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# The Effect of Microcredit on the Migration of Rural Households (Study Case of Sistan Region)

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**Abstract**

This study examines the impact of rural credit on household migration in the Sistan region. Data were collected through questionnaires administered to 522 rural households, and the analysis employed a propensity score matching (PSM) model. The results indicate that credit access had a significant negative effect on the migration propensity of rural households across all three matching algorithms: kernel, nearest neighbor, and radial. Specifically, the Average Treatment Effect on the Treated (ATT) for migration propensity among households receiving credit was, on average, 24.22 to 24.25 points lower than that of the control group. This corresponds to a 34.29 to 34.31 percent reduction in migration propensity for recipient households compared to non-recipient households. These findings suggest that rural credit effectively supports the development of households' agricultural enterprises and consumption expenditures, thereby reducing the incentive to migrate. In particular, credit facilitates investment in household-based businesses, generating sustainable income, enhancing savings capacity, and strengthening rural livelihood resilience. Based on these results, it is recommended that government institutions prioritize credit allocation to rural areas and develop comprehensive plans to ensure adequate resource provision.

**Keywords:** Credits, Migration, Probit Model, Propensity Score Matching (PSM).

## INTRODUCTION

Migration, as a structural phenomenon, poses a significant challenge to achieving balanced regional development. Understanding the motivations and drivers behind this type of population movement is essential for designing effective policies for population management and sustainable rural development. Previous studies generally frame migration as the result of a complex interaction between rural push and urban pull factors. Among the most significant push factors are widespread unemployment and a lack of sustainable job opportunities in rural areas.(Mehmandoost et al.,2025). For example, a study conducted in China's Jiangsu Province concluded that rural unemployment—not higher urban wages or insufficient rainfall—was the

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primary driver of migration (Lyu et al., 2019). This finding underscores that generating employment in rural areas is crucial to alleviating migration pressure.

Conversely, access to financial services—particularly microcredit—can play a dual and seemingly contradictory role. On one hand, this access to capital can cover the initial costs of migration—such as travel, accommodation, and job search expenses—thereby facilitating migration by alleviating liquidity constraints. For instance, Phan (2012) provides strong evidence that the introduction of formal banking and credit to rural areas directly increases out-migration to cities by removing the financial barriers that constrain poor households. On the other hand, microcredit can foster rural transformation and create local livelihood opportunities by financing endogenous economic activities—such as high-value-added agriculture and non-farm enterprises—thereby reducing the incentive to migrate. Evidence for this stabilizing role is provided by Saha et al. (2025), whose study in Bangladesh demonstrated that increased household credit significantly stimulated the production of high-value agricultural goods and the creation of non-farm employment opportunities. This finding indicates that credit can be a vital factor in sustaining a village's vitality and fostering its development by strengthening the local economic base.

Etezadi et al. (2021) demonstrated that increased access to formal credit enhances household satisfaction with rural life and reduces the propensity to migrate. These findings underscore the importance of developing effective financial credit policies to curb migration and sustain rural populations. To maximize their positive impact, credit programs must be carefully tailored to the specific socio-economic needs of the communities they serve. Similarly, Ghanbari and Nouri (2017) identified lending for employment generation and prioritizing investment in new job opportunities as effective strategies to reduce unplanned migration from rural areas.

Moreover, the phenomenon of reverse migration—where individuals return to their villages after acquiring capital and skills in urban areas—adds another layer of complexity to this dynamic. Research indicates that this return flow of migrants can serve as a significant driver of rural entrepreneurship. For example, Zhou et al. (2024), in their study of China, found that the presence of return migrants significantly increased the likelihood of rural households engaging in entrepreneurial activities. These findings underscore the need for targeted financial and educational support for returnees to harness their potential in stimulating rural economic development. Similarly, the emergence of in Turkey—a phenomenon characterized by an return to the land that the flow of capital and skills to rural areas can be reversed, provided migrants possess sufficient financial resources, knowledge, and robust social networks (Turkkan, 2025). Based on existing literature demonstrating the efficacy of microcredit in enhancing rural resilience and mitigating out-migration in diverse settings, this investigation zeroes in on the Sistan region of Sistan and Baluchestan Province, Iran. It aims to causally examine the relationship between access to rural credit and household migration propensity. Characterized by a significant rural population, Sistan is among Iran's most underdeveloped and climatically vulnerable areas, enduring persistent droughts and severe sandstorms. Employing a Propensity Score Matching (PSM) methodology to isolate the net effect of credit, this research seeks to determine whether formal credit access can act as a stabilizing factor, reducing migration pressure in this challenging context. The findings are expected to provide an empirical framework for targeted policy interventions in similar stress-prone regions.

