

The Impact of Shocks from the Emergence of Innovative Activities in the Banking Sector and Credit Risk on the Effectiveness of Monetary Policy, with Emphasis on the Information and Communication Technology Index

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ABSTRACT

The present study aims to examine the impact of shocks arising from the emergence of innovative activities in the banking sector and credit risk on the effectiveness of monetary policy, with an emphasis on the Information and Communication Technology (ICT) index. The study period is quarterly and spans from 2009 to 2023. In this research, a composite index of the emergence of innovative activities was first constructed using Principal Component Analysis (PCA) based on four variables: the ratio of the number of bank accounts to population, the ratio of the number of automated teller machines (ATMs) to population, the ratio of the value of internet banking transactions, and the ratio of the value of mobile banking transactions. The results of the analysis indicated that the first principal component explains the largest share of data variance, and that internet banking has the highest weight in the composite index. Subsequently, to ensure the stationarity of the variables, the Phillips–Perron unit root test was applied, and the results showed that all variables are stationary at the first difference. Given the cointegration among the variables, the Johansen cointegration test was conducted, revealing the existence of at least one cointegrating vector among the model variables; therefore, long-run relationships among them can be examined. The optimal lag length of the model was determined using various criteria, and ultimately, based on the Schwarz–Bayesian criterion, which is more appropriate for a limited sample size, one lag was selected. The Structural Vector Autoregression (SVAR) model was explicitly estimated by imposing theoretical restrictions to assess the effects of monetary policy shocks on economic variables, including the ratio of outstanding loans to deposits, credit risk, inflation rate, interest rate, and the ICT index. The findings indicate that the emergence of innovative activities—particularly through the development of internet banking—exhibits the greatest sensitivity to monetary policy, and that the structural relationships between monetary shocks and innovation indicators play a crucial role in analyzing policy effectiveness. Finally, the proposed model is confirmed to be stable and stationary, showing that the effects of shocks on variables dissipate over time, and it can be used as a reliable tool for analyzing monetary policy and innovation in the Iranian economy.

Keywords: Monetary policy; innovative activities; internet banking; financial innovation; monetary shock.



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Introduction

Over the past decade, banking systems worldwide have been exposed to an unusually dense combination of shocks: persistent inflation episodes, rapid shifts in monetary policy stances, structural changes in credit intermediation, and an accelerating wave of digital transformation that is redefining the production, distribution, and governance of financial services. In such an environment, the effectiveness of monetary policy cannot be treated as a purely macroeconomic outcome that is transmitted mechanically through conventional interest-rate and credit channels; rather, it increasingly depends on how banks price, allocate, and manage credit in real time, and on how digital infrastructures shape the speed and granularity with which policy signals are translated into lending behavior. This is particularly relevant for bank-based financial systems—where bank credit remains central to investment, working capital, and household financing—because the interaction between monetary policy, credit risk, and financial innovation determines whether policy tightening cools demand without destabilizing the balance sheets of intermediaries, and whether policy easing reaches productive borrowers rather than amplifying risk-taking. In recent discussions of monetary governance, the credibility and clarity of central bank actions are repeatedly emphasized as prerequisites for stable expectations and predictable transmission; where credibility is contested, the same instrument settings may yield weaker or noisier effects on inflation, lending, and risk premia (1, 2). At the same time, country-specific monetary and banking structures—ranging from institutional constraints to market depth and the configuration of bank liabilities—can reshape both the timing and the magnitude of policy pass-through, making it essential to study transmission mechanisms in context rather than relying on generic stylized facts (3, 4).

A central mechanism through which monetary policy influences the real economy is the credit channel, which includes both the bank lending channel and the balance-sheet channel. When central banks tighten policy, funding costs increase and banks may adjust loan supply, lending standards, and pricing; conversely, during easing cycles, banks may expand credit, but the extent of expansion depends on their risk appetite, capital buffers, and the perceived creditworthiness of borrowers. Credit risk therefore sits at the core of monetary policy effectiveness: it is not merely an outcome variable but a constraint and amplifier that can weaken or strengthen the transmission of policy shocks. If banks face heightened non-performing loans, rising expected losses, or a deteriorating credit environment, they may ration credit even under accommodative policy, blunting the intended stimulus. Conversely, when risk-taking incentives are strong, banks may expand credit aggressively, potentially improving short-run policy traction but increasing medium-term financial fragility. Recent work in the Iranian context has explicitly underscored that monetary policy and credit risk jointly shape investment behavior and the broader financing environment, suggesting that policy evaluations must incorporate banking-sector risk conditions rather than treating them as peripheral controls (5, 6). From a policy design standpoint, the bank risk-taking channel—where monetary conditions influence banks' portfolio risk choices—has also become increasingly salient, particularly when tighter policy is intended to stabilize inflation but may induce balance-sheet adjustments that propagate stress through the credit system (7).

Simultaneously, the inflation–interest rate nexus has re-emerged as a dominant factor shaping lending dynamics and monetary transmission. In high-inflation environments, nominal rates, real rates, and borrower expectations interact in complex ways, affecting not only borrowing costs but also maturity choice, refinancing, and default incentives. Evidence from different settings shows that inflation experiences can shape household and borrower decisions in credit markets—such as mortgage choices—thereby altering the distribution of interest-rate sensitivity

across borrowers and potentially changing how monetary policy affects consumption and housing-related credit demand (8). Empirical analyses using cointegration-based frameworks (e.g., VECM) also document that inflation dynamics can influence the formation of loan interest rates and industrial production outcomes through the credit channel, reinforcing the idea that policy effectiveness is contingent on both inflation regime characteristics and credit market structures (9). In mortgage lending specifically, the interaction between policy rates and lending volumes during periods of high inflation and elevated asset prices has drawn attention to the possibility that conventional rate hikes may not uniformly restrain lending if market expectations, collateral values, and institutional features offset the tightening impulse (10). Taken together, these strands suggest that measuring monetary policy effectiveness in modern banking systems requires going beyond single-equation correlations and instead modeling the joint dynamics of inflation, interest rates, credit growth, and risk conditions.

