.796302	0.982542	0.007396	0.183572	-1.41404	5.247132
SIZE	8.605571	8.559826	9.878567	7.487017	0.496341	0.200945	2.518193

Table2. result of regression model number 1

Dependent Variable: LOAN				
Date: 04/28/22 Time: 05:29				
Sample (adjusted): 1 133				
Included observations: 133 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
PROFIT	0.008643	0.002104	4.107254	0.0001
SIZE	-0.033456	0.007405	-4.517927	0.0000
LIQUDITY	0.572224	0.073846	7.748881	0.0000
GROWTH	-0.001474	0.001482	-0.994605	0.3218
RISK	0.482112	0.045794	10.52785	0.0000
R-squared	0.657542	Mean dependent var		0.511086
Adjusted R-squared	0.646840	S.D. dependent var		0.162747

Dependent Variable: LOAN				
Date: 04/28/22 Time: 05:29				
Sample (adjusted): 1 133				
Included observations: 133 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
S.E. of regression	0.096716	Akaike info criterion		-1.797201
Sum squared resid	1.197317	Schwarz criterion		-1.688541
Log likelihood	124.5138	Hannan-Quinn criter.		-1.753046
Durbin-Watson stat	0.768638			

For testing the first hypothesis(**H1**), to know if the bank characteristics affect its loan-lending decision, we used the estimated results of the first model in Table (2). According to the results of this hypothesis, the probability value (or significance level) F is equal to 0.000; as this value is less than 0.05, the null hypothesis is rejected at the 95% confidence level; which means that the model is significant. The results of the determination coefficient show that 65% of the changes in the dependent variable can be explained by modeling the independent and control variables.

The results show that all research variables are significant at the 95% confidence level. In general, and according to the estimation results of the first model:

The significant level of banks profitability is equal to 0.001, and its coefficient is 0.008. So, the bank's profitability variable has a positive and significant impact on bank loan lending decisions.

The significant level of bank size is equal to 0.000, and its coefficient is -0.033. It shows that the size of the bank has a negative and significant impact on banks' loan lending decisions. The significant level of liquidity of the bank is equal to 0.00, and its coefficient is 0.55. Therefore, bank liquidity has a positive and significant impact on lending decisions and its more than other variables effect. The significant growth level of the bank is equal to 0.32 and The growth of the bank has no statistical impact on the bank's lending decisions. The significant level of bank risk is equal to 0.00, and its coefficient is 0.48. Therefore, bank risk has a positive and significant impact on lending decisions.

so, in each bank`s characteristic its profitability, liquidity and credit risk have positive impact on bank loan lending but the size of bank has a negative effect on it.

For testing the second hypothesis**(H2)**, we used the estimated results of the second model in Table (3). The results of the determination coefficient show that approximately 97% of the changes in the dependent variable are explained by the independent and control variables. It should be noted that we can measure convergence or divergence of loan lending decisions using this model.

The results from Table 3 show that at the 95% confidence level, all research variables are significant. In general, according to the estimation results of the second model:

The level of significance of the average ratio of industry loan lending to bank loan lending is equal to 0.00, and its coefficient is -16.92. Therefore, the average lending ratio of the industry has a negative and significant impact on bank loan lending decisions.

Table3. result of regression model number 2

Dependent Variable: LOAN				
Date: 03/10/22 Time: 02:15				
Sample (adjusted): 1 133				
Included observations: 133 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
A_LOAN	-16.92328	0.397722	-42.55055	0.0000
A_PROFIT	0.003019	0.002050	1.472513	0.1435
A_SIZE	-1.157200	0.029126	-39.73115	0.0000
A_LIQ	14.09643	0.329446	42.78826	0.0000
A_RISK	10.22150	0.249605	40.95077	0.0000
A_GROWTH	-0.010834	0.001514	-7.156259	0.0000
PROFIT	0.000758	0.000580	1.306813	0.1937

