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Trends in Transition: Fintech Credit Effects on Romanian Bank Stability

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Abstract

This research aims to look into the link between fintech lending and bank stability. In order to establish how fintech lending influences the stability of banks in Romania, regression analysis was performed for the timeframe 2017-2020. In this sense, indicators pertaining to fintech lending, Z-scores, and liquidity were used in the research. The findings of the study underline that improvements in fintech lending impact in a negative way the bank's Z-score. Given the altered competition between organisations in Romania, bank stability might have been threatened by an increase in fintech lending. Due to the availableness of credits, fintech organisations have the possibility to gain customers from traditional banking entities. As a result, competition will face an improvement and banks will find it difficult to keep fulfilling essential banking benchmarks. Additionally, changes in the legislation governing the two financial systems may limit the capacity of authorities to conduct supervision and thus hinder their ability to detect potential dangers within the financial system. On the other hand, it is possible to talk about a positive correlation between bank Z-score and liquid assets to deposits. Depending on that result, an increase in the ratio of liquid assets to deposits may a positive effect on the bank Z-score.

Keywords: Fintech, Fintech Lending, Romania Fintech Lending, Romania Bank Stability.

JEL Classification: F65, G21, E51.

1. Introduction

As technology-driven business models and digital developments change the shape in which companies create value and supply goods or services, they may allow new business opportunities for established players. On the other hand, it can contribute to the creation of strong lines by creating a deep relationship within the

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financial sector and reduce the human factor and allow all activities to be carried out on machines. In addition, with the existence of the entrepreneurial ecosystem, fintech technology has the ability to facilitate access to financial services and to compete among companies in the early stages. Of course, if companies want to survive here, they must first provide a good response system and follow a new effective strategy in order to adapt to tough competitive conditions (European Economy, 2018, p. 3). The term fintech can be expressed in various ways in the literature. Some of these are FinTech, Fintech, or Fin-Tech. However, all of these uses come to the same point. The term fintech is simply formed by combining the words technology and finance. To explain the term fintech, it covers the harmonisation of the financial service sector with these technologies, such as basic banking services, with mobile or cloud technologies playing a leading role as primary services (Gomber et al., 2017, p. 540). To define it from another perspective, it can be expressed as a collection of advanced technologies that can be applied to the financial system. This explains, for instance, the efforts of established traditional financial institutions to embrace technology or the efforts of major technology companies like Apple, which offers Apple Pay (World Economic Forum, 2017, p. 8). Fintech, as defined by the Financial Stability Board, is the application of technology to promote innovation in the financial services industry, potentially resulting in the creation of new business models, operational procedures, standards, or products that have the potential to significantly transform the financial markets, institutions, and financial services' delivery system. Consequently, this definition implies that fintech innovations have impacted and still do impact a wide range of financial services domains (FSB, 2017).

In its simplest form, fintech lending encompasses lending services that bring together borrowers and lenders, i.e., investors. These lending platforms are known as "peer-to-peer (P2P) lenders", "credit-based crowdfunders, or "marketplace lenders". Fintech companies have their own balance sheet systems as in the traditional banking system and therefore, since customer data is digital and they interact through online channels, they differ from the traditional banking system in terms of lending. This interaction is achieved through digital technologies that allow fintech companies to perform all their transactions, especially basic banking transactions such as providing loans and collecting deposits, through developed platforms. The first example of this technology was launched in the UK in 2005 with the Zopa application, but this structure later became complex. The reason for this complexity is that it is not as secure as the traditional banking system and therefore the system is still subject to various regulations (Claessens et al., 2018, pp. 30-31). In more detailed terms, these platforms are considered to be part of Internet finance or digital finance, they are distinct from traditional banking, and they reshape the manner in which financial services are supplied and provide their structure within a distinct area. This kind of platforms supply a variety of financial services in the financial field, for instance equity crowdfunding, donation-based crowdfunding, asset management services, and insurance solutions. Examples of

US companies in this sense are AmeriSave, Guaranteed Rate, Loandepot, and Quicken Loans

For example, Alifinance has provided short-term credit facilities to small and medium-sized companies since 2010 in order to contribute to their economic development (Chen, 2016). In Romania, in recent years, fintech companies such as Credius, NEO Finans and Viva Credit have made significant progress and enabled the development of Romania's fintech ecosystem.