A further complication—and an opportunity for deeper insight—is the structural transformation driven by financial technology (FinTech) and broader digitalization of banking services. Digital transformation affects banks at multiple layers: operational processes, customer acquisition and servicing, data analytics, risk scoring, and product design. As banks integrate Industry 4.0 technologies and digital platforms, they may respond more rapidly to policy signals because pricing engines, liquidity management tools, and credit decision systems become more automated and data-driven. At the same time, digitalization can alter competitive pressures and stability conditions, potentially affecting risk-taking behavior and the resilience of the banking sector under monetary shocks (11, 12). System-level supervision is also evolving as regulators attempt to keep pace with technology-driven structural change; supervisory perspectives emphasize that digital transformation requires new approaches to oversight, data governance, cyber resilience, and operational risk management, all of which can indirectly influence the monetary transmission mechanism through the stability and responsiveness of banks (13). Moreover, digitalization can reshape financial inclusion, sometimes expanding access via online channels while also creating “digital barriers” for specific groups; in such cases, the distributional footprint of monetary policy may change because different segments of households and firms face different access costs and credit constraints (14). These transformations matter for a policy-effectiveness study because the same monetary shock can have different real effects depending on whether lending is mediated through traditional branch-based intermediation or digital channels with different cost structures and screening technologies.

At the intersection of FinTech adoption and bank performance, recent synthesis work highlights that FinTech can affect profitability, efficiency, risk, and competitive positioning, implying that monetary transmission is likely to be conditioned by how digital capabilities change bank behavior and balance-sheet composition (15). Micro-level drivers of FinTech adoption and service innovation—such as human resource competency potential and innovation capacity—have also been linked to firm growth in banking settings, suggesting that digital readiness is not homogeneous across institutions and therefore may generate heterogeneous responses to monetary policy shocks (16). From the perspective of smaller economies with bank-centered finance, studies of corporate lending determinants emphasize that macroeconomic factors (including inflation and interest rates) interact with bank-specific features in shaping credit supply, a point made explicit in analyses focused on Latvia’s lending environment (17). Digital-era financial behavior is also shaped by financial literacy and consumer decision-making capabilities; if literacy is low, households may respond sub-optimally to interest-rate changes, affecting credit demand, refinancing behavior, and default risk—all of which feed back into the policy transmission process (18). Complementary evidence on the development of the lending industry in Latvia further reinforces that institutional trajectories and

market evolution influence lending behavior and product structure, which are directly relevant for understanding monetary-policy pass-through into credit outcomes (19, 20).

Another increasingly relevant contextual factor for banking-sector dynamics—especially in emerging and transition economies—is the presence and scale of the shadow economy. Shadow activity can distort the measurement of income, consumption, and creditworthiness; it can also affect banks' risk assessments and the effectiveness of policy transmission because informal economic activity reduces the transparency of borrower cash flows and can shift financing demand toward non-bank channels. Regional evidence and measurement initiatives, such as the Baltic shadow economy index, provide a structured way to think about how informal activity varies over time and may correlate with macro-financial conditions (21). Beyond measurement, cross-country empirical work suggests that relationships between foreign direct investment and the shadow economy can be complex and potentially bidirectional, implying that macroeconomic openness and institutional quality interact with informality—factors that may also condition banking outcomes and policy effectiveness (22). For countries grappling with both inflation volatility and constraints in formal financing, shadow economy dynamics can serve as a competing channel that weakens the reach of monetary policy through formal banks, or alternatively as a background risk factor that changes banks' portfolio choices and risk premia.

Given these overlapping forces—monetary-policy credibility and stance, inflation dynamics, credit risk and bank risk-taking, and the digitization of intermediation—the methodological challenge is to identify causal ordering and dynamic interactions in a way that respects economic structure. Structural models are particularly useful when the goal is not only to measure correlations but also to isolate policy shocks and trace their propagation through banking and macroeconomic variables. From a theoretical and empirical standpoint, it is also essential to recognize that uncertainty and intertemporal preference structures can shape how agents react to shocks over time; frameworks that emphasize the temporal resolution of uncertainty and the role of preference features such as correlation aversion provide a conceptual lens for understanding why responses to identical shocks may vary across regimes and horizons (23). In the banking context, this matters because policy shocks affect not only current-period lending and rates but also expectations about future inflation, refinancing opportunities, credit losses, and regulatory constraints, all of which influence dynamic adjustment paths.

The Iranian economy offers an especially informative setting for studying these issues because banking intermediation plays a central role in financing, monetary policy operates in an environment where inflation and expectations management are persistent challenges, and digital banking services have expanded rapidly in recent years. The joint evolution of internet banking, mobile banking, and digital transaction intensity suggests that innovation in service delivery is not a marginal add-on but a potentially meaningful structural shift that could modify the responsiveness of loan supply and the pass-through of policy rates to effective borrowing costs. At the same time, credit risk indicators—such as non-performing loans and broader measures of banking risk exposure—remain critical constraints on how banks respond to monetary impulses. Existing domestic-focused studies emphasize that macroeconomic stability objectives and the central bank's role are closely tied to the effectiveness of policy instruments, and that banking-sector reactions to monetary policy changes are not uniform across time and policy regimes (2, 4). In addition, broader assessments of monetary and banking economics in Iran suggest that structural and institutional factors—including market structure, regulatory practices, and the composition of bank assets and liabilities—need to be incorporated when interpreting policy effectiveness (3). These features make a structural

approach to identifying monetary shocks and quantifying their effects on banking-sector innovation and risk both appropriate and necessary.

Accordingly, the present study positions itself at the intersection of three literatures that are often treated separately: (1) monetary policy effectiveness and credibility; (2) banking-sector credit risk, loan growth, and risk-taking behavior; and (3) digital transformation, FinTech adoption, and the ICT-enabled restructuring of financial intermediation. By integrating these strands, the study seeks to clarify whether the emergence of innovative banking activities strengthens the transmission of monetary policy by increasing responsiveness and reducing frictions, or whether it introduces new forms of heterogeneity and risk that complicate policy outcomes. It also aims to show how credit risk conditions can amplify or dampen monetary shocks, and how inflation and interest-rate dynamics interact with banking innovation to produce the observed trajectories in a bank-based financial system.

This study aims to examine the effects of shocks arising from the emergence of innovative activities in the banking sector and credit risk on the effectiveness of monetary policy in Iran, with emphasis on the role of the Information and Communication Technology (ICT) index.

Methods and Materials

The present study is applied in terms of purpose and descriptive–analytical in terms of nature, and the Structural Vector Autoregression (SVAR) approach is employed to estimate the model. The study period spans **2009 to 2023** and uses quarterly data. In this study, a structural VAR model is specified to examine the effects of monetary policy shocks in Iran in the presence of the emergence of innovative activities. To assess the robustness of the results, a large number of alternative VAR specifications as well as alternative identification schemes, including the standard Cholesky decomposition, are considered.