## MATERIALS AND METHODS

Sistan and Baluchestan Province, the second most extensive province in Iran, is situated in the country's southeast (Figure 1). Owing to its ethnic and cultural diversity, the province comprises two distinct regions: Sistan in the north and Baluchestan in the south. This study focuses on Sistan, a region encompassing five counties: Zabol, Zahak, Hirmand, Hamun, and Nimrouz. Sistan is a closed drainage basin whose viability depends entirely on the Hirmand River (also known as the Helmand River). Originating in the mountains of Afghanistan, this river flows a considerable distance before terminating in the internationally recognized Hamun Wetland. Historically, the lakes and marshes of Hamun constituted one of the most extensive wetland ecosystems in Iran and the world, serving as a fundamental livelihood source for the local population.

In recent decades, however, the region has confronted a severe environmental crisis marked by persistent drought. A combination of declining precipitation, upstream dam construction on the Hirmand River in Afghanistan, and inadequate water management has drastically reduced river flows, leading to the complete desiccation of Lake Hamun. Sistan's economy, which is heavily dependent on traditional agriculture and pastoralism, has been severely impacted by this water scarcity, resulting in profound economic and subsistence challenges for the local population. Consequently, these pressures have triggered the forced migration of a significant segment of inhabitants to neighboring provinces.

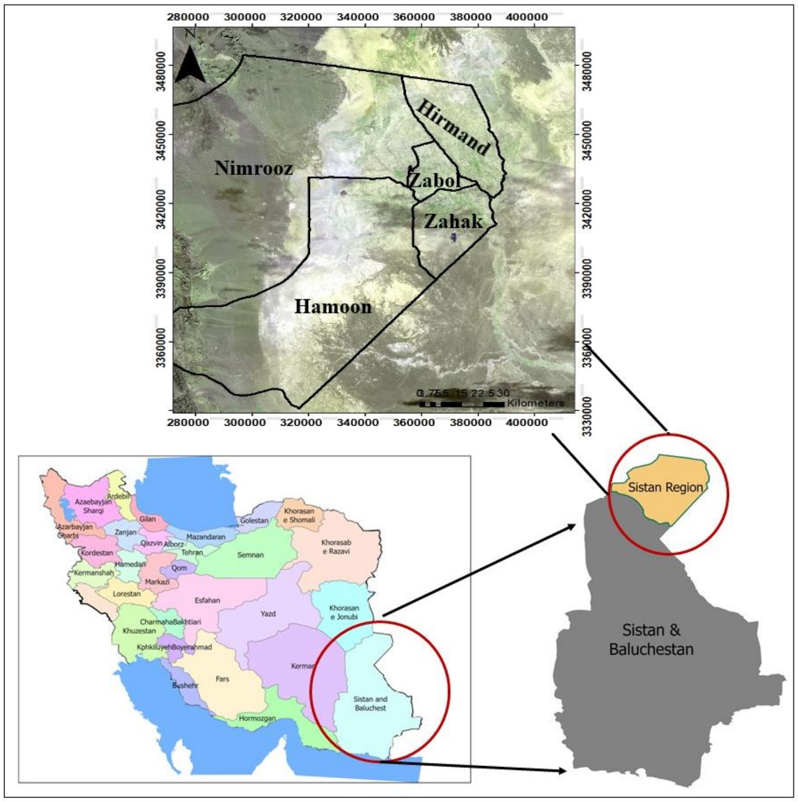


**Figure 1.** Map of the Sistan region in Iran, highlighting the study area.

This study employs a matching method to estimate the effect of credit on reducing migration among rural households. A central challenge in such an analysis is selection bias, a common issue in social science research when evaluating interventions. A direct comparison of outcomes between credit recipients and non-recipients can be misleading due to systematic differences in their observable and unobservable characteristics. In other words, the treatment and control groups are not initially homogeneous. To address this issue, researchers have proposed various methods (Gitonga, 2013; Luan & Bauer, 2016). These methods include:

a) Randomized treatment distribution;

b) Use of special composite data for each observation;

c) Instrumental variable methods based on Heckman correction;

d) Using a propensity score matching method with randomized treatment distribution.

