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Threshold Dynamics of Digital Innovation, Credit Risk, and Monetary Policy in Iran

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ABSTRACT

This study investigates the threshold effects of digital innovation on the interaction between credit risk, ICT, and monetary policy effectiveness in Iran, using seasonal data covering the period 2009 to 2024. Monetary policy effectiveness is proxied by the ratio of loan balances to deposits. A robust digital innovation index is constructed via principal component analysis, incorporating key indicators such as bank account density, ATM usage, and the growing value of internet and mobile financial transactions. The empirical model incorporates several control variables, including credit risk, bank loan growth, bank size, inflation, short-term interest rates, ICT development indices, and return on assets. Preliminary diagnostic analysis, utilizing the Phillips–Perron stationarity and Johansen cointegration tests, confirms that all variables are integrated of order one and maintain long-term cointegration relationships. To specifically analyze nonlinear behavior and threshold effects, a smooth transition regression model with a logistic transition function (LSTR) is employed. Linearity tests identify the digital innovation index as the optimal transition variable, favoring the LSTR1 specification. Empirical findings demonstrate that in the nonlinear regime, digital innovation exerts a positive and statistically significant effect on monetary policy effectiveness, indicating that higher levels of innovative financial activity improve policy performance in Iran. Conversely, credit risk shows a significant negative impact; rising non-performing loans effectively weaken the monetary policy transmission mechanism. This research underscores how digital transformation can mitigate structural barriers to policy efficacy, offering crucial insights for policymakers aiming to enhance economic stability through technological integration. ©**authors**

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Introduction

The evolution of financial systems from traditional, judgment-based models to smart, data-driven architectures represents a fundamental paradigm shift in the banking sector. The emergence of decision-making systems underpinned by Artificial Intelligence (AI), big data analytics, and intelligent financial infrastructures has revolutionized how credit risk is managed and mitigated (Shariati et al., 2025). Credit risk, stemming from the potential inability of borrowers to fulfill obligations, remains a central threat to banking stability and the effective transmission of monetary policy. Given that credit facilities constitute the bulk of bank assets, deficiencies in risk management can lead to significant deviations in monetary policy outcomes. In this modern era, risk assessment has transitioned from static, subjective models to dynamic, self-learning architectures, enhancing the precision of credit decisions (Naseri et al., 2025).

At the infrastructure level, Information and Communication Technology (ICT) has significantly mitigated information asymmetry between financial institutions and customers. By integrating multi-source data—including tax, insurance, registration, and transactional behavioral patterns—banks can now aggregate information in complex data architectures. In the Iranian context, the emergence of smart credit assessment, electronic checks, and interbank data exchange systems signifies a strategic movement toward a digital financial ecosystem (Mohaghegh et al., 2025). These advancements utilize machine learning algorithms to detect hidden risk patterns, upgrading credit decision-making from empirical human judgment to algorithmic precision.

Furthermore, these digital innovations facilitate continuous post-disbursement monitoring through Early Warning Systems (EWS), which are critical for the Iranian banking sector, characterized by high volumes of overdue claims and non-performing loans (NPLs). Unlike traditional approaches that focused primarily on pre-loan verification, contemporary systems allow for real-time risk identification—such as fluctuations in firm turnover or increased debt obligations—enabling proactive debt restructuring and credit limitation (Qaderi et al., 2025). Additionally, the digitalization of processes, including digital signatures and electronic registration, enhances institutional transparency and internal governance, thereby reducing the scope for corruption and ensuring credit discipline (Baghban et al., 2025).

The implications for monetary policy are profound. Because monetary policy transmission in Iran relies heavily on the credit channel, improvements in credit risk management directly enhance policy efficacy. Accurate risk identification facilitates optimized resource allocation, preventing the accumulation of hidden systemic risks (Olia et al., 2025). Moreover, precise credit data empowers policymakers to monitor liquidity and credit distribution in real-time, allowing for more agile adjustments to macroeconomic instruments (Zangeneh et al., 2025). When banking networks function with higher discipline and transparency, the central bank's decisions have a more immediate and predictable impact on the real economy (Yousefi et al., 2025).

Despite the growing literature on digital transformation, credit risk management, and monetary policy, existing studies have largely examined these relationships within linear frameworks and have generally treated digital innovation as a complementary technological factor rather than as a potential nonlinear driver of financial and monetary dynamics. In particular, limited attention has been paid to whether the effects of credit risk and ICT on monetary policy effectiveness vary across different levels of digital innovation. This limitation is especially relevant in emerging economies such as Iran, where the adoption of digital technologies has been uneven and characterized by structural transitions in the banking sector.

Accordingly, an important research gap remains regarding the threshold role of digital innovation in shaping the interaction between credit risk, ICT development, and monetary policy outcomes. It is plausible that digital innovation does not exert a uniform effect across all conditions; rather, once a certain level of digital development is achieved, the capacity of banks to process information, monitor borrowers, and allocate credit may improve substantially, thereby altering the effectiveness of monetary policy transmission. Motivated by this gap, the present study investigates whether digital innovation acts as a nonlinear threshold variable influencing the relationship among credit risk, ICT, and monetary policy in Iran. To capture these potential regime-dependent effects, the study employs a Logistic Smooth Transition Regression (LSTR) model, which enables the identification of gradual transitions between different levels of digital innovation and provides a more realistic representation of the evolving digital financial environment.