Blanchard and Bernanke (1986), and Sims and Watson (1986), by imposing theoretical restrictions on the contemporaneous effects of shocks, developed the SVAR framework; subsequently, Blanchard and Quah (1989), Clarida and Gali (1994), and Ashley and Granger (1996), by applying theoretical restrictions on the long-run effects of shocks, identified impulse response functions. Therefore, unlike unrestricted VAR models in which the identification of structural shocks is carried out implicitly and arbitrarily, structural vector autoregressive (SVAR) models explicitly incorporate economic logic or rely on economic theory to impose constraints and restrictions.

In other words, model stability depends on whether the effect of a shock on the disturbance term is transitory or persistent. If the effect of a shock on the disturbance term dissipates over time, the model is stable; if the effect is persistent, the model is unstable. It is noteworthy that a stable model is also stationary, meaning that its first- and second-order moments are not functions of time.

Accordingly, the fundamental relationship established between the reduced form and the structural form in an SVAR model is expressed as follows:

$$A\varepsilon_t = BU_t$$

$$X_t = a_0 + a_1^t + a_2^{t^2} + B^{-1}A(L)X_{t-1} + B^{-1}e_t$$

In the above equations, ε_t and U_t denote the vectors of reduced-form disturbance terms (ε_t) and structural disturbance terms (U_t), respectively. Both ε_t and U_t are $(K \times 1)$ vectors, and A and B are $(K \times K)$ matrices. According to the studies by Blanchard (1989), Giannini (1992), and Sims (1986), contemporaneous correlations among variables can be represented through the two invertible square matrices A and B .

$$\begin{bmatrix} \varepsilon_{INOV} \\ \varepsilon_{NPL} \\ \varepsilon_{LoanG} \\ \varepsilon_{CR} \\ \varepsilon_{INF} \\ \varepsilon_{INR} \\ \varepsilon_{ICT} \\ \varepsilon_{LR} \\ \varepsilon_{CD\ Ratio} \end{bmatrix} = \begin{bmatrix} a_{11}(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21}(1) & a_{22}(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{31}(1) & a_{32}(1) & a_{33}(1) & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{41}(1) & a_{42}(1) & a_{43}(1) & a_{44}(1) & 0 & 0 & 0 & 0 & 0 \\ a_{51}(1) & a_{52}(1) & a_{53}(1) & a_{54}(1) & a_{55}(1) & 0 & 0 & 0 & 0 \\ a_{61}(1) & a_{62}(1) & a_{63}(1) & a_{64}(1) & a_{65}(1) & a_{66}(1) & 0 & 0 & 0 \\ a_{71}(1) & a_{72}(1) & a_{73}(1) & a_{74}(1) & a_{75}(1) & a_{76}(1) & a_{77}(1) & 0 & 0 \\ a_{81}(1) & a_{82}(1) & a_{83}(1) & a_{84}(1) & a_{85}(1) & a_{86}(1) & a_{87}(1) & a_{88}(1) & 0 \\ a_{91}(1) & a_{92}(1) & a_{93}(1) & a_{94}(1) & a_{95}(1) & a_{96}(1) & a_{97}(1) & a_{98}(1) & a_{99}(1) \end{bmatrix} \begin{bmatrix} U_{INOV} \\ U_{NPL} \\ U_{LoanG} \\ U_{CR} \\ U_{INF} \\ U_{INR} \\ U_{ICT} \\ U_{LR} \\ U_{CD\ Ratio} \end{bmatrix}$$

The left-hand side of the above equation represents the logarithmic first differences of the dependent variables. On the right-hand side, $A(L)$ is a square matrix containing polynomials in the lag operator. For example, the element in the i -th row and j -th column of the matrix $A(L)$, denoted as $a_{ij}(L)$, represents the response of the i -th variable to the j -th structural variable. The vector $E = [U_{ij}]$ contains the structural disturbance terms, which are defined as follows:

$U_{CDRATIO}$: shocks related to the ratio of outstanding loans to deposits, representing the effectiveness of monetary policy.

U_{INOV} : shocks related to the emergence of innovative activities.

U_{NPL} : shocks related to the ratio of non-performing loans to total loans.

U_{LoanG} : shocks related to the growth of bank loans.

U_{CR} : shocks related to credit risk (defined as the ratio of (outstanding bank loans + outstanding bank commitments) to total assets).

U_{INF} : shocks related to inflation.

U_{INR} : shocks related to the short-term nominal interest rate.

U_{ICT} : shocks related to the information technology index.

U_{LR} : shocks related to liquidity risk (defined as [(liabilities of state-owned banks to the central bank + current, savings, and short-term deposits) minus (cash + coins + net balance with the central bank + deposits with other state-owned banks + purchased participation bonds)] divided by total assets).

In the Blanchard–Quah (1989) approach, the identification of structural shocks is fundamentally carried out by imposing a set of restrictions on the long-run effects of shocks on certain variables, and within this framework, the effects of variables are subsequently evaluated.

Findings and Results

Initially, the measurement and extraction of the index of the emergence of innovative activities are carried out using the Principal Component Analysis (PCA) method.

In this study, the following variables are used to construct the composite index of the emergence of innovative activities:

Variable — Definition:

BAC — Ratio of the number of bank accounts to population

ATM — Ratio of the number of automated teller machines (ATMs) to population

INTB — Ratio of the value of transactions conducted through internet banking

MOBB — Ratio of the value of transactions conducted through mobile banking

To determine the general direction of the data points, an ellipse is drawn to identify the correlation among the variables.

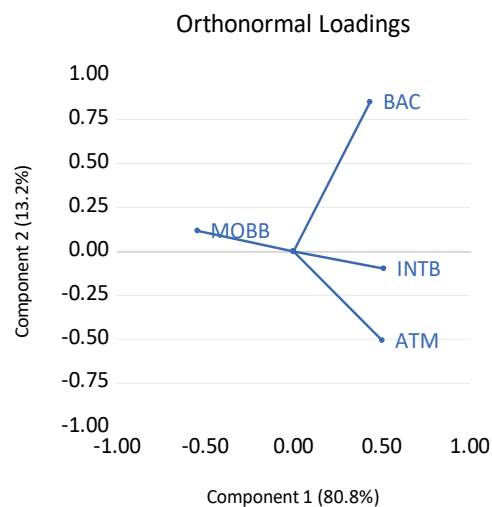


Figure 1. Transformation of data into principal components

The main direction of the dispersion of points is neither along X_1 nor along X_2 nor along the other variables; rather, it lies between them and predominantly along the major diagonal of the ellipse. This axis is referred to as **PC1**, which represents the first principal component of the variability in X_1 , X_2 , and the other variables. The second component (**PC2**) lies along the minor diagonal of the ellipse, is exactly orthogonal to PC1, and explains the remaining variation in X_1 , X_2 , and the other variables. PC1, PC2, and the remaining components constitute the new axes for explaining X_1 , X_2 , and the other variables. Therefore, it can be stated that X_1 , X_2 , and the remaining variables up to X_4 are linear combinations of PC1, PC2, ..., PC4.