In social science research, the randomization of treatment is often infeasible, rendering experimental methods unsuitable. Furthermore, the use of composite data for evaluation is frequently constrained by data unavailability. The instrumental variable approach also presents limitations, as a valid and strong instrument is often difficult to identify. Consequently, these three common methods pose significant challenges for empirical analysis.

Given these constraints, the matching method has emerged as a prominent econometric technique for addressing sample selection bias in non-experimental, cross-sectional data, without relying on strict functional or distributional assumptions (Gitonga, 2013). This method operates on the principle that bias can be reduced by conditioning on observable variables. It achieves this by matching each treated household (credit recipient) with one or more control households (non-recipients) that exhibit similar observable characteristics. In essence, the matching method constructs a quasi-experimental setting by creating a comparison group that approximates the counterfactual condition of random assignment.

The matching framework facilitates the identification of a causal relationship between credit receipt and outcome variables (Gitonga, 2013; Luan & Bauer, 2016). In this research, propensity score matching (PSM) is employed to assess the impact of rural credit on migration. The initial step in this method involves a simple comparison of means between the treatment group (households receiving credit) and the control group (households not receiving credit) using a t-test.

The causal effect of rural credit is estimated in two stages. First, the propensity scores—the conditional probabilities of receiving credit—are estimated. This probability is modeled on the basis that a household's decision to seek credit is influenced by its expected benefits and costs.

Therefore, in this stage, factors influencing households' decisions to take credit are analyzed using Equation 1 (Luan & Bauer, 2016).

$$AC_i^* = \beta Z_i + U_i, \qquad \forall i = 1,2,\ldots M \tag{1}$$

In Equation 1, $Ui$ is the error term, which follows a normal distribution with a mean of zero and a variance of $\sigma^2$.

$$AC_i = \begin{cases} = 1 : if \ AC_i^* \geq 0 \\ = 0 : \text{otherwise} \end{cases} \tag{2}$$

In Equation 2, $AC_i$ represents the credit status of the household, which is equal to one if the household has received a loan in the past 24 months and zero otherwise. The estimation of propensity scores for recipients is performed using the probit method as follows:( Sani Heidary et al., 2019)

$$\Pr(AC_i = 1) = \Pr(AC_i^* > 0) = 1 - F(-\beta Z_i) \quad (3)$$

In the second stage, recipients and non-recipients of rural credits are matched based on their propensity scores using three algorithms: a) Nearest Neighbor Matching; b) Kernel Matching; c) Radius Matching (Gitonga et al., 2013). The second stage of matching based on propensity scores estimates the impact of rural credits on outcome variables by calculating the average treatment effects on the treated group, defined as follows in Equation 4 (Luan & Bauer, 2016):

$$\mathrm{ATT} = \mathrm{E}(\mathrm{Y}^1 \mid \mathrm{D} = 1) - \mathrm{E}(\mathrm{Y}^0 \mid \mathrm{D} = 1) \quad (4)$$

In Equation 4, ATT represents the average treatment effects in the treatment group. The first component of the right-hand side reflects the results for households that received credits, while the second component represents a hypothetical outcome for households that had access to credits but did not receive them.

$$\mathrm{ATC} = \mathrm{E}(\mathrm{Y}^0 \mid \mathrm{D} = 0) - \mathrm{E}(\mathrm{Y}^0 \mid \mathrm{D} = 1) \quad (5)$$

In Equation 5, ATC represents the average treatment effects in the control group. The first component of the right-hand side reflects the results for households that did not receive credits, while the second component represents a hypothetical outcome for households that had access to credits but did not receive them. The bias between these two values is estimated as follows (Luan & Bauer, 2016):

$$\begin{aligned} \mathrm{Bias} &= \mathrm{ATT} - \mathrm{ATC} \\ \mathrm{Bias} &= \mathrm{E}(\mathrm{Y}^1 \mid \mathrm{D} = 1) - \mathrm{E}(\mathrm{Y}^0 \mid \mathrm{D} = 0) \end{aligned} \quad (6)$$

The Propensity Score Matching (PSM) method has become a prominent and suitable tool for mitigating selection bias in observational studies within the social sciences.