In general, the fintech system is developing its current and potential areas in various areas such as payments, clearing, lending, deposits, capital increase, investment, fund management, risk, and insurance. This situation evolves and exerts major influence on traditional banking. To be more accurately, fintech companies provide lower search expenses, scale economies, cheap, and secure information transfer, and reduced verification expenses (European Economy, 2018, p. 12). Initially developed as decentralised platforms, fintech lending models allowed individuals to select borrowers to lend to within the parameters of the loans they offered. However, over time, institutional investors in addition to private investors have joined these platforms. On the other hand, platforms also aid in resolving the problem of asymmetric information as they offer data regarding borrowers and credit risks (Cornelli et al., 2023, p. 2).

Recently, together with the development of the fintech ecosystem, changes also took place in credit markets, thus producing new intermediaries apart from lenders, credit unions, and traditional banks. Although traditional capital markets and banks continue to be a source of financing for individuals and businesses, the transformation of the financial services system will accelerate with the entry of new digital financial institutions into the market. This type of loans, which are given through online platforms, unlike traditional banks or loans, are called “debt-based alternative finance”, which has gained momentum especially in the form of P2P loans and invoice trading, with the digital lender feature at the forefront (Cornelli et al., 2023, p. 1). While banks and other financial intermediaries remain the main source of financing for borrowers in most markets, fintech lending models are among the new financial institutions gaining popularity recently (Liem et al., 2022, p. 1).

This article examines the connection between fintech lending and bank stability. For this purpose, the relationship between Z-score values of commercial banks and fintech loans in the digital system in Romania for the years 2017-2020 is investigated. Regarding the rest of the research, section 1 details the literature and hypothesis, section 2 displays the data and the research methodology, while section delineates the analysis findings.

2. Related Literature and Hypothesis

In what regards the research that scrutinises the impact of fintech loans on bank stability, the work of Liem et al. (2022), who performed an analysis building on fintech loans, credit information sharing, and bank stability data that was sourced from different countries in the timeframe 2013-2017, found out that fintech loans

as well as the increase in this type of loans had a significant impact on bank stability. An additional study by Le et al. (2021), who employed data from 80 countries in the period 2013-2017 and explored the linkage between fintech loans and bank efficiency, revealed that this situation occurred more frequently in countries with a poorly developed fintech system, also underlining the negative influence of fintech loans on bank stability. The work of Le et al. (2021) also highlighted that bank stability alleviation was associated with fintech loans. Supplementary evidence was brought by Oh and Rosenkranz (2020), who researched the reverberations financial development and financial literacy on P2P loans, associated to different countries, between 2015 and 2017, and who acknowledged the positive correlation between financial institutions' steadiness and the amount of the P2P loan. In addition, the study of Yeo and Jun (2020) indicated that bank stability was influenced by the improvement in P2P loans. Moreover, in his study aiming to understand the influence of P2P loan platforms in the traditional banking system, Tang (2019) asserted that a swapping process took place digital banking and traditional banking, in terms of the loan volume augmentation. The work of De Roure et al. (2016) aimed to determine if P2P loan transactions acted as replacements of complements in the case of Germany and indicated that this loan type had a gap-filling role for the traditional banking demand regarding small-scale and high-risk loans. Furthermore, Cornelli et al. (2023) indicated that alternative financing methods were complementary for traditional credit channels and did not replace them. The study of Claessens et al. (2018), performed on 63 countries in 2016, noted the positive association between fintech credit volume and GDP per capita, and consequently digital lending was linked with the economic and institutional progress of countries.