Research Gap and Objectives

Beyond the adoption of ICT infrastructure, the contemporary banking industry is increasingly shaped by broader processes of digital transformation and virtual transformation. Digital transformation refers to the strategic integration of digital technologies into organizational processes, decision-making mechanisms, and service delivery systems, while virtual transformation emphasizes the migration of financial interactions, monitoring activities, and customer services toward digitally mediated environments. In the banking sector, these transformations have fundamentally altered the mechanisms through which information is collected, processed, and utilized for credit allocation and risk management. Technologies such as artificial intelligence, cloud computing, digital platforms, electronic banking, and real-time data analytics have created virtual financial ecosystems in which credit assessment and monetary transmission processes operate with greater speed, transparency, and efficiency. Consequently, digital innovation should not be viewed merely as a technological enhancement but rather as a core component of the broader digital and virtual transformation of financial systems. Understanding how this transformation influences credit risk dynamics and monetary policy effectiveness is therefore essential for evaluating the future performance of modern banking systems, particularly in emerging economies undergoing rapid digital change. Despite the acknowledged benefits of digital innovation, the introduction of these technologies introduces new challenges, including cyber risks, algorithmic bias, and privacy concerns, which necessitate robust regulatory frameworks (Maleki et al., 2025). While existing literature has explored the isolated effects of digitalization or credit risk management, there remains a critical research gap regarding the nonlinear nature of the interaction between these elements. It is not fully understood whether digital innovation acts as a catalyst that fundamentally reconfigures the relationship between credit risk and monetary policy transmission through threshold effects.

Research Question

Does digital innovation serve as a threshold variable that generates nonlinear effects in the relationship between credit risk, ICT development, and the effectiveness of monetary policy in Iran? This study aims to bridge this gap by utilizing a smooth transition regression model to empirically test whether a nonlinear regime exists, where digital innovation enhances the responsiveness of monetary policy to credit risk management.

Literature Review

Credit risk management has long been recognized as a critical component of banking stability and financial system performance. Credit risk arises from the possibility that borrowers may fail to meet their financial obligations, and because a large share of banks' assets consists of loans and credit facilities, ineffective risk management can threaten both bank solvency and broader financial stability. In recent years, rapid advances in information and communication technology (ICT) have significantly transformed credit risk management practices. These technologies enable financial institutions to process large volumes of financial and behavioral data, thereby improving the accuracy and efficiency of credit assessment processes and supporting more informed economic policymaking (Tang et al., 2024).

Traditionally, credit risk assessment relied on limited financial records, collateral requirements, and the judgment of banking experts. Such approaches were often constrained by information asymmetry and incomplete borrower information, which could lead to inaccurate credit evaluations and higher default rates. The development of digital infrastructures and data-processing technologies has expanded the scope of credit evaluation by enabling financial institutions to analyze diverse data sources, including payment histories, transaction patterns, and income stability. By integrating these datasets, modern credit assessment systems are able to predict the probability of default more accurately and reduce the uncertainty associated with lending decisions (Zhao et al., 2024).

A major driver of this transformation has been the integration of big data analytics and machine learning techniques into financial decision-making. Intelligent algorithms can identify complex and previously hidden patterns within large datasets, enabling banks to classify borrowers according to their risk profiles with greater precision. These data-driven models allow financial institutions to evaluate creditworthiness using a broader set of indicators, such as transaction behavior, consumption patterns, and repayment records, shifting credit decisions from subjective judgment toward more systematic and analytical processes (Chen et al., 2024).

ICT has also enabled financial institutions to move beyond static credit evaluation toward dynamic risk monitoring. In traditional banking systems, credit assessment was concentrated primarily at the pre‑loan stage, while post‑disbursement monitoring was relatively limited. With the adoption of digital financial systems, banks are now able to monitor borrowers' financial conditions continuously and detect early warning signals of financial distress. Sudden changes in transaction patterns, income levels, or repayment behavior can signal rising credit risk, allowing financial institutions to take preventive actions before defaults occur (Duan & Chen, 2024).

In parallel, the expansion of digital financial platforms and FinTech services has further reshaped credit markets. FinTech firms often employ alternative data sources and advanced analytical models to evaluate borrowers, enabling faster and more inclusive credit provision. These platforms can assess creditworthiness even in the absence of traditional collateral by analyzing behavioral and transactional data, thereby expanding financial access while maintaining effective risk management mechanisms (Lee et al., 2025). Moreover, the widespread adoption of digital banking has reduced information asymmetry between lenders and borrowers by facilitating the collection and exchange of financial information. Greater data transparency improves the quality of credit screening and reduces the likelihood of lending to high‑risk borrowers (Liang et al., 2024).

Beyond improving credit assessment, technological innovations also contribute to transparency and accountability in financial systems. Digital recording and processing of credit information allow lending decisions to be traced and evaluated, which strengthens internal controls and reduces the likelihood of non‑transparent practices. In addition, digitalization lowers operational costs and accelerates financial service delivery, enabling banks to allocate resources more efficiently and improve risk management performance (Liu et al., 2025).

The relationship between credit risk management and monetary policy has also received considerable attention in the literature. Monetary policy is largely transmitted through the banking system and the supply of credit in the economy. When central banks adjust monetary conditions through interest rates or liquidity management tools, the response of banks in adjusting credit supply determines how effectively these policies influence economic activity. If banks are burdened with high levels of non‑performing loans, their ability to expand or contract lending becomes constrained, weakening the transmission of monetary policy (Ma et al., 2024). Conversely, improvements in credit risk assessment and management enhance the quality of bank assets and strengthen the responsiveness of the banking system to policy changes.