Dependent Variable: LOAN				
Date: 03/10/22 Time: 02:15				
Sample (adjusted): 1 133				
Included observations: 133 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
SIZE	-0.066830	0.004868	-13.72987	0.0000
LIQUDITY	0.813630	0.022378	36.35843	0.0000
RISK	0.596573	0.013319	44.79172	0.0000
GROWTH	-0.000684	0.000381	-1.798044	0.0746
R-squared	0.978989	Mean dependent var		0.511086
Adjusted R-squared	0.977267	S.D. dependent var		0.162747
S.E. of regression	0.024538	Akaike info criterion		-4.498088
Sum squared resid	0.073459	Schwarz criterion		-4.259036
Log likelihood	310.1228	Hannan-Quinn criter.		-4.400946
Durbin-Watson stat	2.433482			

We also use Table 3 for the results of testing **H3** which is the impact of average of other banks characteristics (A-profit, A-size, A-liq, A-risk and A-growth) on the bank loan`s ratio.
The results of Table 3 show that all research variables are significant at the 95% confidence level. In general, according to the estimated results of the second model:

The significant level of the average profitability of the bank is equal to 0.1435. Therefore, the average profitability of the bank does not have any impact on the loan lending decisions of banks.

The mean level of the average bank size is 0.00, and its coefficient is equal to -1.157. Therefore, the average bank size has a negative and significant impact on banks' loan lending decisions. The significant level of the bank's average liquidity is equal to 0.00, and its coefficient is 0.81. Therefore, the average bank liquidity has a positive and significant impact on loan lending decisions. The significant growth level of the bank is equal to 0.07. Therefore, the average growth of the bank has no statistical impact on the bank's lending decisions. The significant level of bank risk is equal to 0.00, and its coefficient is 0.59. Therefore, the average risk of the bank has a positive and significant impact on lending decisions.

As said before for **H4,** we used CNN model to measure the convergence between banking behaviors in lending decisions

To make the convolutional neural network models, we have adopted the LeNet model. This is known as the first CNN model with an acceptable result on the MNIST photo set. The photos in MNIST set consist of 70000 photos of man scripted numbers with the dimension of 32*32, which are used as reference data to test new CNN models.
The Model in this research is:

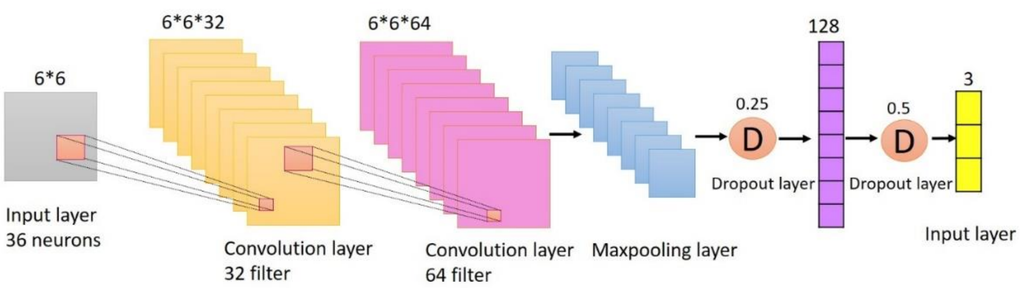

Fig2: used convolution model

The above model has 8 layers:

- The input layer with the dimensions and 6*6
- Convolutional layer (6*6*32) with 32 filers
- Convolutional layer (6*6*64) with 64 filers
- Max Pooling layer
- Dropout Layer with the ratio of 0.25
- Fully connected layer
- Dropout layer with the ratio of 0.5
- The output layer

In the input layer, the model receives the created figure. Each of these photos has 6*6= 36 neurons. These neurons are connected to the next layer through the filters in each convolutional layer.

The clutter matrix has been used to evaluate the classification models' performance. After calculating this matrix, the Recall, Precision and F1 Score criteria can be calculated. These measures are shown in the following table based on the optimized model in the last section.

The larger the number of criteria, the corresponding feature is identified. As it can be seen, in the convergence, the value of Recall shows a high percentage, but the Precision is lower; this can be due to two reasons. First is the overfitting of the model. Due to the increase in iterations, the other model data are also labeled as convergent points. Because the number of convergence labels in the examining group is equal to 10% of the number of labels in the training group. The second reason is the similarity of points that have divergence labels but are next to points that have convergence labels.