The number of extracted components in each model equals the number of variables under consideration; however, a specific number of components can be selected. Typically, the first two or three components account for a substantial portion of the data variance. Hence, selecting the first two or three components is usually sufficient for further analysis, although in some cases it is necessary to consider additional criteria to determine the appropriate number of components. These criteria include:

First criterion (Scree test): plotting eigenvalues against the associated principal components yields the scree plot. This plot illustrates changes in the importance of eigenvalues for each principal component. **Figure 2** presents a hypothetical scree plot. As observed, the eigenvalue of the first vector (the variance explained by the first vector) is approximately 3.2, the eigenvalue of the second vector is about 0.5, and ultimately the eigenvalue of the fourth vector is less than 0.1. This indicates a rapid initial decline in importance followed by a leveling-off. The breakpoint

indicates the maximum number of principal components that should be retained. One fewer component than the breakpoint may also be appropriate. Accordingly, in Figure 2, the first component can be selected.

Second criterion (Eigenvalue): components with eigenvalues greater than one are retained, while the remaining components are discarded.

Third criterion (Variance): components that explain a larger percentage of the variance are sufficient for further analysis; typically, the first component accounts for the largest share of variance.

Scree Plot (Ordered Eigenvalues)

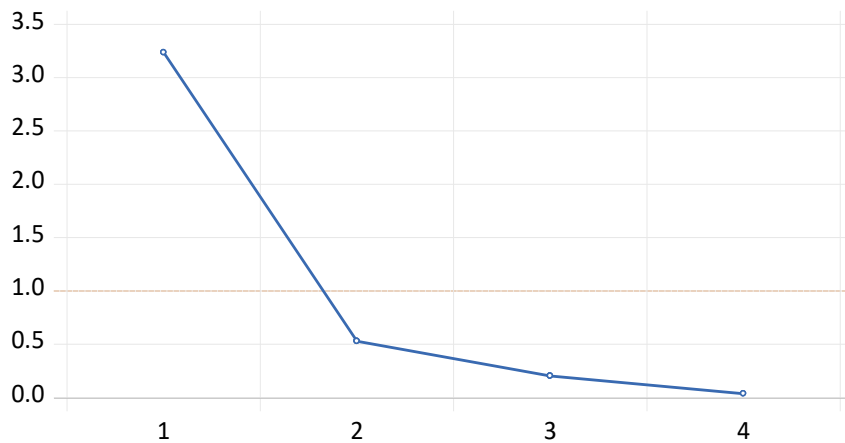


Figure 2. Eigenvalues of the Principal Components

To extract the index of the emergence of innovative activities, four variables were used: the ratio of the number of bank accounts to population, the ratio of the number of automated teller machines (ATMs) to population, the ratio of the value of transactions conducted through internet banking, and the ratio of the value of transactions conducted through mobile banking.

Table 1. Correlation Matrix of the Indicators of the Emergence of Innovative Activities

	BAC	ATM	INTB	MOBB
BAC	1.000000			
ATM	0.500500	1.000000		
INTB	0.644274	0.788457	1.000000	
MOBB	-0.715569	-0.921545	-0.860885	1.000000

Table 1 shows that there is a relatively high correlation among the above-mentioned indicators. Therefore, by reducing the dimensionality of the variables, the index of the emergence of innovative activities is extracted using the Principal Component Analysis (PCA) method.

Table 2 indicates that the eigenvalue of the first component is larger than those of the other components and that approximately 60% of the total data variance is explained by this component. Accordingly, this component is selected as the most appropriate representation for the index.

Table 2. Results of Estimating the Composite Index of the Emergence of Innovative Activities Using PCA

Number	Value	Difference	Proportion	Cumulative Value
1	3.233975	2.706256	0.8085	3.233975
2	0.527720	0.325370	0.1319	3.761695
3	0.202349	0.166394	0.0506	3.964045
4	0.035955	—	0.0090	4.000000

Eigenvectors (Loadings)

Variable	PC1	PC2	PC3	PC4
BAC	0.434627	0.848401	-0.189454	0.235420
ATM	0.502621	-0.506836	-0.423262	0.557977
INTB	0.512378	-0.098674	0.848081	0.092150
MOBB	-0.544004	0.116604	0.256350	0.790410

Eigenvalues (Sum = 4, Average = 1)

The relationship between the observed variables and the principal components can be expressed using factor loadings, and the estimation of the principal components using factor scores can be written as follows:

$$PC1 = 0.43 BAC + 0.50 ATM + 0.51 INTB - 0.54 MOBB$$

Accordingly, the linear combination of the first principal component (PC1), representing the index of the emergence of innovative activities, is specified as above.

Finally, the weight of each sub-index in the composite index of the emergence of innovative activities is presented in the following table.

Table 3. Relative Importance of Variables in the Composite Index of the Emergence of Innovative Activities

Variable	Relative Importance (%)
INTB	60.85
ATM	13.19
BAC	9.06
MOBB	16.19

Table 3 presents the relative importance of the components of the overall index by selected variables using the rotational elements regression approach. Based on the obtained weights, internet banking has the greatest contribution to the composite index of the emergence of innovative activities. Finally, using the *Make Principal Component Analysis* command, the composite index related to the emergence of innovative activities is extracted and employed in the final model of the study.

First, to ensure the absence of spurious regression, unit root and cointegration tests are applied. In this study, the commonly used Phillips–Perron (PP) test is employed.

Table 4. Results of the Phillips–Perron (PP) Test for Model Variables

Variable	Test Statistic	Probability	Stationarity Status
CDRATIO	-1.376700	0.1549	—
D(CDRATIO)	-16.49681	0.0000	I(1)
ICT	-0.652788	0.4302	—
D(ICT)	-13.38912	0.0000	I(1)
INF	-1.005227	0.2792	—
D(INF)	-8.548167	0.0000	I(1)
INR	0.229527	0.9026	—
D(INR)	-10.34210	0.0001	I(1)
INVO	-0.550667	0.4744	—
D(INVO)	-14.51887	0.0000	I(1)
LOANG	-1.246608	0.1931	—
D(LOANG)	-11.39086	0.0000	I(1)
NPL	-0.197986	0.6107	—
D(NPL)	-11.91252	0.0000	I(1)
CR	0.737323	0.9258	—
D(CR)	-12.10128	0.0001	I(1)
LR	3.556761	0.9956	—
D(LR)	-12.52480	0.0000	I(1)

Considering the theoretical foundations of stationarity tests, the null hypothesis (H_0) in these tests assumes non-stationarity of the variable. Based on the test results, it can be concluded that all variables in the model are stationary at the first difference, that is, they are integrated of order one, $I(1)$.