From this point of view, the hypothesis for this study is that fintech lending is expected to contribute positively to the stability of the Romanian banking system. Because, although the banking system is based on the traditional system, there are many digital applications. As a matter of fact, one of the studies conducted in the literature addresses the question of whether fintech loans are alternative or complementary for banks. Cornelli et al. (2023) and Tang (2019) find that fintech lending complements the banking system. Therefore, this study's hypothesis is as follows:

Hypothesis: There is a positive and significant relationship between fintech lending and bank stability.

3. Data and Research Methodology

3.1 Data

The study investigates the relationship between fintech lending and bank stability. For this purpose, regression analysis is applied to reveal what kind of impact fintech lending has on bank stability in Romania between 2017 and 2020. The bank stability (Z-score) is based on Liem et al. (2022) and the fintech lending is based on Le et al. (2021). Liquid assets to deposits variable is also used as an exogenous variable. Moreover, the study tried to use return on assets and return

on equity as dependent variables and inflation, growth, the number of mobile banking and branch banking users, bank cost to income ratio and banking system concentration as independent variables, but these variables were excluded from the model due to the multicollinearity problem. Therefore, these results were not reported in this study. In the study, the fintech credits are obtained from the Cambridge Centre for Alternative Finance (The CCAF), while the banking system Z-scores and the liquid assets to deposits data are obtained from The Global Economy.

Platform-based data by The CCAF was collected using an online benchmarking survey. The survey was hosted by the CCAF, Judge Business School. The CCAF and its academic and industry research partners identified the participating platforms. The benchmark survey sought both quantitative and qualitative data on alternative finance platforms. This covers the following: total startup and company financing, yearly transaction volumes, geographic distribution, number and activities of funders and fundraisers, most financed sectors, longitudinal data on platform launches and approvals, and loan performance statistics. According to the classification developed by the CCAF, fintech lending is divided into two groups as: level 1 (subsegment) and level 2 (business model). Level 1 comprises invoice trading, debt-based securities, P2P marketplace lending, and balance sheet lending. The topics that each group in level 1 addressed are included in level 2 (business models). The lending operations that are included in the balance sheet lending category are balance sheet consumer, balance sheet property, and balance sheet commercial lending. In the same way, the P2P marketplace lending industry encompasses debt-based securities in addition to P2P marketplace business, property, and consumer loans. Debt-based securities include mini-bonds.

The dependent variable is banking system z-scores. The Z-score represents the likelihood that a nation's financial system will fail. The Z-score contrasts the capitalisation and return buffer of a nation's banking system with the return volatility of those assets. It is calculated using the formula (ROA + (equity/assets)) / sd(ROA), where sd(ROA) is the ROA standard deviation. At the national level, assets, equity, and ROA reflect aggregated statistics. Another important factor to consider is the ratio of liquid assets (assets that can be quickly converted into cash) to total deposits plus short-term funding. Liquid assets include cash, bank loans, trading securities that are fairly priced and earned through proceeds, bank loans and advances, reverse repos, and cash collateral. Deposits and short-term funding items include total customer deposits as well as short-term borrowings. Money market instruments, certificates of deposit, and other deposits are examples of short-term debt; Short-term funding, current deposits, savings accounts, and time deposits constitute total customer deposits.

Furthermore, all variables' natural logarithms are employed. In this way, the analysis is conducted by eliminating the difference in scale between the dependent and independent variables. On the other hand, the study abbreviates the fintech lending as lnFintech, the banking system z-score as lnZ-score, and the ratio of liquid assets to deposits as lnLIQ.

3.2 Research Methodology

The model established to investigate the relationship between fintech credits and banking system Z-score is as follows:

$$lnZscore_t = \beta_0 + \beta_1 lnFintech_t + \beta_2 lnLIQ_t + \varepsilon_t$$

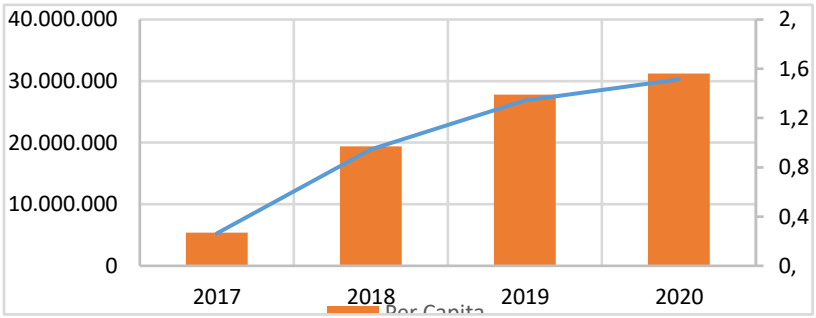
where lnZ-score is the dependent variable; β_0, is the value of the dependent variable, i.e., lnZ-score, if the independent variables are zero; $\beta_1 and \beta_2$ represent the amount by which the dependent variable changes in response to one unit change in the independent variables, holding constant the factors expressed by the error term ε.

The impact of fintech lending on banking system Z-scores is measured with least squares method. Prior to conducting the analysis, the basic assumptions of the model are tested, and the deviations resulting from these tests are controlled using various methods. The first is to investigate whether there is a problem of heteroskedasticity in the model. The test proposed by Breusch-Pagan (1979)/Cook-Weisberg (1983) is used for this purpose. Secondly, it is investigated whether there is an autocorrelation problem in the model. The Breusch-Godfrey (1978; 1978) LM test is used to detect the autocorrelation problem. According to Tatoğlu (2023, p. 137), this test checks whether there is a higher order autocorrelation in the model. As a result of the analysis, it is determined that there is first order autocorrelation in the model. In order to correct this autocorrelation problem, the approach proposed by Newey-West (1987, 1994) is preferred. This approach thus produces more consistent estimators with strong standard errors, which fixes the autocorrelation issue in the model. Last but not least, obtaining the normal distribution requirement is one of the presumptions of least squares. For this objective, the Jarque-Bera (1987) normality test is used to determine whether the error terms in the model are normally distributed.

4. Empirical Results

This section presents descriptive statistics, correlation matrix, and regression analysis results for the relationship between fintech lending and bank stability.

Graph 1. Fintech Lending and Lending per capita Volume, 2017-2020 (USD)



Source: The CCAF, 2024.

Graph 1 illustrates the fintech lending and lending per capita in Romania between 2017 and 2020. According to the graph, in 2017 the digital fintech lending volume amounted to more than $5 million, while this number quintupled in 2019, reaching more than $25 million. After 2019, it is going to increase less compared to the previous one. On the other hand, the lending per capita has been increasing from 2017 to 2020. While fintech lending per capita was USD 0.27, it increased to USD 1.56 in 2020.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lnZ-score	4	2.412	.013	2.398	2.425
lnFintech	4	16.641	.801	15.476	17.225
lnLIQ	4	3.598	.420	2.870	3.711

Source: calculation from the dataset.

Table 1 displays the descriptive statistics of the variables. According to the descriptive statistics, the number of observations is four. Among the variables, the bank Z-score has the lowest mean, while the fintech lending have the highest mean. The bank Z-score also has the lowest standard deviation and the lowest minimum and maximum values. On the other hand, the fintech lending has the highest standard deviation, minimum, and maximum value.

Table 2. Correlation matrix between variables

	(1)	(2)	(3)
lnZ-score (1)	1.000		
lnFintech (2)	-0.629	1.000	
lnLIQ (3)	-0.412	0.968	1.000

Source: calculated from the dataset.

Table 2 displays the correlation relationship between the variables. According to the table, lnFintech, and lnLIQ have a negative correlation with lnZ-score. On the other hand, there is a highly positive correlation between lnFintech and lnLIQ.