The other method for evaluating the convergence or divergence of banks' behavior in convolutional neural networks is to use statistical criteria, which can be seen in the following table.

Error measurement criteria will be used to measure the conformity of a figure (in a convolutional neural network) with a time series data pattern. If y and ŷ represent the actual and predicted value of the variable at time t, the prediction error is e = y-ŷ. For a time period and for n predicted values, the prediction measurement criteria are showed in table 6.

Among the above criteria, the MSE criterion is more appropriate for detecting divergence or convergence for its accuracy.

Table5: measures for evaluating the convergence or divergence of banks

		precision	recall	F1-score
measures	divergence	1.00	0.80	0.89
	convergence	0.96	1.00	0.98

Table 6: evaluation parameters

Equation No	Equation	Criteria
۱-٤	$MSE = \frac{\sum_{i=1}^{n}(e_i)^2}{n}$	MSE (average prediction error squared)
۲-٤	$\sqrt{\frac{1}{N} * \sum_{i=1}^{N}(f_i - y_i)^2}$	RMSE
۳-٤	$R^2 = 1 - \frac{SSE}{SSy}$	R2 (coefficient of determination)

Table 4-12: Assessment result of convergence or divergence of banks' behavior

MSE	
۰,۰۳۵	divergence
۱	convergence

According to the table, MSE (average square of forecast errors) has a lower rate of divergence, and the CNN model is more accurate for detecting divergence; so, banks act "divergent" in making lending decisions.

Here The results of CNN model confirms results of panel-data model used before, so banks do not imitate their rival's decisions in loan-lending, actually they are influenced by their decisions but in opposite way, it means they behave divergent from the average loan-lending in industry. So banks can be more aggressive at lending when their rivals are more conservative which can be because of firm`s decisions on credit Risks, and also due to firm`s policy and characteristic. the results are similar to Ogura (2006), Bernardo and Welch (2013), and Fricke (2016) study results and not similar to Margaretic et al (2021).

Discussion and conclusion

Banking is one of the essential economic sectors of any country, and the assets of the banking system are one of the most important components of the national capital. Granted loans make up the main part of banks' assets and interest income; these loans are an essential element in a bank's financial performance and stability. In this study, the type of lending behavior of banks and financial institutions was examined according to the characteristics of the bank and its counterparts. According to the results of the first hypothesis, characteristics (size, profitability, liquidity and risk) have a significant impact on loan lending decisions of the bank or financial institution; but the growth of the bank has no significant impact on lending decisions. Also, the impact of bank size on loan lending decisions is negative. It shows that the more total bank assets (including the lending facility), the banks gradually reduce their lending rate. According to the results of the second hypothesis, the average lending rate of banks and financial institutions has a negative impact on bank loan lending behavior. So, lending decisions in banks are not convergent, and banks do not imitate their counterparts in making their lending decisions; it may have some competitive reasons meaning that banks can be more aggressive at lending when their rivals are more conservative. And this can be because of their desire to reduce credit risk. According to the results of the third hypothesis, the average liquidity in the industry and the average credit risk of the industry have a positive and significant impact on loan lending and lending and crediting decisions of the bank. Among the factors mentioned in these three hypotheses, industry lending decisions have been identified as the most impact negative factor in the amount of bank loan lending which, probably is because banks infer that the firm may be more promising than they had thought. From this consideration, they loosen their creditworthiness tests and lower the interest rates they offer in the next lending competition for the firm.

Also, by comparing the coefficient of determination between the two models, we find that the credit and characteristics of similar banks are more influential in making lending decisions than the characteristics of the bank itself. In this results we should consider that some external factors like economic policy uncertainty (EPU) can influence these behaviors in homogenous ways which has not been applied as an affecting factor in this study. Examining hypotheses by the convolutional neural network method also shows a divergent relationship between lending decisions of similar banks by considering all the features. In fact, banks do not imitate lending decisions in the same way, but they consider the information of industry and similar banks in their decisions. Therefore, banks should be aware of the psychological impact of competitors' decisions and the characteristics of similar banks to make financial and lending decisions. They must also consider the financial health, growth opportunities and value process of their counterparts.

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