ICT also supports monetary policymaking by improving the availability and timeliness of financial information. Access to comprehensive data on credit allocation, repayment behavior, and sectoral lending allows policymakers to better monitor financial conditions and evaluate the impact of policy interventions. This data-driven environment enables more evidence‑based policymaking and facilitates timely adjustments to monetary policy instruments (Sun et al., 2024). Furthermore, technological improvements in credit evaluation can strengthen the credit channel of monetary policy by directing financial resources toward more productive activities and improving the efficiency of credit allocation within the economy (Tang & Yang, 2024).

Despite these benefits, the growing reliance on digital technologies in financial systems also introduces new challenges. The increasing volume of digital financial data raises concerns about cybersecurity risks and the protection of sensitive information. Additionally, algorithm‑based credit evaluation models may introduce unintended biases if not properly designed and monitored (Wu & Zheng, 2025). Policymakers therefore face the challenge of balancing financial innovation with effective regulatory oversight. Many countries have adopted regulatory sandbox frameworks to support innovation while maintaining financial stability (Xie & Yu, 2024).

Overall, the literature highlights the important role of ICT and technological innovation in improving credit risk management and strengthening financial systems. However, most existing studies examine these relationships in a linear framework or focus on individual aspects of digitalization, credit risk, or monetary policy separately. Limited attention has been given to the possibility that digital innovation may alter the interaction between credit risk, ICT development, and monetary policy through nonlinear or threshold effects.

Accordingly, this study seeks to fill this gap by investigating whether digital innovation acts as a threshold variable that changes the relationship between credit risk, ICT development, and the effectiveness of monetary policy in Iran. By employing a nonlinear modeling framework, this research aims to provide new insights into how digital transformation in the banking sector may reshape monetary policy transmission mechanisms.

Method

This study examines the threshold effects of the emergence of innovative activities on the relationship between credit risk and information and communication technology with monetary policy in Iran. This study is applied in terms of its purpose and descriptive in terms of its analytical nature and is classified as post-event research. The statistical population of the study is Iran and the econometric time series and interval range from 2009 to 2024 and is seasonal.

Justification of the Study Period and Data Frequency

The study employs quarterly data covering the period 2009–2024. The selection of quarterly observations is motivated by the need to capture short-run fluctuations and dynamic adjustments in credit risk, ICT development, digital innovation, and monetary policy transmission mechanisms that may not be observable in annual data. Moreover, quarterly data provide a sufficient number of observations for estimating the nonlinear LSTR model while preserving the medium- and long-term characteristics of the underlying economic relationships.

The selected period encompasses several important developments in the Iranian economy and banking sector, including the expansion of digital banking services, the gradual adoption of fintech solutions, episodes of intensified economic sanctions, exchange-rate volatility, the COVID-19 pandemic, and regulatory reforms in the financial sector. These events have contributed to substantial changes in financial behavior and monetary transmission mechanisms, making the period particularly suitable for investigating potential nonlinear and regime-dependent effects. Given that the LSTR framework is specifically designed to capture gradual structural changes and transitions between regimes, it provides an appropriate empirical framework for analyzing the evolving role of digital innovation during this period. Nevertheless, the potential influence of major economic shocks is acknowledged as a limitation of the study and should be explored further in future research through formal structural break analyses.

Practical Implications of the Identified Threshold Effect

The identified threshold effect suggests that the influence of credit risk and ICT on monetary policy effectiveness is conditional upon the level of digital innovation achieved within the financial system. For central banks, this finding implies that investments in digital financial infrastructure should be considered an integral component of monetary policy effectiveness rather than merely a technological modernization initiative. Once digital innovation exceeds a critical threshold, improvements in information processing, risk monitoring, and credit allocation can significantly strengthen policy transmission through the banking channel.

For digital banking platforms, the results highlight the importance of expanding data-driven credit assessment systems, artificial intelligence applications, and real-time monitoring mechanisms. The benefits of these technologies appear to increase substantially after reaching a sufficient level of digital maturity, suggesting that partial or fragmented digitalization may not generate the full efficiency gains expected from digital transformation.

For financial regulators, the findings indicate the need to establish regulatory frameworks that facilitate digital innovation while maintaining financial stability. Policies supporting data integration, digital identity systems, open banking architectures, and advanced supervisory technologies can help financial institutions move beyond the identified threshold level, thereby enhancing both risk management quality and the effectiveness of monetary policy implementation. Consequently, digital innovation should be viewed not only as a technological objective but also as a strategic policy instrument for strengthening financial resilience and improving macroeconomic governance.

In this study, following the studies of Kulu et al. (2024), Gianni Carvelli et al. (2024), Greta Benedetta Ferilli (2024) and Zahid Irshad Younas et al. (2023), the following model has been estimated using the LSTR method.

$$(1)\ CD\ Ratio_{\mathrm{t}} = \alpha_0 + \beta_1 INOV_t + \beta_2 NPL_{\ t} + \beta_3 LoanG_t + \beta_4 Size_t + \beta_5 INF_t + \beta_6 INR_t + \beta_7 ICT_t + \beta_8 ROA_t(\theta_1 INOV_t + \theta_2 NPL_{\ t} + \theta_3 LoanG_t + \theta_4 Size_t + \theta_5 INF_t + \theta_6 INR_t + \theta_7 ICT_t + \theta_8 ROA_t)F(S_t, \gamma, c) + u_t$$