The statistical population of this study comprised all rural households in the five counties of the Sistan region (Zabol, Zahak, Hirmand, Hamoon, and Nimrouz). The sample size was determined to be 522 households, calculated using Cochran's formula with a 95% confidence level. Participants were selected through simple random sampling from the list of households receiving services in each county. Data were collected using both library research and field methods. The primary field research instrument was a researcher-administered questionnaire, which consisted of four sections: demographic characteristics, economic components, social components, and policy effectiveness evaluation. Responses were recorded on a 5-point Likert scale.

This study employs a Propensity Score Matching (PSM) methodology to evaluate the impact of rural credit on households' migration intentions. The central hypothesis posits that access to rural credit, on average, reduces the inclination to migrate among recipient households compared to non-recipient households. To test this hypothesis, the analysis begins with a simple comparison of means between the treatment group (households receiving credit) and the control group (households not receiving credit) using a t-test.

The validity of the survey instrument was established through two methods:

*a. Content Validity*: The initial questionnaire was reviewed by a panel of 10 professors and experts in rural development and economics. Their feedback on the relevance, clarity, and comprehensiveness of the indicators and items was incorporated into the final instrument.

*b. Face Validity:* A pilot study was conducted by administering the questionnaire to 30 households in the study region. The instrument was subsequently refined to address any grammatical, terminological, or perceptual ambiguities identified during this phase.

The reliability of the questionnaire was assessed using Cronbach's alpha. Following data collection from all 522 households, the data were analyzed using Stata software, yielding a Cronbach's alpha coefficient of 0.82, which indicates high internal consistency and desirable reliability for the research instrument.

For data analysis, Stata was used for advanced statistical procedures, including the estimation of the propensity score matching model, while Microsoft Excel was utilized for initial data organization and chart creation.

The research methodology is visually summarized in the conceptual framework of Figure 2, which will be subsequently elaborated in a detailed, step-by-step explanation.

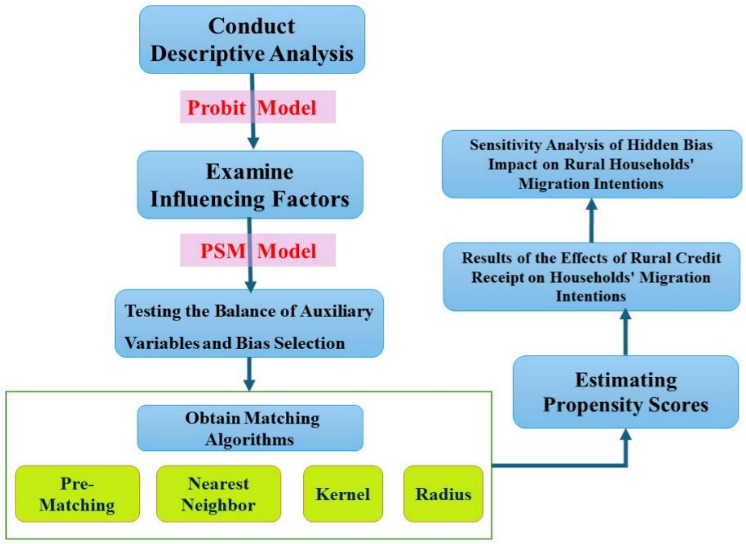


**Figure2**. Conceptual research model

In this figure, the stages of conducting the research are outlined as follows:

1. *Descriptive Analysis of Credit-Receiving and Non-Credit-Receiving Households*: This initial step involves a comparative analysis of the characteristics of credit-recipient and non-recipient households.
2. *Examining Factors Influencing Rural Households' Access to Credit (Probit Model)*: Following the descriptive analysis, a Probit model was employed to identify the factors influencing access to rural credit.
3. *Testing the Balance of Auxiliary Variables in the PSM Model and Selection Bias*: This step involves testing the balance of covariates and addressing potential selection bias.
4. *Obtaining Matching Model Algorithms*: We employed several matching algorithms, including pre-matching, nearest neighbor, kernel, and radius techniques.
5. *Estimating Propensity Scores*: Propensity scores were estimated, and their distribution was evaluated to ensure common support.
6. *Results of the Effects of Rural Credit Receipt on Households' Migration Intentions*: Finally, we estimate the causal effect of receiving rural credit on households' migration intentions.
7. *Sensitivity Analysis of Hidden Bias Impact on Rural Households' Migration Intentions*: This step involves assessing the sensitivity of the results to potential latent bias.

