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The Spillover Effects of Agricultural Credit on Agricultural Value Added in Selected Western Provinces of Iran: Spatial Panel Approach

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Abstract

The Agricultural Bank is the primary official financial institution in Iran's agricultural sector, playing an irreplaceable role in financing agricultural activities. This study examines the spillover effects of Agricultural Bank credit allocations on the growth of agricultural value-added in Iran's western provinces from 2001 to 2019. Using a spatial panel econometric approach and the Solow growth model, the findings reveal that the nominal value of credits has a positive impact on the nominal value-added of the agricultural sector. However, the real value of credits does not significantly affect real agricultural value-added, indicating that credit allocations have not kept pace with inflation. Additionally, the study confirms the presence of spillover effects and inter-provincial linkages in agricultural sector growth. Based on these results, we recommend that Agricultural Bank credit allocations be tailored to each province's potential—meaning provinces with higher productivity and production capacity should receive more substantial credit support.

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INTRODUCTION

Increasing agricultural production—a fundamental driver of economic development—depends on targeted investments, technological innovations, and enhanced efficiency in continuous production (Terin et al., 2014). Financing, particularly through bank credit, plays a critical role in enabling farmers' economic access to production factors, thereby facilitating agricultural output (Bahşi & Çetin, 2020). As a core requirement for the agricultural sector and other commercial activities, credit supports the commercialization and modernization of agriculture in rural economies (Rehman et al., 2017). Moreover, it serves as a key instrument for improving production structures and fostering investment in both developed and developing countries (Adanacıoğlu et al., 2017). Access to credit offers three primary benefits: 1) Overcoming financial constraints by enabling farmers to secure essential production inputs, 2) Enhancing technical efficiency through the adoption of advanced technologies and, 3) Optimizing resource allocation and increasing profitability (Sial et al., 2011).

The agricultural sector faces higher production risks than other economic sectors, making its financing more challenging. Due to credit risk concerns, private and commercial banks are often reluctant to extend loans to agriculture. Given the limited savings of most farmers, government-backed bank credits remain the primary source of capital for agricultural producers (Sharifi Renani et al., 2014).

Credit facilities allocated to the agricultural sector can significantly enhance value-added growth by boosting input purchasing power (current expenses) and stimulating investment. Proper credit allocation helps alleviate financial constraints, thereby improving input efficiency and increasing agricultural value-added. Globally, agricultural credit demand primarily stems from the need to expand cultivation areas, purchase machinery and inputs (e.g., seeds), and cover labor costs (Chandio et al., 2017). Financing in this sector occurs through both formal channels—such as government banks, private banks, and credit cooperatives—and informal sources, including loans from relatives and local lenders (Bahşi & Çetin, 2020).

In Iran, the Agricultural Bank serves as a primary source of financing for the agricultural sector. As a specialized financial institution, it plays a pivotal role in allocating credit to agriculture, significantly supporting the sector's development. One key impact of these agricultural credits is fostering technological advancement and promoting modern production methods. Such regional technological progress can generate positive spillover effects, stimulating further innovation and productivity growth in neighboring areas.

In western Iran, characterized by distinct climatic, geographical, and socio-economic conditions, most farmers engage in subsistence agriculture through small-scale landholdings. This pattern is particularly evident in the provinces of Kurdistan, Kermanshah, Hamedan, Lorestan, and Ilam, where agricultural census data (2013) shows that 72, 81, 73, 80, and 85 percent of farming households respectively operate on less than 10 hectares of land. These small-scale operations significantly limit investment capacity in the region. The prevalence of small landholdings presents a major constraint to agricultural development across the country. Consequently, agricultural credit plays a crucial dual role in these areas - supporting both individual smallholder producers and contributing to the broader national economy. The typical small-scale farmer, constrained by limited assets, fragmented landholdings, modest production volumes, and inadequate income and savings, lacks the financial capacity to self-fund agricultural production.

According to official statistics for the 2019-2020 agricultural year, the five selected western provinces of Iran (Hamadan, Kermanshah, Kurdistan, Ilam, and Lorestan) accounted for 25.3 percent of the nation's total cultivated area (Ministry of Agriculture, 2022). However, these provinces received only 9.7 percent of the Agricultural Bank's total specialized credit facilities in 2019, a share that further declined to 7.1 percent in 2020. This disproportionate allocation persists despite the region's significant agricultural output. Notably, while the Agricultural Bank's nationwide credit allocation increased by 19.3 percent in 2020, three western provinces experienced sharp reductions: Hamedan (-25%), Kermanshah (-0.9%), and Kurdistan (-61.5%) compared to 2019 levels (Agricultural Bank, 2020). These cuts occurred despite the region's already inadequate credit access relative to its agricultural activity.