Table 3 illustrates the regression analysis on the impact of the fintech lending on the bank stability. According to the table, the analysis is conducted using four-year data. The F-value of the model is significant. Accordingly, lnFintech and lnLIQ variables in the model are significant in explaining LnZ-score variable. Before explaining the coefficients of the model, the results obtained from the fundamental assumption tests will be explained. First, according to the Breusch-Pagan (1979)/Cook-Weisberg (1983) test for heteroskedasticity, there is no heteroskedasticity problem in the model. Second, the hypothesis tested in the Breusch-Godfrey (1978; 1978) LM test for autocorrelation is that there is first

order autocorrelation in the model, as indicated by both the test statistic (4.000) and the probability value (0.045). In the lagged value taken to test for second-order autocorrelation, it is found that there is no second-order autocorrelation in the model. We can see this from the probability value of 0.135. Robust standard errors are used to eliminate the autocorrelation problem. In this context, the method proposed by Newey-West (1987, 1994) can be used in the presence of heteroskedasticity and autocorrelation. When autocorrelation is present, the approach produces consistent estimators. Finally, for the normality test, the Jarque-Bera (1987) test statistic (.361) and the probability value (0.835) indicate that the error terms of the model are normally distributed.

Table 3. The effect of fintech lending on bank stability

Dependent Variable: lnZ-score			
Independent Variables	**Coeff.**	**Newey-West Std. Err.**	**t-Statistic**
Constant	3.032	.006	499.18
lnFintech	-.057**	.000	-99.80
lnLIQ	.092**	.000	96.59
No. Obs	4		
F-Statistic	5414.47 (0,009)		
Diagnostic Test Results			
Breusch-Pagan (1979) / Cook-Weisberg (1983) test for heteroskedasticity	1.27 (0.259)		
Breusch-Godfrey (1978; 1978) LM test for autocorrelation	4.000(0.045) (First order)	4.000 (0.135) (Second order)	
Jarque-Bera (1987) normality test	.361 (0.835)		

Notes: ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. Brackets indicate p-values. The lnZ-score, the natural logarithm of the banking system Z-score; the lnFintech, the natural logarithm of the fintech lending; the lnLIQ, the natural logarithm of the ratio of liquid assets to deposits.

Source: calculated from the dataset.

The coefficients in Table 3 indicate that the logarithm of the fintech lending has a negative effect on the logarithm of the bank Z-score. In other words, an increase in the fintech lending has a negative impact on the bank Z-score. The suggestion that there is a negative correlation between bank strength and fintech lending has thus been refuted. Le et al. (2021) examined the relationship between the fintech lending and the bank efficiency and found a negative relationship. Put another way, the inverse correlation found in Romania between fintech lending and bank stability offers the question that the rise in fintech lending may have had a negative effect on bank stability. One of the reasons for this could be increased competition. Given that fintech credit organisations are able to supply banking services to traditional bank users, the consequence of this fact is the altered competition between credit institutions, that can threaten bank stability and minimise profit margins. The components of the central regulatory framework are another factor which can raise the pressure put on traditional banks and reduce the strain on fintech institutions. In addition, high financing costs and market volatility can be among other problems. All contemplations, research is still being done on the effect of fintech lending on Romanian banking stability.

On the other hand, in the table, there is a positive relationship between lnLIQ and lnZ-score. Accordingly, an increase in lnLIQ has a positive impact on the Z-score. Liem et al. (2022) similarly find that LIQ has a positive effect on Z-score. This suggests that higher liquidity assets increase the stability of the banking system.

5. Conclusions

The goal of this research is to assess the linkage between fintech lending and bank stability. Regression analysis was employed for the timeframe 2017-2020 to understand the manner in which fintech lending influences the stability of banks in Romania. Fintech lending influences in a negative way bank Z-score.

Correctly understood, an expansion in fintech lending results in reduced in in the bank Z-score. The negative relation between fintech lending and bank stability displayed in Romania raises the possibility that a rise in fintech lending has had a negative effect on bank stability. Competition might have been the factor that determined the appearance of this situation. Knowing that fintech organisations are able to supply loans to traditional banking institutions, competition between fintech entities and the traditional banking field is enhanced, this influencing in a negative way the cohesion of the traditional banking structure, triggering the lowering of profit margins. A supplementary cause can be represented by regulatory aspects. On the other hand, it has been found that there is a positive relationship between bank stability and liquid assets/deposit ratio.

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