8. *Investigating Factors Influencing Households' Migration Intentions Using the Ordered Logit Model*: The final step employs an ordered logit model to identify the determinants of migration intentions.

## RESULTS AND DISCUSSION

This study's primary objective is to evaluate the effectiveness of rural credit programs in reducing migration among rural households in the Sistan region. Propensity Score Matching (PSM) was employed for this purpose, and the results are analyzed in the following section.

Table 1 presents a descriptive analysis of the households that received credit (the treatment group) and those that did not (the control group). Of the total households studied, 256 (49%) received rural credits, compared to 266 (51%) that did not. Given this distribution, identifying the factors influencing a household's access to credit is critical. These factors will be addressed in the first stage of the matching procedure.

**Table 1.** Household Participation Levels in Microcredit Programs.

| Group | Dependent Variable | Frequency | Percentage Frequency |
|---|---|---|---|
| Control | 0 | 266 | 50.96% |
| Treatment | 1 | 256 | 49.04% |
| Total | - | 522 | 100% |

Source**:** Research Findings.

A Probit model was employed to analyze the direction and magnitude of factors influencing access to rural credit; the results are presented in Table 2. The propensity score matching (PSM) approach is based on the assumption that credit access is non-random and influenced by observable household characteristics. Consequently, the explanatory variables from the Probit model—including the age of the household head, savings, household size, cultivated area, livestock units, number of visits to extension agents, access to cooperatives, number of employed individuals in the household, and exposure to agricultural shocks—were used as covariates to evaluate the effects of the credit programs. The results indicate that the age of the household head and the level of savings have statistically significant negative effects on the probability of receiving microcredit. This suggests that households with younger heads and lower levels of liquid assets are more likely to access credit, which may reflect a greater need for capital to initiate new economic activities and investments.

Conversely, household size, cultivated land area, livestock ownership, and the frequency of contact with agricultural extension agents all show significant positive relationships with the likelihood of obtaining credit. These findings suggest that larger households may experience increased subsistence pressures, while those with more substantial agricultural assets likely require greater inputs for farming and livestock activities, thereby raising their demand for credit. Furthermore, regular interaction with extension services likely enhances access to credit by improving awareness of available financial programs. Households that experienced agricultural shocks exhibited a significantly higher rate of credit adoption, highlighting the crucial role of microcredit as a risk management tool. This finding indicates that credit services serve not only as developmental resources but also as financial safety nets, enabling households to mitigate production losses and maintain livelihood stability amid environmental challenges. And this finding is consistent with the results of studies by Luan & Bauer (2016) and Story & Carpiano (2015).

**Table 2.** Results of Probit Model Estimation in PSM Approach.

| Variables | Coefficients | Standard Error | Z Statistic | Significance Level | Marginal Effects | VIF |
|---|---|---|---|---|---|---|
| Age of Household Head | -0.016 | 0.007 | -2.380 | 0.018 | -0.006 | 1.06 |
| Savings | -0.008 | 0.004 | -1.990 | 0.047 | -0.003 | 1.06 |
| Household Size | 0.024 | 0.013 | 1.750 | 0.080 | 0.009 | 1.01 |
| Cultivated Area | 0.029 | 0.011 | 2.710 | 0.007 | 0.012 | 1.03 |
| Livestock Units | 0.049 | 0.021 | 2.300 | 0.022 | 0.019 | 1.04 |
| Frequency of Visits to Promoters | 0.074 | 0.026 | 2.840 | 0.004 | 0.010 | 1.03 |
| Access to Cooperatives | 0.065 | 0.123 | 0.530 | 0.599 | 0.049 | 1.04 |
| Employed Individuals in Household | 0.096 | 0.077 | 1.250 | 0.210 | 0.078 | 1.02 |
| Agricultural Shock | 0.004 | 0.000 | 8.300 | 0.000 | 0.002 | 1.12 |
| Constant | -2.464 | 0.632 | -3.900 | 0.000 | - | - |
| Mean VIF | - | - | - | - | - | 1.05 |
| Number of Observations | 522 | | | | | |
| LR chi2(9) | 151.600 | | | | | |
| Prob > LR chi2 | 0.000 | | | | | |
| Pseudo R2 | 0.210 | | | | | |
| Correct Classification Rate | 80% | | | | | |
| Hosmer–Lemeshow chi2(9) | 6.740 | | | | | |
| Prob > Hosmer–Lemeshow chi2 | 0.346 | | | | | |

Source: Research Findings.