Where the transition function F is equal to:

$$F(\gamma, s_t, c) = (1 + CDRATIO\{-\gamma(s_t - c)\})^{-1}, \qquad \gamma > 0$$

In order to investigate the properties of the LSTR model with a logistic transfer function based on the Van Dijk (1999) model, it is assumed that the dependent variable is a function of its own interpolated values only. In this case, assuming a two-regime transfer function, the following relationship is obtained:

$$CD\ Ratio_t = \left(\theta_0 + \theta_1 CD\ Ratio_{t-1} + \cdots \theta_p CD\ Ratio_{t-p}\right) + \left(\phi_0 + \phi_1 CD\ Ratio_{t-1} + \cdots \phi_p CD\ Ratio_{t-p}\right) G(INF_t, \gamma, c) + u_t$$

$$\mathrm{G}(CDRATIO_{\mathrm{t}}, \gamma, \mathrm{c}) = \frac{1}{1 + \exp\{-\gamma(CDRATIO_{\mathrm{t}-}\mathrm{c})\}}$$

The results of this model are called a two-regime PSTR model, where the location parameter c represents a point of transition between two extreme regimes $G(INF_{t,\gamma,c})=0$ and $G(INF_{t,\gamma,c})=1$, which is $G(INF_{t,\gamma,c})=0.5$. indicates the speed of transition between regimes, and higher values of γ indicate a faster regime change.

CDRatio: The ratio of loan balances to deposits as an indicator of monetary policy effectiveness, *INOV:* Following the study by Sadigov et al. (2020), in this study, to obtain the index of emergence of innovative activities, after calculating the index of emergence of innovative activities in different sectors including; the ratio of the number of bank accounts to the population, the ratio of the number of ATMs to the population, the ratio of the value of transactions via the Internet, the ratio of the value of transactions via mobile phones, the variables reflecting the index of emergence of innovative activities are calculated using principal component analysis (PCA).

NPL Credit risk (ratio of non-performing loans to total loans),

LoanG: Bank loan growth (percentage of change in bank loans), Bank size (Size) (logarithm of total bank assets), INR: Short-term interest rate on bank deposits,

INF: Inflation rate,

ROA: Return on assets ratio as an indicator of profitability: It is calculated by dividing net profit after tax by average assets.

ICT: New Technology Development Index: It indicates the development index of new technology. This index is published by the World Telecommunication Union and includes three main components: access, use and skills. The ranking of this index is based on a score of zero to ten. A higher score means a high degree of ICT development and a lower score means a low degree of ICT development of the countries.

The selection of the Logistic Smooth Transition Regression (LSTR) model is motivated by both the theoretical characteristics of the research problem and the nature of the data. Unlike conventional linear models, which assume constant relationships among variables over time, the interaction between digital innovation, credit risk, ICT development, and monetary policy effectiveness is expected to evolve gradually as the level of digitalization increases. Therefore, the assumption of a single and stable coefficient structure may not adequately capture the underlying economic dynamics.

Although several nonlinear approaches such as Threshold Autoregressive (TAR), Smooth Transition Autoregressive (STAR), Markov-Switching, and Threshold Regression models are available, these methods either assume abrupt regime changes or focus primarily on univariate dynamic processes. In contrast, the LSTR model allows for smooth and continuous transitions between different regimes through a transition function determined by a threshold variable. This feature is particularly suitable for the present study because digital innovation is not expected to alter banking behavior and monetary transmission mechanisms instantaneously; rather, its effects are likely to emerge progressively as digital capabilities, technological infrastructure, and data-processing capacities improve over time.

Furthermore, the LSTR framework enables the estimation of both the threshold value and the speed of transition between regimes, providing additional insights into how varying levels of digital innovation modify the relationship between credit risk, ICT, and monetary policy. Given the gradual nature of digital transformation in the Iranian banking sector and the objective of identifying regime-dependent effects, the LSTR model offers a more realistic and theoretically consistent representation of the underlying economic processes than alternative nonlinear specifications.

Findings

Initially, to ensure the absence of spurious regression, the unit root and cointegration tests are used. In this study, the conventional Phillips-Perron test is used.

***Table 1**. Results of the pp test on the model variables*

pp statistics		
Variables	**Probability**	**Variable status**
CDRATIO	0.2773	---
D(CDRATIO)	0.0000	I(1)
ICT	0.3215	---
D(ICT)	0.0000	I(1)
INF	0.4378	---

D(INF)	0.0000	I(1)
INR	0.1365	---
D(INR)	0.0000	I(1)
INVO	0.3905	---
D(INVO)	0.0000	I(1)
LOANG	0.2761	---
D(LOANG)	0.0000	I(1)
NPL	0.6522	---
D(NPL)	0.0000	I(1)
CR	0.4300	---
D(CR)	0.0000	I(1)
ROA	0.4008	---
D(ROA)	0.0000	I(1)

Source: Research findings

Considering the theoretical foundations of reliability tests, the null hypothesis *H* is defined in these tests as the lack of reliability of the variable, and considering the test results, it can be stated that all model variables are stable at the first level *I(1)*.

To assess the potential presence of multicollinearity among the explanatory variables, the Variance Inflation Factor (VIF) test was conducted. VIF values lower than the commonly accepted threshold of 10 indicate that multicollinearity is not a serious concern and that the estimated coefficients are reliable. The results presented in Table X demonstrate that all variables exhibit acceptable VIF values, confirming the absence of severe multicollinearity in the model.