Since the variables of the model are integrated of the same order, $I(1)$, a cointegration test is employed to identify the existence of a long-run equilibrium relationship among the model variables. For this purpose, the Johansen–Juselius method is used. Implementing this test requires determining the number of cointegrating vectors. To evaluate the cointegration test results, an appropriate specification must be selected regarding the presence or absence of a deterministic trend and an intercept in the cointegrating vector. In this regard, five alternative specifications are considered: (1) no intercept and no deterministic trend; (2) restricted intercept and no deterministic trend; (3) unrestricted intercept and no deterministic trend; (4) unrestricted intercept and restricted deterministic trend; and (5) unrestricted intercept and unrestricted deterministic trend. These five specifications are estimated from the most restrictive (Specification 1) to the least restrictive (Specification 5). Subsequently, the null hypothesis of no cointegrating vector is tested against the alternative of one cointegrating vector, followed by testing the null hypothesis of at most one cointegrating vector against the alternative of two vectors. This procedure continues until testing for the existence of up to $n - 1$ cointegrating vectors, where n denotes the number of variables. A summary of the results of the trace test (λ_{Trace}) and the maximum eigenvalue test (λ_{Max}) regarding the number of cointegrating vectors across the five specifications is reported in Table 5. As shown, the null hypothesis of no cointegrating vector against the existence of at least one cointegrating vector among the variables is rejected; therefore, at least one cointegrating relationship exists among the variables under study.

Table 5. Summary of Results on the Number of Cointegrating Vectors

Specification	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
Trace Test	4	4	9	5	7
Maximum Eigenvalue Test	6	3	5	8	2

The estimation results of the model and the cointegration tests corresponding to Specification 3 of the Johansen test are reported in the following table. Based on the trace test results, the existence of nine cointegrating vectors is confirmed, and according to the maximum eigenvalue test results, the existence of five cointegrating vectors at the 5% significance level is also confirmed.

Table 6. Cointegration Test Results

Max-Eigen Statistic	95% Critical Value	Probability	Trace Statistic	95% Critical Value	Probability	H1	H0
101.5471	58.43354	0.0000	348.5925	197.3709	0.0000	r = 1	r = 0
58.01775	52.36261	0.0119	247.0454	159.5297	0.0000	r = 2	r ≤ 1
51.93304	46.23142	0.0111	189.0276	125.6154	0.0000	r = 3	r ≤ 2
42.46551	40.07757	0.0264	137.0946	95.75366	0.0000	r = 4	r ≤ 3
37.25294	33.87687	0.0190	94.62909	69.81889	0.0002	r = 5	r ≤ 4
20.76930	27.58434	0.2904	57.37616	47.85613	0.0050	r = 6	r ≤ 5
15.61305	21.13162	0.2483	36.60685	29.79707	0.0070	r = 7	r ≤ 6
14.20228	14.26460	0.0511	20.99380	15.49471	0.0067	r = 8	r ≤ 7
6.791517	3.841466	0.0092	6.791517	3.841466	0.0092	r = 9	r ≤ 8

After establishing the stationarity of the model variables, the first issue in vector autoregressive models is determining the optimal lag length. Here, the Schwarz–Bayesian criterion (SC), Akaike Information Criterion (AIC), Final Prediction Error (FPE), Hannan–Quinn criterion (HQ), and the Likelihood Ratio (LR) test are used to determine the optimal lag length. The results reported in Table 7 indicate that, based on the likelihood ratio, final prediction error, Akaike, and Hannan–Quinn criteria, a lag length of one is selected as optimal. Similarly, according to the Schwarz–Bayesian criterion, a lag length of one is chosen as optimal. Ultimately, since the Schwarz–Bayesian criterion follows the principle of parsimony and assigns greater importance to reducing the number of parameters or simplifying the system (as opposed to achieving a better fit), it is more appropriate for small sample sizes—particularly the selected sample size in this study. Accordingly, one lag is chosen as the optimal lag length for the model.

Table 7. Determination of the Optimal Lag Length in the VAR Model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	423.5732	NA	3.00e-18	-14.80619	-14.48068	-14.67999
1	550.8794	209.1459	6.95e-19*	-19.45998*	-15.20495*	-15.19801*
2	648.1923	128.5920	4.13e-19	-17.04258	-10.85803	-14.64484
3	760.9417	112.7494*	2.51e-19	-18.17649	-9.062405	-14.64298
4	864.1143	70.01001	5.16e-19	-18.96837	-6.924758	-14.29909

LR: Likelihood Ratio criterion; FPE: Final Prediction Error; AIC: Akaike Information Criterion; SC: Schwarz–Bayesian Criterion; HQ: Hannan–Quinn Criterion.

To ensure that the regression is not spurious, a unit root test for the entire regression model is also conducted. If the SVAR model is unstable, the obtained results are not reliable. To assess the stability of the estimated model, the AR roots diagram is used. This diagram displays the inverse roots of the characteristic polynomial of an AR process. If the absolute values of all roots are less than one and lie within the unit circle, the estimated SVAR model is stable. The AR roots diagram of the model shown in Figure 3 indicates that the inverses of all characteristic roots lie within the unit circle, confirming that the estimated SVAR model satisfies the stability condition.

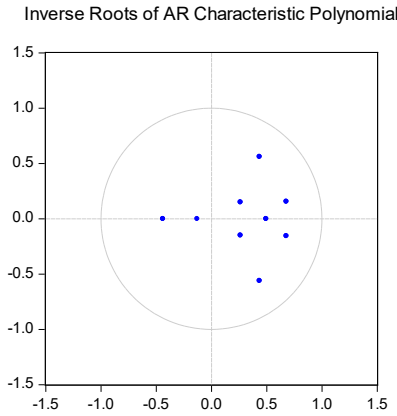


Figure 3. Unit Root Test

The SVAR results aimed at examining the effects of the explanatory variables on monetary policy effectiveness are reported in the table below. This table presents the system of equations for structural shocks and reduced-form shocks. In the table below, @e1 denotes shocks related to the emergence of innovative activities; @e2 denotes shocks related to the ratio of non-performing loans to total loans; @e3 denotes shocks related to bank loan growth; @e4 denotes shocks related to credit risk; @e5 denotes shocks related to inflation; @e6 denotes shocks related to the short-term nominal interest rate; @e7 denotes shocks related to the information technology index; @e8 denotes shocks related to liquidity risk; and @e9 denotes shocks related to the loans-to-deposits ratio as an indicator of monetary policy effectiveness. The estimation results are presented in Table 8.