A review of existing literature on the impact of agricultural credits on sectoral value-added reveals extensive research conducted in Iran, developing countries, and developed economies. These studies provide valuable economic insights that facilitate comparative analysis and inform future research directions.

Multiple studies demonstrate the significant impact of agricultural financing on economic indicators. Shabani Koshalshahi et al. (2018) found that while both liquidity and credit positively affect agricultural value-added in Iran, credit shows substantially greater elasticity. Arabmazar et al. (2018) established that both working capital and investment credits significantly enhance value-added, investment, and employment in the agricultural sector. Zoldgadr et al. (2019) revealed that bank loans significantly boost provincial economic growth, with particularly strong effects in low-income provinces, suggesting that regional income levels should guide credit allocation strategies. Fathi Aghababa et al. (2020) demonstrated that both voluntary and mandatory credit programs positively influence sectoral value-added. Finally, Parva et al. (2021) identified a dual effect: agricultural credits correlate positively with sectoral growth but negatively with agricultural employment levels.

Empirical studies across different contexts reveal nuanced relationships between agricultural financing and productivity outcomes. Ogbuabor and Nwosu (2017) demonstrated that while deposit bank loans significantly enhance long-term agricultural productivity (a key growth component), they show no measurable short-term effects. Yalcinkaya (2018) established unidirectional causality, finding agricultural loans Granger-cause agricultural GDP growth without reverse causality. Rehman et al. (2019) identified three significant production drivers: fertilizer use (β=0.32), improved seeds (β=0.28), and bank credit access (β=0.24), all showing $p<0.01$ significance. Bahşi and Çetin (2020) confirmed credit's positive production impact while noting that temporal production conditions (good/bad years) exert 1.8 times greater influence than credit availability. Nakazi and Sunday (2020) further corroborated these findings, showing credit accessibility increases production yields by 18-22 percent across studied regions.

The reviewed literature consistently demonstrates that agricultural credits have a more substantial impact on productivity when allocated directly to production activities rather than to processing and marketing. Most existing studies confirm the positive effect of agricultural financing on both value-added and production outputs. However, these studies predominantly employ time-series analysis at the national level, overlooking potential spatial spillover effects. This methodological gap may lead to underestimating the true importance of agricultural investments. Our study addresses these limitations by conducting a regional analysis that explicitly accounts for spatial spillovers. The findings provide actionable insights for optimizing credit allocation across regions while considering these spatial interdependencies.

This study examines the spillover effects of specialized agricultural credits on agricultural value-added in five western Iranian provinces (Hamadan, Kermanshah, Kurdistan, Ilam, and Lorestan). The research has two specific objectives: (1) to analyze the differential effects of nominal versus real credit values on agricultural value-added, and (2) to assess the spatial spillover effects of credit allocation on agricultural growth using spatial econometric methods.

METHODOLOGY

This study employs Solow's (1956) economic growth theory to analyze the relationship between agricultural credits and sectoral value-added. The Solow-Swan growth model, a foundational neoclassical framework, characterizes long-run economic growth through exogenous factors. Following Abunoori and Khaje Zadeh's (2020) specification, the model is expressed as:

$$Y_t = f(K_t, A_t, L_t) \qquad (1)$$

In the above relation, Y_t is the amount of production, K_t is capital stock, A_t is technical progress and is labor force. This relationship in the form of Cobb-Douglas and its logarithmic form is shown as relations (2) and (3) (Mensah et al., 2019):

$$Y_t = A_t . K_t^{\alpha} . L_t^{\beta} \qquad (2)$$

$$\text{Ln } Y_t = Ln\, A_t + \alpha\, Ln\, K_t + \beta L_t \qquad (3)$$

In the above relations, α and β respectively represent the elasticity of production with respect to capital stock and labor inputs and are 0<β,α<1. In this study, instead of the variable of capital stock (due to lack of access to capital stock in the agricultural sub-sector by selected provinces), agricultural credits were used (Parva et al., 2021) and some other influential variables were also added in the above relation. These variables include people's deposits in the agricultural bank (deposit), the area under cultivation of agricultural products (cropland) (Sharifi Renani et al., 2014) and the amount of rainfall (precip) (Parva et al., 2021). The final model, which was estimated in the study, is presented in equation (4):

$$Ln\, VA_t = Ln\, A_t + \beta_1\, Ln\, credits_t + \beta_2\, Ln\, labor_t + \beta_3\, Ln\, deposit + \beta_4\, Ln\, cropland_t + \beta_5\, Ln\, precip_t + \varepsilon_t \qquad (4)$$

In equation (4), Ln VA_t is the logarithm of the value added of the agricultural sector. Also, in order to investigate the effect of spatial spillovers, the spatial econometric approach was used.