Table 2. *Variance Inflation Factor (VIF) Results*

Variable	VIF
CDRATIO	2.14
D(CDRATIO)	1.97
ICT	2.83
D(ICT)	2.11
INF	3.25
D(INF)	2.46
INR	2.74
D(INR)	2.18
INVO	1.89
D(INVO)	1.76
LOANG	2.57
D(LOANG)	2.04
NPL	3.41
D(NPL)	2.68
CR	2.23
D(CR)	1.95
ROA	2.87
D(ROA)	2.16

The findings indicate that all VIF values are substantially below the critical threshold of 10, with the highest value observed for NPL (3.41). Therefore, no evidence of harmful multicollinearity is detected among the independent variables. Consequently, all variables were retained in the empirical model, and the estimated regression coefficients can be interpreted with confidence.

Cointegration test results

Since the model variables have the same degree of integration *I(1)*, the cointegration test is used to detect the existence of a long-term equilibrium relationship between the model variables, and the Johansson-Usielius method is used to perform this test. To perform this test, it is necessary to determine the number of cointegration vectors. To examine the results of the cointegration test, it is necessary to select an appropriate model regarding the presence or absence of a time trend and the width from the origin in the cointegration vector. In this context, five models are proposed: the first model, without width from the origin and time trend; the second model, with a restricted width from the origin and without a time trend; the third model, with an unrestricted width from the origin and without a time trend; The fourth pattern, with the width from the unconstrained origin and the constrained time trend, and the fifth pattern, the width from the unconstrained origin and the unconstrained time trend. These five patterns are estimated from the most constrained (first pattern) to the most unconstrained (fifth pattern) form for the variables. Then, the null hypothesis of the absence of a cointegration vector is tested against the presence of a cointegration vector, followed by the hypothesis of the existence of at most one cointegration vector against two vectors. This test continues until there are n-1 (n is the number of variables) cointegration vectors. A summary of the results of the trace (λ_{Trace}) and maximum eigenvalue (λ_{Max}) tests regarding the number of cointegration vectors based on the five patterns mentioned is given in Table 2. As can be seen, the null hypothesis of the absence of a cointegration vector is rejected against the presence of a cointegration vector between the variables in the pattern, so there is at least one cointegration vector between the variables under study.

Table 2. *Summary of results of the number of cointegration vectors*

Pattern	First pattern	Second pattern	Third pattern	Fourth pattern	Fifth pattern
Effect test	2	5	3	3	4
Maximum specific value test	4	3	2	3	2

Source: Research findings

The results of the model estimation and cointegration tests for the third model of the Johansen test are reported in the table below. According to the results based on the effect test, the existence of 5 cointegration vectors and based on the results of the maximum eigenvalue test, the existence of 3 cointegration vectors at the 5 percent level is confirmed.

Table 3. *Cointegration test results*

Test statistic Maximum eigenvalues	Critical quantity at 95% level	Probability level	Test statistic effect	Critical quantity at 95% level	Probability level	Hypothesis H_1	Hypothesis H_0
98.16357	58.43354	0.0000	303.0342	197.3709	0.0000	r=1	r=0
71.63297	52.36261	0.0002	204.8707	159.5297	0.0000	r=2	r≤1
46.15312	46.23142	0.0510	133.2377	125.6154	0.0158	r=3	r≤2
24.59407	40.07757	0.7922	87.08456	95.75366	0.1700	r=4	r≤3
19.89911	33.87687	0.7636	62.49049	69.81889	0.1670	r=5	r≤4
17.64616	27.58434	0.5248	42.59138	47.85613	0.1428	r=6	r≤5
11.51158	21.13162	0.5962	24.94522	29.79707	0.1634	r=7	r≤6
7.134031	14.26460	0.4734	13.43364	15.49471	0.0998	r=8	r≤7
6.299611	3.841466	0.0121	6.299611	3.841466	0.0121	r=9	r≤8

Smooth Transition Regression (STAR) Model

Due to the limitations of linear models, many studies have proposed the use of various types of nonlinear models to specify the nonlinear behavior in time series. In this study, in order to model the threshold effects of the emergence of innovative activities in the relationship between credit risk and information and communication technology with monetary policy in Iran, the smooth transition regression model, which was developed by Ter¨asvirta and Anderson (1992) and Ter¨asvirta (1994), is used. Unlike TAR models that use an indicator function to control the regime change process, the STAR model uses exponential and logistic functions for this purpose. According to Van Dijk and Terasvirta (2002), these models are very suitable for analyzing asymmetric cycles of variables, and many studies have shown that they fit the regime change mechanism well to examine the nonlinear dynamics of variables. In fact, the STAR model models the nonlinear relationship between variables in a continuous manner using the transition variable and the value of the slope parameter. The Trasorta smooth transition regression model is specified as a general regression as follows.

(1) $$y_t = \pi' z_t + \theta' z_t + F(s_t, \gamma, c) + u_t$$

where z_t is a vector containing the exogenous variables of the model; π is a vector of linear parameters; θ is a vector of nonlinear parameters of the model; u_t is a residual component that is assumed to be identically and independently distributed with zero mean and constant variance $(u_t \approx iid(0, \sigma^2))$. The transfer function $F(s_t, \gamma, c)$ can also be specified as a logistic or exponential function in the form of the following relation.