Table 8. Estimation of the Long-Run Equilibrium Relationship for the Research Model

Variable	Coefficient	Std. Error	t-Statistic	Probability
C(37)	0.197885	0.085146	2.324058	0.0201
C(38)	-0.405377	0.164099	-2.470328	0.0135
C(39)	0.053752	0.022425	2.396934	0.0165
C(40)	-0.092756	0.043199	-2.147184	0.0318
C(41)	-0.065123	0.032376	-2.011449	0.0443
C(42)	-0.197044	0.186457	-1.056781	0.2955
C(43)	0.032906	0.013605	2.418698	0.0234
C(44)	-0.097980	0.028983	-3.380603	0.0008
C(45)	0.433451	0.159418	2.718959	0.0218

Structural VAR Estimates

Model: $Ae = Bu$ where $E[uu'] = I$

Restriction Type: short-run text form

$$@e1 = c(1)*@u1$$

$$@e2 = c(2)*@e1 + c(3)*@u2$$

$$@e3 = c(4)*@e1 + c(5)*@e2 + c(6)*@u3$$

$$@e4 = c(7)*@e1 + c(8)*@e2 + c(9)*@e3 + c(10)*@u4$$

$$@e5 = c(11)*@e1 + c(12)*@e2 + c(13)*@e3 + c(14)*@e4 + c(15)*@u5$$

$$@e6 = c(16)*@e1 + c(17)*@e2 + c(18)*@e3 + c(19)*@e4 + c(20)*@e5 + c(21)*@u6$$

$$@e7 = c(22)*@e1 + c(23)*@e2 + c(24)*@e3 + c(25)*@e4 + c(26)*@e5 + c(27)*@e6 + c(28)*@u7$$

$$@e8 = c(29)*@e1 + c(30)*@e2 + c(31)*@e3 + c(32)*@e4 + c(33)*@e5 + c(34)*@e6 + c(35)*@e7 + c(36)*@u8$$

$$@e9 = c(37)*@e1 + c(38)*@e2 + c(39)*@e3 + c(40)*@e4 + c(41)*@e5 + c(42)*@e6 + c(43)*@e7 + c(44)*@e8 + c(45)*@u9$$

where

@e1 represents INVO residuals

@e2 represents NPL residuals

@e3 represents LOANG residuals

@e4 represents CR residuals

@e5 represents INF residuals
 @e6 represents INR residuals
 @e7 represents ICT residuals
 @e8 represents LR residuals
 @e9 represents CDRATIO residuals

To examine the statistical significance of the coefficients of the independent variables in each model, the t-statistic is used. The null hypothesis in the t-test is formulated as:

$$H_0: \beta_i = 0$$

which is evaluated using the following statistic:

$$t = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}$$

To decide whether to accept or reject the null hypothesis, the computed t-statistic is compared with the critical value from the t-distribution with $N - K$ degrees of freedom at the 95% confidence level. If the absolute value of the computed t-statistic exceeds the tabulated critical value, the test statistic falls within the critical region and the null hypothesis is rejected. In this case, at the 95% confidence level, the relevant coefficient is statistically significant, indicating the existence of a relationship between the independent and dependent variables.

The SVAR estimation results indicate that the coefficients of most of the main variables influencing business cycles are statistically significant and consistent with the conditions of the Iranian economy. The key variables that are necessary and meaningful to interpret in the SVAR results include shocks originating from the index of the emergence of innovative activities, bank loan growth, and the information technology index, all of which have positive and statistically significant effects on monetary policy effectiveness in Iran. Specifically, a shock to the index of the emergence of innovative activities improves monetary policy effectiveness by approximately 19%, and a shock to bank loan growth improves monetary policy effectiveness by about 5%. Finally, a shock to the ICT index improves monetary policy effectiveness by approximately 3%.

To appropriately analyze the long-run equilibrium relationship in the structural VAR (SVAR) model, it is necessary to examine impulse response functions and variance decomposition. In other words, the SVAR framework provides two powerful tools for analyzing macroeconomic fluctuations: impulse response functions (IRFs) and variance decomposition. Therefore, after estimating the SVAR model, the results of the IRFs and variance decomposition can be examined. An impulse response function reflects the effects of a one-standard-deviation shock to the endogenous variables in the model. For the model used in this study, the response of the monetary policy effectiveness variable to a one-standard-deviation shock (i.e., a sudden change) in each endogenous variable is illustrated in the figure below. The horizontal axis represents time in annual periods, and the vertical axis shows the percentage change in the variable.