Table 3 presents the balance of covariates between the treatment and control groups before and after matching. Prior to matching, independent samples t-tests (Table3) revealed statistically significant differences in the means of all covariates. This indicates that the groups were not comparable at baseline, and any direct estimation of the credit effect would have been subject to **selection bias**. This finding, in itself, underscores the critical importance of employing causal inference methods like Propensity Score Matching (PSM) in such non-experimental settings, as credit receipt is typically non-random and correlated with observable household characteristics (e.g., asset ownership or education level).

Following the matching procedure, no statistically significant differences were observed between the groups, confirming that the balance condition was satisfied. Furthermore, the standardized percentage bias for all covariates was substantially reduced. This methodological success has two key implications. First, it demonstrates that the propensity score estimation model was correctly specified and succeeded in constructing a comparable control group that can serve as a valid counterfactual for the treatment group. Second, it establishes the essential foundation for reliable causal inference in the subsequent stage—estimating the treatment effect (ATE/ATT). In other words, we can now assert with greater confidence that any observed difference in the outcome variable (migration propensity) between the two groups is primarily attributable to **credit access** itself, rather than to pre-existing differences in other characteristics. This step, consistent with established methodological literature (e.g., Etezaz et al., 2021), is considered a fundamental prerequisite for the unbiased interpretation of policy impacts.

**Table 3.** Balance Test of covariates in the PSM Model and Selection Bias.

| Variables | UnMatched (U) Matched (M) | Treatment (T) | Control (C) | Percentage Bias | Percentage Reduction in Bias | T Statistic | Significance Level |
|---|---|---|---|---|---|---|---|
| Age of Household | U | 48.18 | 51.55 | -37.00 | 81.6 | -4.22 | 0.00 |
| Head | M | 48.92 | 49.54 | -6.80 | | -0.74 | 0.46 |
| Savings | U | 43.79 | 48.98 | -34.10 | 87.3 | -3.89 | 0.00 |
| | M | 44.61 | 45.27 | -4.30 | | -0.47 | 0.64 |
| Household Size | U | 22.60 | 22.27 | 7.10 | -25.7 | 2.71 | 0.04 |
| | M | 22.57 | 22.98 | -8.90 | | -0.96 | 0.34 |
| Cultivated Area | U | 15.09 | 13.27 | 32.60 | 84 | 3.72 | 0.00 |
| | M | 14.84 | 14.54 | 5.20 | | 0.57 | 0.57 |
| Livestock Units | U | 5.74 | 4.78 | 33.50 | 99.9 | 3.82 | 0.00 |
| | M | 5.75 | 5.75 | 0.00 | | 0 | 1.00 |
| Frequency of | U | 7.14 | 6.33 | 34.60 | 92.8 | 3.96 | 0.00 |
| Visits to Promoters | M | 6.98 | 6.92 | 2.50 | | 0.27 | 0.79 |
| Access to | U | 0.57 | 0.51 | 13.40 | 66.2 | 1.53 | 0.13 |
| Cooperatives | M | 0.56 | 0.58 | -4 .50 | | -0 .49 | |
| Employed | U | -2 .11 | -1 .90 | -26 .60 | -91 .3 | -3 .03 | |
| Individuals in Household | M | -2 .08 | -2 .09 | -2 .30 | | -0 .24 | |
| Agricultural | U | -448 .36 | -323 .64 | -95 .50 | -97 .5 | -10 .93 | |
| Shock | M | -431 .88 | -435 .02 | -2 .40 | | -0 .24 | |

Source: Research Findings.

The pseudo-$R^2$ values from the Probit model, reported in Table 4, reflect the extent to which the covariates explain the variation in credit receipt. The pseudo-$R^2$ was substantially higher prior to matching but decreased sharply afterward. Correspondingly, the model was statistically significant before matching, whereas after matching, the joint significance tests from the matching algorithms were no longer significant. This confirms that no systematic differences remain in the covariate distributions between the treatment and control groups. Finally, the post-matching mean and median bias were reduced to below 10%, which further indicates a high-quality match.