(2) $$F(s_t, \gamma, c) = \left[\frac{1}{1 + \exp(-\gamma(s_t - c))} - \frac{1}{2} \right]$$

(3) $$F(s_t, \gamma, c) = \left[1 - \exp\left(-\gamma(s_t - c)\right)^2 \right]$$

So that equation (2) represents the logistic transfer function and equation (3) represents the exponential transfer function. In the above functions, s_t represents the transfer variable; γ represents the slope parameter; c represents the threshold limit or the place where the regime change occurs. If the slope parameter γ, which represents the speed of the transfer from one regime to another, tends towards infinity, the STAR model becomes a threshold TAR model, meaning that if the transfer variable is greater than the threshold limit; ($c < s_t$) the transfer function becomes one (F=1). On the other hand, if ($c > s_t$) the value of the transfer function will be zero (F=0). Also, if the value of the slope parameter tends towards zero, the STAR model becomes a linear model.

The process of estimating the autoregressive STAR smooth transition model is as follows: in the first step, the dynamic model or the optimal number of breaks are selected, then the existence of a nonlinear relationship between the variables under study is tested, and based on that, the transition variable and the number of regime changes are selected. In the second step, the selected STAR model is estimated using the Newton-Raphson algorithm and the maximum likelihood method, and finally diagnostic tests are performed to ensure that reliable results are achieved.

Linearity test, selection of transition variable, and model type

To estimate the smooth transition regression model, in order to select the transition variable, all variables in the model have been tested, and all variables in the model have been tested to select the transition variable. Among the tested variables, any variable that most likely rejects the null hypothesis of linearity will be selected as the transition variable. It should be noted that the proposed (STAR) model is selected as the optimal model by the selected transition variable to estimate the threshold effects of the emergence of innovative activities in the relationship between credit risk and information and communication technology with monetary policy in Iran. The results of Table 4 show that the transition variable in the estimated model is the indicator of the emergence of innovative activities and the null hypothesis that the model is linear is rejected and the first-order (LSTR) model is confirmed and the main emphasis of the study is on the results of the nonlinear part.

***Table 4**. Linearity test, selection of transition variable and model type*

Proposed Model	Statistic F	Statistic F2	Statistic F3	Statistic F4	Variable
1LSTR	**0.8958**	**0.3896**	**0.5425**	**0.7745**	**invo (t)**

Model estimation results

In the next step, using a 1LSTR model in which the transmission variable is the indicator of the emergence of innovative activities, the analysis function will be modeled to examine the threshold effects of the emergence of innovative activities in the relationship between credit risk and information and communication technology with monetary policy in Iran. For this purpose, first, initial values were selected for the threshold value of the transmission variable (C) and the slope parameter (γ), and then, using these initial values and using the Newton-Raphson algorithm, the model parameters were estimated by the likelihood maximization method, the results of which are reported in Table (5).

Based on the estimation results of the nonlinear part of the model (second regime), it is shown that the variable of the emergence of innovative activities has a positive and significant effect on monetary policy. The effect of the credit risk variable on monetary policy is negative and significant, and the effect of the information and communication technology index on monetary policy is positive and statistically significant at the 5% error level. Also, the results of the present study are consistent with the results of studies; Ahmed et al. (2022), Ferreira et al. (2022), Younes et al. (2022), Kaneshba et al. (2022), and Berisha et al. (2021) are in line.

Table 5. Model estimation using LSTR model

Model (monetary policy)				
Estimating the linear part of the model				
Probability	T-statistic	Standard deviation	Coefficient	Variable
0.0200	2.782475	0.230948	0.642607	CONSTANT
0.0008	3.380603	0.028983	0.097980	INVO
0.0013	-3.377149	0.014301	-0.048297	NPL
0.0412	2.085195	0.050647	0.105609	LOANG
0.0000	4.783861	0.006071	0.029044	SIZE
0.0229	-2.334024	0.043898	-0.102458	INF
0.0013	-3.361392	0.171988	-0.578120	INR
0.0124	2.575931	0.004132	0.010643	ICT
0.0480	2.018095	0.082766	0.167030	ROA
Estimation of the nonlinear part of the model				
0.0049	2.796881	0.006021	0.016839	CONSTANT
0.0491	1.982849	0.055542	0.110132	INVO
0.0355	-2.335214	0.007091	-0.016559	NPL
0.0015	3.195642	0.027937	0.089278	LOANG
0.0201	2.324058	0.085146	0.197885	SIZE
0.0274	-2.205968	0.010298	-0.022717	INF
0.0165	-2.396934	0.022425	-0.053752	INR
0.0077	2.675502	0.004822	0.012901	ICT
0.0053	2.762255	0.085117	0.235516	ROA
0.0000	-4.851588	0.043521	-0.211146	Threshold(C)
0.0007	3.411155	0.215697	0.735776	Slope parameter(γ)
Adjusted coefficient = 0.88 (R^2)				

The comparison of coefficients in two different regimes is based on the transmission variable and its values, and the value of the transmission variable can determine the transmission function and, consequently, the governing regime. In fact, the transmission variable being less than or greater than the threshold can create two different regimes in the estimated function. In the above estimation, the transmission variable is the innovative activity emergence index, and the estimated threshold value for this variable was equal to -0.21 in the model. Based on the distance of the innovative activity emergence index from this threshold value, the model follows two different limit regimes. By comparing the model coefficients in two different regimes, it is observed that when the innovative activity emergence index passes the threshold, the monetary policy response to changes in this variable increases sharply, so that the higher the innovative activity emergence index, the better the monetary policy is.