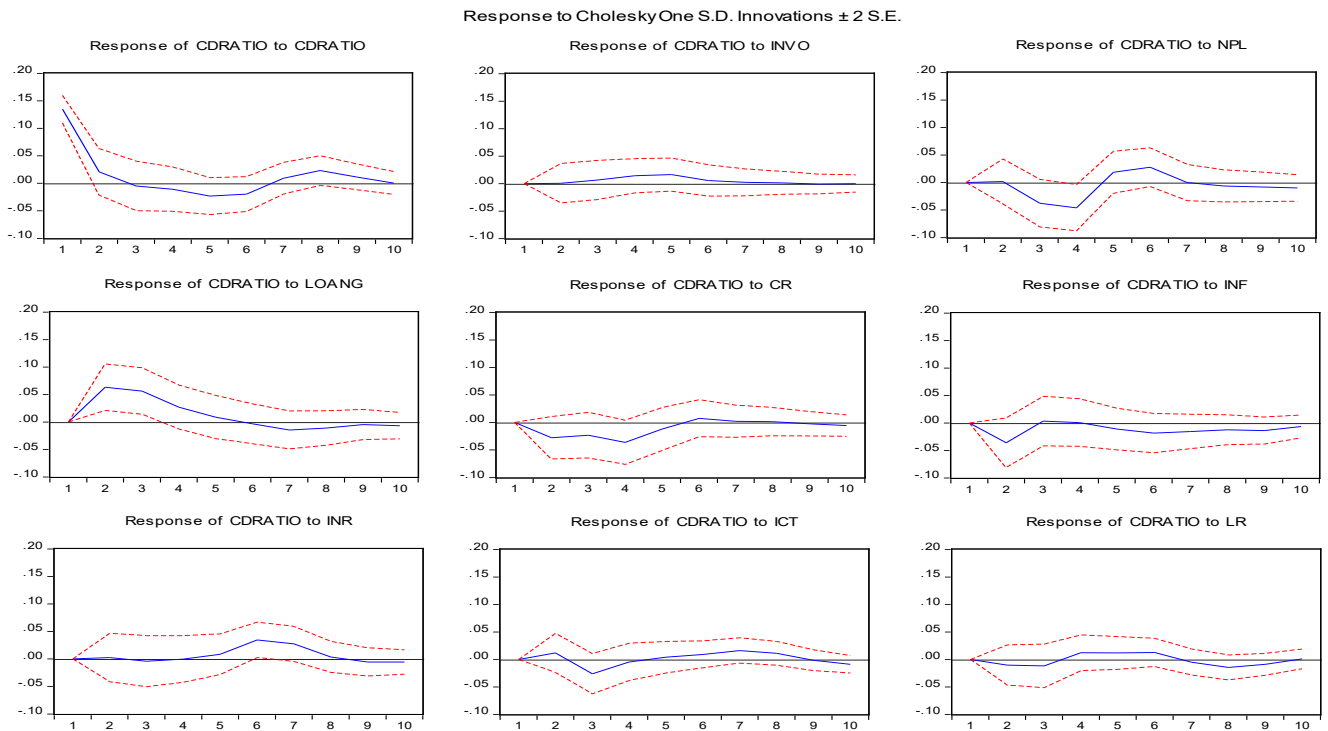


Figure 4. Impulse Response Function Results for the Model

The IRF results (Figure 4) indicate that the effects of shocks originating from the index of the emergence of innovative activities on monetary policy effectiveness follow an increasing trend up to the first five periods; thereafter, the effect gradually diminishes, and the shock dissipates over time. Moreover, the IRF results for bank loan growth (i.e., the loan shock) show that an increase in bank lending during the first four periods leads to an increase in monetary policy effectiveness, after which the response follows a downward trajectory and converges toward zero in the long run. Similarly, the shock to the ICT index increases monetary policy effectiveness in the first two periods, then declines and converges to zero in the long run. Regarding the other variables, as shown, shocks from NPL reduce monetary policy effectiveness for up to four periods, shocks from CR reduce it for up to four periods, and shocks from LR reduce it for up to three periods; subsequently, these effects converge toward zero over time and the shocks dissipate.

In this section, based on the estimated model, variance decomposition of the model variables is performed, and the results are reported in Table 9. In this table, the S.E. column denotes the forecast error for the relevant variables across different periods.

Table 9. Variance Decomposition Results for the Model

Period	S.E.	CDRATIO	INVO	NPL	LOANG	CR	INF	INR	ICT	LR
1	0.134846	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.157939	74.60829	0.014521	0.554772	5.249523	0.025091	15.99725	0.001177	3.112939	0.436432
3	0.175993	60.16163	4.601049	2.665209	4.264973	0.074596	23.06621	0.138022	4.222359	0.805956
4	0.188689	52.66060	9.926841	2.378240	3.710816	0.064970	22.11663	0.690022	7.346549	1.105327
5	0.193196	51.68035	10.39394	2.309338	3.876038	0.258881	21.30341	1.364661	7.390998	1.422384
6	0.200883	48.75043	11.51820	2.340029	4.440441	3.209813	19.73103	1.335658	6.976354	1.698048
7	0.204805	47.10233	11.08126	2.875195	4.852991	4.874420	19.49932	1.296884	6.724407	1.693186
8	0.207735	47.02068	10.86005	3.075252	5.078803	4.765962	19.24371	1.263373	6.541527	2.150644
9	0.209005	46.75220	10.87011	3.044451	5.453137	4.778327	19.06144	1.249892	6.474496	2.315952
10	0.209795	46.40130	11.01184	3.208462	5.506204	4.811711	19.02088	1.240509	6.498534	2.300566

Because this forecast error is computed each year based on the previous year's error—and its source is changes in current values and future shocks—it increases over time. The results in Table 9 show that the forecast error in the first period is 0.1348 and in the second period is 0.1579, and it increases over time. The subsequent columns report the percentage of variance attributable to a sudden change or a specific shock. The third column indicates that although in the first period 100% of the variation is explained by shocks to monetary policy effectiveness itself and in the second period 74.60% of the variation is due to shocks to monetary policy effectiveness, by the tenth period the variation in this index is explained as follows: 46.40% by shocks to monetary policy effectiveness, 11.01% by shocks to the index of the emergence of innovative activities, 19% by inflation shocks, and 6.49% by shocks to the ICT index. The remaining fluctuations are explained by other explanatory variables. Among the model variables, inflation shocks and the index of the emergence of innovative activities account for the largest shares of explanatory power over the examined period, which is fully justifiable for the Iranian economy and was discussed in general terms above. Meanwhile, the interest rate variable has the lowest explanatory power, which is also clearly observed in both the model estimation results and the impulse response analysis.

Discussion and Conclusion

The findings of this study provide robust evidence that the effectiveness of monetary policy in Iran is significantly shaped by the interaction between banking-sector innovation, credit risk conditions, and macroeconomic variables, particularly inflation and interest rates. The SVAR results indicate that shocks associated with the emergence of innovative banking activities—proxied through a composite index capturing internet banking, mobile banking, ATM density, and bank account penetration—exert a positive and statistically significant effect on monetary policy effectiveness. This result suggests that financial innovation, especially ICT-enabled service delivery, enhances the responsiveness of the banking system to policy signals and improves the transmission of monetary impulses to credit markets. Such an outcome aligns closely with recent theoretical and empirical arguments emphasizing that digital transformation can reduce informational frictions, accelerate balance-sheet adjustments, and increase operational flexibility in banks, thereby strengthening the monetary transmission mechanism (11, 15).

More specifically, the estimated coefficients show that a positive innovation shock leads to a measurable improvement in the loans-to-deposits ratio, which is used in this study as an indicator of monetary policy effectiveness. This finding can be interpreted as evidence that innovative banking channels allow banks to adjust their lending behavior more efficiently in response to policy changes. Digital platforms reduce transaction costs, improve customer reach, and enable more granular credit assessment, all of which facilitate faster and more targeted credit expansion or contraction following policy shocks. These results are consistent with evidence from European banking systems, where digitalization has been shown to reshape lending behavior and alter the spatial and functional organization of banks, with implications for inclusion and policy pass-through (13, 14). In this sense, the Iranian experience appears to mirror broader international patterns, despite institutional and macroeconomic differences.