Spatial econometrics represents a specialized branch of econometrics that incorporates spatial relationships into regression analysis. As Almasi et al. (2021) explain, these techniques account for two key spatial characteristics: (1) spatial interdependence (spatial dependence/autocorrelation) and (2) spatial heterogeneity (spatial heteroscedasticity) in cross-sectional or panel datasets. Following Zarei et al. (2021) and Askary and Shafie Kakhaky (2017), the general spatial regression model can be specified as:

$$Y_{it} = \alpha + Ty_{it-1} + \rho \sum_{j=1}^{n} W_{ij} y_{jt} + \sum_{k=1}^{K} X_{itk}\beta_k + \sum_{k=1}^{K}\sum_{j=1}^{n} W_{ij} X_{jtk}\theta_k + \mu_i + \gamma_t + v_{it}$$

$$V_{it} = \lambda \textstyle\sum_{j=1}^{n} m_{ij} v_{it} + \epsilon_{it} \qquad i = 1,2,\dots,n \qquad t = 1,2,\dots,t \qquad (5)$$

In the above relationship, if T=0, the model is static and if T≠0, the model is dynamic. The simplest model in spatial regression models is the spatial autoregression (SAR) or spatial lag model, where λ=0 and θ=0. In studies where the data have a spatial dimension, the concept of spatial lag means observations that are one or more distance units away from a specific location, which distance unit s can be measured in two or four directions. Due to the fact that the application positions of observations are irregularly drawn on the map of the regions and are not in the form of a regular grid or string, therefore the concept of spatial lag includes a set of specific spatial neighbors. In this regard, the lag operator actually creates the weighted average of neighboring observations. In the above relation, if ρ=0 and θ=0, the above relation becomes the spatial error model (SEM). In spatial econometric methodology, the spatial durbin model (SDM) has a special place among spatial models. The feature of this model compared to other spatial models (including SAR and SEM) is the simultaneous entry of the spatial lag of the dependent variable and the spatial lag of explanatory variables as new explanatory variables in the model.

In other words, according to equation (4), if λ=0, it will be the spatial durbin model (SDM), and if θ=0, it will be a combination of the spatial autoregression model with autoregressive disturbances (SAC) (Belotti et al., 2013). Fig.1 shows the different types of spatial econometric models along with the features of the estimation model of each model.

In spatial regression models, before addressing spatial dependence and heterogeneity, it is necessary to determine the quantity and numerical value of neighborhood coefficients. Two sources of information are available for this purpose. The first is proximity and neighborhood, which reflect the relative spatial position of a regional observation unit compared to others. The second is the contiguity matrix based on distance. In the first method, the contiguity matrix is formed with elements on the main diagonal set to zero, as econometric models assume that each spatial unit is not a neighbor to itself. The other elements are assigned a value of one or zero, depending on whether the countries or regions