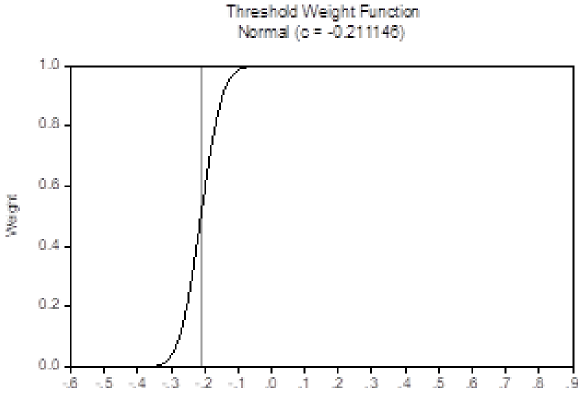

Figure 1. *Relationship between the transfer function and the transfer variable of the index of emergence of innovative activities*

Diagnostic tests

According to the estimation, there is no correlation error and variance heterogeneity in the estimated LSTR1 model. The test of the absence of residual nonlinearity also shows that the LSTR1 model has specified all the nonlinear behaviors present in the model.

Table 6. *Results of diagnostic tests*

P-value	F-value	Test
0.6525	0.9748	ARCH LM-test
0.4785	1.4525	No remaining nonlinearity test
0.3968	1.5414	Parameters constancy test

The results of the parameter stability test in different regimes also show that the null hypothesis of the test based on the stability of the coefficients and parameters of the model in two different regimes is rejected, and this result, i.e. the coefficients of the explanatory variables in two different regimes, is acceptable, and the asymmetric effects on the dependent variable are confirmed. Therefore, based on the estimated results of the model and the diagnostic tests performed, it seems that the LSTR1 model is a suitable model for analyzing the threshold effects of the emergence of innovative activities in the relationship between credit risk and information and communication technology with monetary policy in Iran, and we can trust the accuracy of the results obtained from the estimation of this model.

Discussion

The findings of this study showed that the relationship between credit risk, information and communication technology and the effectiveness of monetary policy in Iran is not a purely linear and uniform relationship, but rather undergoes regime and threshold changes under the influence of the level of emergence of innovative activities. This result is consistent with the recent literature in monetary and financial economics, which emphasizes that monetary policy transmission in the era of digital economy and smart banking has become increasingly nonlinear, dependent on institutional structure, and influenced by new technologies (Bank for International Settlements, 2003; Adrian & Mancini-Griffoli, 2021). In fact, recent studies by the International Monetary Fund also show that the digitalization of banks can change the intensity and speed of monetary policy effectiveness in different financial regimes and lead to the formation of threshold behaviors in the credit channel (IMF, 2023). The results of the cointegration and unit root tests also confirmed that the relationship between the variables under study is structural and long-term. This finding is consistent with studies that show that in digitally evolving banking systems, traditional variables such as credit risk, interest rates, and inflation, along with technological variables such as the level of digitalization and financial innovation, form a long-run equilibrium network (Feyen et al., 2021; Dias et al, 2026). Therefore, monetary policy in such a structure is no longer solely a function of classical instruments, but also depends on the quality of data infrastructure and the level of maturity of financial technology.

One of the most important findings of the research was the confirmation of the role of the variable “emergence of innovative activities” as a threshold variable. This result shows that financial innovation and banking smartness are not simply a linear explanatory factor, but rather a regime-forming variable that changes the structure of monetary policy effectiveness. This is consistent with the FinTech and digital banking literature, which suggests that new technologies (including artificial intelligence, big data, and smart credit systems) can redesign the structure of the credit channel and nonlinearly increase the efficiency of monetary policy at higher levels of innovation (Jarvis et al., 2021; IMF, 2024).

The results also showed that the innovation index has a positive and significant effect on the effectiveness of monetary policy. This finding is consistent with recent studies in the field of digital economy that show that the expansion of digital banking services, electronic payments, and smart banking reduces information friction, increases the speed of liquidity circulation, and improves the transmission of monetary shocks (BIS, 2023). In this framework, innovation is not only a technological variable, but also an institutional infrastructure to enhance the effectiveness of monetary policy.

On the other hand, the results of the study showed that credit risk (NPL) has a negative and significant effect on the effectiveness of monetary policy. This result is consistent with the literature on banking crises and bank balance sheet constraints, which shows that increasing non-performing loans weaken the lending channel and reduce the effectiveness of central bank expansionary policies (Aikman et al., 2015). In fact, when banks’ balance sheets are burdened with non-performing and frozen assets, the transmission of monetary policy through the credit channel is structurally disrupted.

The findings on information and communication technology also showed that ICT has a positive and significant effect on the effectiveness of monetary policy. This result is consistent with recent studies on digital banking and data-driven governance, which show that the development of ICT infrastructure increases financial transparency, reduces transaction costs, and improves central bank systemic oversight (World Bank, 2023; BIS, 2024). In such circumstances, monetary policy is transmitted to the real sector of the economy through faster and more accurate channels.

Finally, the existence of significant effects of variables such as loan growth, bank size, and profitability also suggests that the institutional structure of banks, along with technology, plays a decisive role in the effectiveness of monetary policy. This result is consistent with the new macroprudential banking literature, which emphasizes that the health of banks’ balance sheets and the level of their digitalization jointly affect the effectiveness of monetary policy (Adrian & Liang, 2018). The threshold estimate also showed that the effect of innovation on monetary policy has a gradual but regime-like behavior; such that after passing a certain level, the intensity of the effect increases significantly. This result is consistent with recent studies in the field of soft transition models in the digital economy, which show that new technologies usually have nonlinear and step-wise effects on macro variables (Bank for International Settlements, 2003).