The positive role of bank loan growth in enhancing monetary policy effectiveness further reinforces the importance of the credit channel. The results indicate that shocks to loan growth have a statistically significant and positive impact on the policy effectiveness indicator, particularly in the short to medium term. This finding is consistent with the traditional bank lending channel, whereby changes in policy conditions affect banks' ability and willingness to supply credit, which in turn influences real economic activity. Empirical studies focusing on corporate

investment and banking behavior in Iran have similarly documented that monetary policy and credit conditions jointly determine investment flows and financial decision-making (5, 6). The present study extends this literature by showing that loan growth does not operate in isolation; rather, its effect on policy effectiveness is amplified in an environment characterized by higher levels of banking innovation and ICT penetration.

Inflation shocks emerge as one of the most influential factors in explaining variations in monetary policy effectiveness over time. The variance decomposition results demonstrate that, beyond the own shocks of the policy effectiveness indicator, inflation accounts for a substantial share of forecast error variance, particularly in longer horizons. This underscores the central role of inflation dynamics in shaping the success or failure of monetary interventions. In high-inflation environments, banks and borrowers may focus more on nominal variables, expectations, and short-term adjustments, potentially weakening the real effects of policy instruments. The finding that inflation shocks can dampen or complicate policy transmission is consistent with international evidence showing that inflation experiences influence credit behavior, mortgage choices, and interest rate sensitivity (8, 9). Moreover, studies examining interest rate formation and lending behavior under inflationary pressure suggest that policy rate adjustments alone may be insufficient to control credit dynamics when inflation expectations are poorly anchored (10).

Credit risk variables, including non-performing loans (NPLs) and broader credit risk measures, are found to have a negative and statistically significant impact on monetary policy effectiveness in the short run. Impulse response functions indicate that shocks to NPLs and credit risk reduce the effectiveness of policy for several periods before their effects dissipate. This pattern highlights the constraining role of bank balance-sheet health in the transmission process. When credit risk rises, banks tend to tighten lending standards, increase provisioning, and reallocate portfolios toward safer assets, even in the presence of accommodative monetary conditions. This behavior weakens the pass-through of policy easing and can delay or blunt its intended stimulative effects. The result is fully in line with the bank risk-taking and balance-sheet channels emphasized in recent studies, which argue that monetary policy can influence bank risk behavior, but that elevated risk levels can also feedback negatively into policy effectiveness (7, 12).

The negative response of monetary policy effectiveness to liquidity risk shocks further supports the view that financial stability conditions are integral to policy transmission. Liquidity risk shocks initially reduce the policy effectiveness indicator, reflecting banks' precautionary behavior when faced with funding uncertainty or maturity mismatches. Over time, as the shock dissipates, the effect converges toward zero, indicating a degree of system resilience. This dynamic is particularly relevant in bank-based systems, where liquidity management plays a critical role in determining lending capacity. Similar concerns have been raised in analyses of banking systems in small open and transition economies, where structural features of the lending industry and funding markets condition banks' responses to macroeconomic shocks (19, 20).

An important contribution of this study lies in demonstrating that the ICT index has an independent and positive effect on monetary policy effectiveness, even after controlling for loan growth, inflation, and credit risk. Although the magnitude of this effect is smaller than that of innovation and inflation shocks, it is statistically significant and persistent in the short run. This finding suggests that ICT infrastructure acts as an enabling factor that enhances the speed and clarity with which policy signals are transmitted through the banking system. By improving payment systems, data processing, and customer interaction, ICT reduces operational frictions and supports more synchronized responses across banks. This result resonates with evidence highlighting the role of digital readiness,

human capital, and service innovation in shaping bank performance and growth outcomes (15, 16). It also complements studies emphasizing that digital transformation can alter the competitive landscape and stability properties of the banking sector, with downstream implications for policy effectiveness (11, 12).

From a broader macro-financial perspective, the results underscore the importance of monetary policy credibility and institutional context. The positive response of policy effectiveness to innovation and ICT shocks is more likely to materialize in an environment where policy signals are perceived as credible and consistent. Previous work on central bank credibility and macroeconomic stability in Iran emphasizes that unclear or inconsistent policy frameworks can weaken expectations and reduce the effectiveness of policy tools (1, 2). The present findings suggest that even with advanced digital tools and innovative banking practices, weak credibility or unstable macroeconomic conditions—such as persistent inflation—can undermine transmission.

Finally, the findings should be interpreted in light of structural features of the Iranian economy, including the role of informality and the shadow economy. While not directly modeled, shadow economic activity can influence credit demand, risk assessment, and the reach of formal banking channels. Evidence from regional and cross-country studies suggests that shadow economy dynamics interact with financial development and investment flows, potentially affecting how monetary policy is transmitted through banks (21, 22). In economies where informal activity is sizable, innovations in digital banking may also serve as a bridge to formalization, indirectly strengthening policy effectiveness over time.

Despite its contributions, this study faces several limitations. First, the analysis relies on aggregate banking and macroeconomic data, which may mask heterogeneity across individual banks in terms of size, ownership, digital readiness, and risk profiles. Second, the composite index of innovative activities, while comprehensive, cannot fully capture qualitative differences in the depth and sophistication of digital banking services. Third, the SVAR framework, although well-suited for identifying structural shocks, depends on identifying restrictions that may be sensitive to alternative theoretical assumptions. Finally, the study does not explicitly model the role of expectations or informal financial channels, which may be particularly relevant in the Iranian context.

Future research could extend this analysis by employing bank-level or borrower-level data to explore heterogeneous responses to monetary policy across different types of banks and customer segments. Incorporating explicit measures of expectations, financial literacy, and informal economic activity could further enrich the understanding of transmission mechanisms. Comparative studies across countries with similar banking structures but different levels of digitalization would also help clarify the generalizability of the findings. Moreover, applying alternative identification strategies or nonlinear models could shed light on potential asymmetries in policy transmission across tightening and easing cycles.

From a practical standpoint, policymakers should view banking innovation and ICT development as complementary tools for enhancing monetary policy effectiveness rather than as purely operational upgrades. Strengthening digital infrastructure, improving data integration, and promoting secure digital banking can increase the responsiveness of credit markets to policy actions. At the same time, maintaining financial stability through effective credit risk management and liquidity oversight is essential to prevent innovation-driven expansion from undermining policy goals. Finally, consistent communication and credibility-building measures by the central bank can help ensure that the benefits of innovation and digitalization translate into more predictable and effective monetary outcomes.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adhered in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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