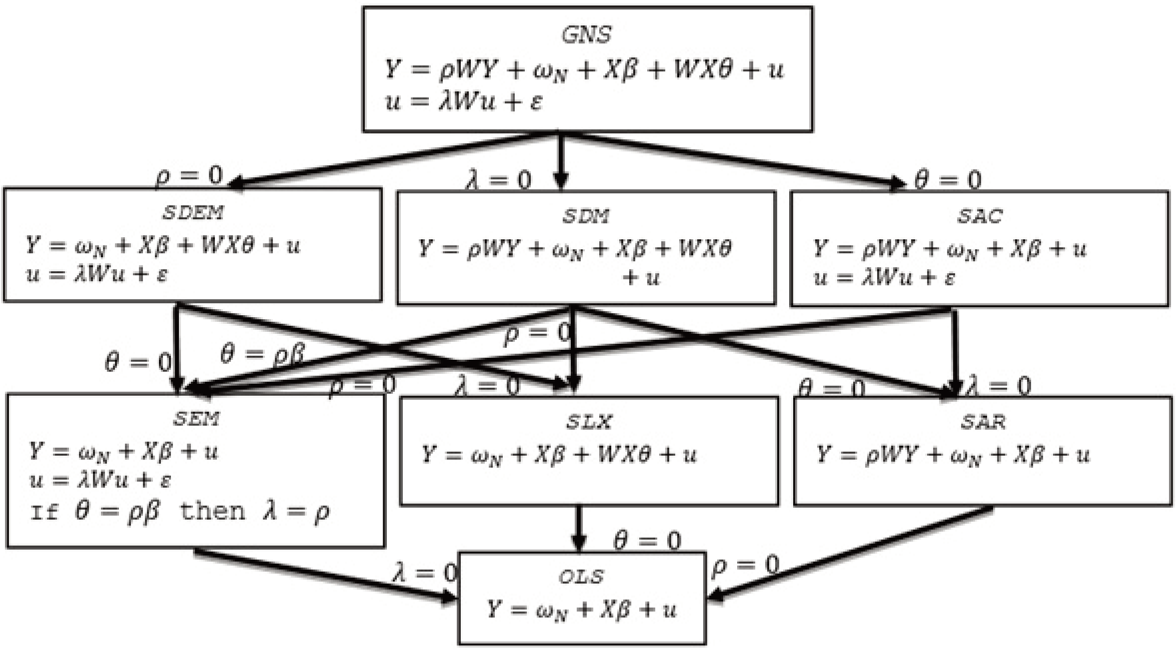

Figure 1. Comparison of Features and Types of Spatial Econometrics Models
Elhorst (2014)

are neighbors. Violating this assumption leads to complex results that are not easily interpretable. Spatial spillovers do not affect only one neighbor but also extend to neighbors of neighbors, continuing in a chain until the effects reach the original study area. First-order neighbors are the closest to the target spatial unit. Second-order neighbors are those adjacent to the first-order neighbors, and third-order neighbors are adjacent to the second-order ones. In the second method, the contiguity matrix is based on the distance element. Observations closer to each other should reflect higher spatial dependence, while dependence and its effects should decrease with increasing distance. This matrix is thus formed using the inverse of the distance or the inverse of the squared distance between each observation and all others.

Next, the contiguity matrix should be standardized, resulting in the standardized first-order contiguity matrix. By standardizing the weight matrix and multiplying it by the vector of the dependent variable, a new variable is generated that represents the average of the observations from adjacent areas; this is referred to as the spatial lag variable. In the Spatial Durbin Model (SDM), in addition to the spatial lag variable, another variable is created by multiplying the standardized weight matrix by the vector of explanatory variables. This variable captures the effects of the explanatory variables from other units (e.g., countries or provinces) on the dependent variable, reflecting spatial spillover effects and the influence of third-party regions. In this study, the contiguity matrix is defined based on the existence of shared borders and neighboring provinces. Adjacency is considered symmetric; therefore, two adjacent areas are assigned the value 1, and non-adjacent areas are assigned the value 0. To measure spatial dependence or spatial autocorrelation among observations, several methods are available, with Moran's test being the most commonly used. Equation (6) presents Moran's test (Wang et al., 2019).

$$I = \frac{\left({}^{N}/_{S_0}\right)\sum_i \sum_j W_{ij}.t_i.t_j}{\sum_i t_i^2} \tag{6}$$

Where are the entries of the contiguity matrix; D_i is obtained from the difference between the share of the desired variable (for example, agricultural credits) in province i and the relative weight of that variable in province i from the total value of the variable in the country and t_i represents the difference between D_i and the average D_is. The maximum value for Moran's statistic is equal to one and $S\_0=\sum_i\sum_j W_{ij}$.

The data for this research, structured as a time series covering the period from 2001 to 2019, pertain to five selected provinces in the west of the country: Hamedan, Kermanshah, Kurdistan, Lorestan, and Ilam. These data were collected from the Statistical Yearbooks of the Iran Statistical Center, the Central Bank, the Agricultural Bank, the Agricultural Statistics of the Ministry of Agriculture, and the National Meteorological Organization. Spatial data analysis was then conducted using GeoDa and Stata 14 software.