Conclusion

This study showed that understanding the performance of monetary policy in the Iranian economy requires moving beyond purely linear and traditional frameworks. The reality is that in the current situation, the country's banking and financial system operates in a context of technological developments, credit constraints, customer behavioral changes, and new policymaking requirements. Therefore, analyzing the effectiveness of monetary policy without considering the role of innovation and ICT provides an incomplete picture of economic reality. The findings of this study confirm that as the level of emergence of innovative activities and technological development increases and at the same time the credit risk of banks is controlled, the capacity of monetary policy to guide credit, regulate liquidity, and influence economic variables will also increase. Therefore, the future of monetary policy efficiency in Iran depends to a large extent on the success of reforming the banking structure, developing technology, and purposefully crossing innovative thresholds.

Finally, it can be said that the main achievement of this study is to provide empirical evidence for the existence of a threshold mechanism in the relationship between innovation, credit risk, information technology, and monetary policy in Iran. This achievement is both theoretically and politically important. From a theoretical perspective, the results emphasize the need to use nonlinear models to study monetary and financial variables. From a policy perspective, it also makes it clear that improving the effectiveness of monetary policy is not possible simply through changes in rates and conventional instruments, but also requires improving the quality of bank intermediation, reducing credit risk, developing information technology, and gradually crossing the innovation thresholds of the financial system.

Accordingly, it can be concluded that strengthening the ecosystem of financial and digital innovation, along with banking reforms, will be one of the most important prerequisites for increasing the efficiency of monetary policy and improving the country's economic performance in the coming years. Given the positive and significant effect of the emergence of innovative activities on the effectiveness of monetary policy, it is suggested that monetary policymakers and banking supervisory institutions provide more opportunities for the development of new financial services and digital banking. The expansion of tools such as internet banking, mobile banking, electronic payments, and online financial services can increase the speed of financial information circulation and the efficiency of monetary policy transmission, and improve the performance of the banking network in mobilizing and allocating resources.

Given the negative impact of credit risk on the effectiveness of monetary policy, it is essential for the Central Bank and regulatory agencies to implement more serious programs to reduce non-performing loans and improve the quality of banks' credit portfolios. Strengthening the customer credit assessment system, developing comprehensive credit databases, increasing supervision of the process of granting facilities, and reforming the risk management structure in banks can help reduce credit risk and, as a result, increase the efficiency of monetary policy.

Given the positive effect of the information and communication technology index on monetary policy, investing in the development of ICT infrastructure in the country should be a priority for economic policies. Developing communication networks, increasing access to high-speed internet, expanding digital services, and improving technology skills in the financial sector can provide the necessary platform for expanding innovative services and strengthening the performance of the banking system.

Given the existence of threshold effects in the relationship between the variables under study, it is suggested that economic policymakers pursue financial innovation development programs gradually, continuously, and purposefully so that the indicator of the emergence of innovative activities crosses the identified threshold level and the financial system enters a regime with higher efficiency in monetary policy transmission. Achieving this requires supporting financial technology (FinTech) companies, developing an innovation ecosystem, and facilitating regulations related to modern financial services.

Given the positive role of bank size and profitability in strengthening the effectiveness of monetary policy, reforming the financial and operational structure of banks and increasing their efficiency should be considered. Strengthening bank capital, improving asset and liability management, increasing financial transparency, and promoting corporate governance can increase the ability of banks to play the role of financial intermediation and appropriately transmitting monetary policies.

Given the negative effect of inflation and short-term interest rates on the effectiveness of monetary policy in some circumstances, it is necessary to establish greater coordination between monetary policies and other macroeconomic policies. Controlling inflation, managing liquidity appropriately, and stabilizing macro variables can provide the necessary basis for more effective monetary policy and increasing the efficiency of the banking system.

It is suggested that the Central Bank, in designing and implementing monetary policies, pay special attention to technological developments and innovations in the financial system, in addition to traditional tools. Creating regulatory frameworks appropriate to digital banking, developing regulations related to new financial services, and utilizing big data and new technologies in banking supervision can improve the monetary decision-making process and increase the effectiveness of economic policies.

The findings of this study suggest that the future effectiveness of monetary policy will increasingly depend on the pace and depth of digital transformation within the financial system. While conventional banking reforms remain important for maintaining financial stability, the results indicate that digital innovation has evolved from a supporting technological factor into a strategic determinant of monetary policy transmission. The identified threshold effect demonstrates that improvements in credit allocation, risk assessment, and policy effectiveness become substantially stronger once a sufficient level of digital maturity is achieved.

Accordingly, future monetary policy frameworks should place greater emphasis on smart financial technologies, including artificial intelligence, big data analytics, digital banking platforms, fintech ecosystems, and real-time supervisory infrastructures. These technologies enhance information transparency, reduce credit market frictions, improve risk monitoring, and enable policymakers to respond more rapidly to economic shocks. In this context, digital transformation should be viewed not merely as a modernization strategy for the banking sector but as a fundamental pillar of next-generation monetary governance.

Therefore, policymakers should complement traditional banking reforms with investments in digital financial infrastructure, data integration systems, intelligent credit evaluation mechanisms, and advanced regulatory technologies. Such measures can strengthen the resilience of the financial system, improve the efficiency of monetary transmission channels, and support the transition toward a more adaptive, data-driven, and digitally enabled monetary policy framework.

Declaration of Competing Interest

The author declares that he has no competing financial interests or known personal relationships that would influence the report presented in this article.

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