RESULTS AND DISCUSSION

Before presenting the estimation results, it is important to note that the monetary data in this research were analyzed using two separate models: one with nominal data and the other with real data (deflated based on the 2011 consumer price index). According to the steps in spatial regression estimation, the existence of spatial dependence must first be confirmed. For this purpose, Moran's test was applied, and its results are presented in Table 1.

Based on the results of Moran's test, the null hypothesis of no spatial dependence is rejected, confirming the presence of spatial dependence in both the nominal and real data models. Therefore, the spatial panel econometric model is more efficient than the standard panel model. Next, the test for the presence of fixed or random effects was conducted to estimate the spatial panel model, and the results are presented in Table 2.

The test results indicate that, based on the probability level obtained in the model with nominal data, the null hypothesis of random effects is rejected. Therefore, estimating the model using the fixed effects method is more appropriate. However, for the real data model, the software was unable to compute the test statistic, likely due to the ineffectiveness of the random effects specification. Consequently, given the higher efficiency of the fixed effects estimation method, it was applied to both the nominal and real data models. To identify the best-fitting model among SEM, SAR, SDM, and SAC, Wald's test—based on spatial error and spatial lag—was used (Elhorst, 2003). The results are presented in Table 3.

Regarding the test for the existence of spatial lag, the null hypothesis—that the spatial autoregression (SAR) model is appropriate—was not rejected and was confirmed for both the nominal and real data models. To assess the presence of spatial error, the test results show that spatial error is rejected in the nominal data model, confirming the SAR model as more efficient. However, in the real data model, the null hypothesis of spatial error cannot be rejected, indicating that the SEM model is more efficient than the SAR model. Since both spatial lag and spatial error were confirmed in the real data model, the SAC model, which incorporates features of both SAR and SEM, was estimated. The estimation results of the spatial panel models based on nominal and real data are presented in Table 4.

Based on the SAR and SAC model estimation results in Table 4, the coefficient of the logarithm of agricultural credits is positive and statistically significant in the nominal data model, indicating that increased agricultural credits lead to higher value added in the agricultural sector. The significance of the spatial dependence coefficient confirms that the agricultural value added of neighboring provinces is spatially dependent and influenced by each other. Therefore, credit allocation in one province positively affects the agricultural value added of adjacent provinces through spatial spillover effects.

In the real data model, the coefficient for agricultural credits is 0.014 and not statisti-

Table 1
Results of Spatial Autocorrelation Test.

Test	**Type of model**	**Test statistics**	***p*-value**
Moran's I	Nominal data	0.1919	0.0177
	Real data	0.2516	0.0020

Table 2
The Result of the Diagnosis Test for Fixed or Random Effects.

Test	**Type of model**	**Test statistics**	***p*-value**
Spatial Hausman	Nominal data	3.9×10^{12}	0.000
	Real data	-	-

Table 3
Test Results for Determining the Best Spatial Model.

Test	Type of model	Criterion	Test statistics	Results
Existence of spatial lag	Nominal data	χ^2<critical value Prob < 0.1	6.22 (0.2857)	SAR is best
	Real data	χ^2<critical value Prob < 0.1	3.93 (0.5588)	SAR is best
Existence of spatial error	Nominal data	χ^2<critical value Prob < 0.1	26.02 (0.0001)	SAR is best
	Real data	χ^2<critical value Prob < 0.1	8.55 (0.1282)	SEM is best

Table 4
Estimation Results of Mixed Spatial Autoregressive Models (SAR), Public Spatial (SAC) Models for Nominal and Real Data.

Variables name	Symbol	SAR Model(Nominal data)			SAC Model(Real data)		
		Estimated coefficient	z statistics	*p*-value	Estimated coefficient	z statistics	*p*-value
Logarithm of agricultural credits	Ln credits	19.89	2.81	0.005	0.0145	0.32	0.749
Logarithm of bank deposits	Ln deposit	22.14	3.63	0.000	0.1250	3.51	0.000
logarithm of agricultural labor	Ln labor	0.0404	0.73	0.467	0.0130	0.31	0.756
Logarithm of crop area	Ln cropland	0.0280	0.18	0.858	0.1024	0.92	0.358
Logarithm of rainfall	Ln precip	0.2152	1.01	0.311	0.0670	0.40	0.688
Spatial autoregressive coefficient(Spatial Lag)	Rho (ρ)	0.5481	8.51	0.000	0.6762	8.25	0.000
Spatial error coefficient	λ	-	-	-	-0.6932	-3.65	0.000
Variance	σ_e^2	0.0192	6.65	0.000	0.0117	4.86	0.000
coefficient of determination	R^2	Within = 0.9748Between = 0.7078Overall = 0.8322			Within = 0.5511Between = 0.7461Overall = 0.2702		

cally significant. This indicates that credit allocations have not kept pace with inflation, rising prices, and production costs in the agricultural sector. As a result, the real value of credits has not had a significant impact on actual agricultural production in the selected western provinces. The variable representing people's deposits in the Agricultural Bank—reflecting the mobilization of microfinance resources—has a positive and significant effect on the agricultural sector's value added in both models. Spatial dependence in the model is confirmed by the estimated spatial autoregressive coefficient (ρ), which is 0.548

for the nominal data model and 0.676 for the real data model. Both are statistically significant and positive, indicating strong spatial interdependence among provinces. Additionally, the spatial error dependence coefficient in the SAC model is also statistically significant. The results of the classical assumption tests are presented in Table 5.

Based on the results in Table 5, there is no heteroscedasticity in the estimated models, and the error terms of both models follow a normal distribution, confirming the validity of the models. Additionally, the test for heteroscedasticity across cross-sections confirms the null hypothesis, indicating variance differences in the error terms between cross-sections. This supports the appropriateness of the panel data estimation method used in the analysis.

CONCLUSION AND POLICY IMPLICATIONS

The purpose of this study was to investigate the effect of agricultural credit spillovers on the value added of the agricultural sector in selected provinces in western Iran. Given the combination of cross-sectional and time series data, along with the spatial adjacency of the studied provinces, the spatial econometric method was employed to examine the credit effect hypothesis and test for the presence of spatial spillovers. To assess spatial correlation in the disturbance components, the I-Moran statistic was used, which confirmed spatial correlation and, consequently, spatial clustering in both nominal and real data models. The fixed effects model results indicated that for nominal data, spatial lag was significant and the SAR model was appropriate. In contrast, for real data, the SEM model was found to be more suitable. To account for the effects of the general spatial autoregression (SAR) model and the suitability of the spatial error model (SEM), the spatial autocorrelation model (SAC) was estimated. The results confirm the existence of spatial spillover effects, meaning that the agricultural value added in one province is influenced by that of neighboring provinces. Therefore, the positive impact of agricultural credits on a province's agricultural value added also affects adjacent provinces. In fact, credit allocation in a province directly impacts its own value added and indirectly influences other provinces through spatial spillovers. Consequently, each variable affecting value added has both direct effects within the same province and indirect effects via spatial spillover on neighboring provinces.

Another key finding from the model estimation is that, while nominal agricultural credits had a positive effect on agricultural value added, real agricultural credits did not significantly affect real agricultural value added. Although various studies confirm the positive impact of investment and bank credits on economic growth and sectoral development, this study found the effect on real value added to be statistically insignificant. This suggests that credit allocation in the western provinces of Iran has not kept pace with in-

Table 5
The Results of Classical Assumptions Tests.

Model	Hall-Pagan LM heteroscedasticity test		Lagrange Multiplier LM Test		Jarque-Bera LM normality Test	
	Test statistics	prob	Test statistics	prob	Test statistics	prob
(Nominal data)	0.9709	0.3224	23.2345	0.0001	0.8367	0.6581
(Real data)	0.5207	0.4705	19.3768	0.0007	0.9436	0.6239

flation, rising prices, and increased production costs, limiting the credits' real impact on agricultural value added.

Given the confirmed spatial effects in this study, agricultural bank credit allocation should be based on the potential of each province—allocating more credits to provinces with higher productivity and capacity. This recommendation stems from Iran's current economic conditions, government budget deficits, and the limited financial resources of the Agricultural Bank for the sector. Such a policy would increase agricultural value added proportionally in the targeted province and positively impact neighboring provinces through spatial spillovers. Additionally, spillover effects support regional planning of credit allocation, enhancing the efficiency of credit policies. Since most farmers in the western provinces are smallholders, credit policies should adopt an equity-focused approach to prioritize financing this community.

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CONFLICTS OF INTEREST

The authors state that there is no conflict of interest.

AUTHORS' CONTRIBUTIONS

MB: Conceptualization, Methodology, Formal Analysis, Writing-Original Draft, Writing, Review & Editing; MHF: Conceptualization, Validation, Writing, Review & Editing; JD: Data Curation, Investigation, Writing-Original Draft.

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