**Table 4.** Statistical Tests for Evaluating Matching Algorithms.

| Matching Algorithms | Pseudo $R^2$ | $\chi2(7)$ | $p>\chi2$ | Mean Bias | Median Bias |
|---|---|---|---|---|---|
| Before Matching | 0.20 | 145.62 | 0.00 | 34.90 | 33.50 |
| Nearest Neighbor | 0.00 | 2.42 | 0.98 | 4.10 | 4.30 |
| Kernel | 0.01 | 6.52 | 0.69 | 6.90 | 7.90 |
| Radius | 0.00 | 2.50 | 0.90 | 5.10 | 5.30 |

Source: Research Findings.

Figure 3 illustrates the propensity score distributions for the treatment and control groups after matching, indicating adequate common support. The substantial overlap between the two density distributions validates the quality of the matching procedure and confirms the appropriateness of the propensity score methodology for this analysis.

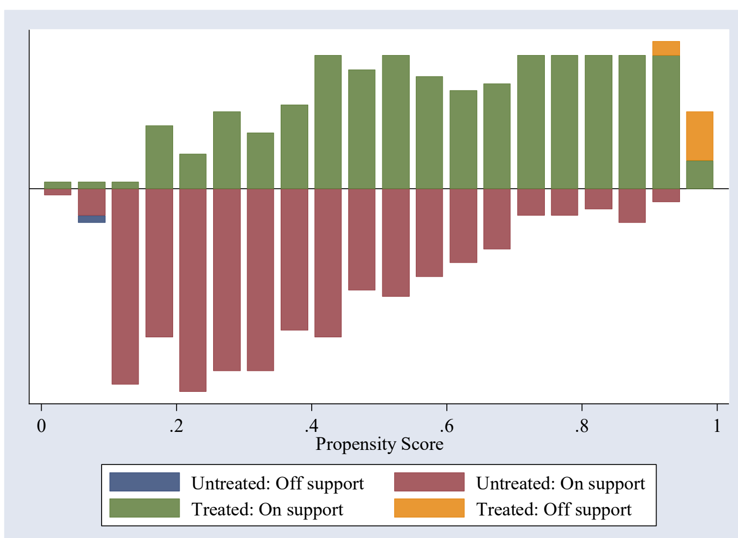


**Figure 3**. Evaluation the distribution of the propensity scores and common Support for propensity score estimation.

This study employed three matching algorithms to estimate the effect of rural credit on the migration inclination of rural households; the results are presented in Table 5. The treatment effect was quantified by calculating the average difference in the outcome variable between the treatment and control groups. This difference, known as the Average Treatment Effect on the Treated (ATT), represents the causal impact of receiving credit for those households that actually received it.

According to Table 5, the received rural credits had a negative effect on the inclination to migrate among rural households across all three matching algorithms (kernel, nearest neighbor, and radius). Specifically, the ATT for the inclination to migrate among households receiving rural credits was, on average, 24.252 -24.227 units lower than that of non-recipients. This indicates that receiving rural credits reduced the inclination to migrate among recipients by an average of 34.31-34.29% compared to non-recipients. These findings imply that rural credit programs play a significant role in stabilizing rural populations by supporting agricultural businesses and smoothing household consumption. The injection of capital facilitates investment in productive economic activities, which generates more sustainable income, increases savings, diversifies livelihood options, and enhances human capital. Consequently, individuals benefiting from these credits exhibit a stronger propensity to remain in their villages.

**Table 5.** Effects of Receiving Rural Credits on the Inclination to Migrate from the Village.

| The output variable | Matching Algorithms | Treatment Group | Control Group | ATT | T-stat | **Observations in Matching** | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | total sample | Control | Treatment |
| The Inclination to Migrate | Neighbor | 46.413 | 70.640 | -24.227 | -11.51*** | 512 | 265 | 247 |
| | Kernel | 46.406 | 70.735 | -24.329 | -12.69*** | 522 | 266 | 256 |
| | Radius | 46.424 | 70.676 | -24.252 | -13.73*** | 501 | 265 | 236 |

Source**:** Research Findings (*** indicates significance at the 1% level).

Finally, the results of the sensitivity analysis for assessing the robustness of PSM estimates against hidden bias are reported in table 6. The lower bound of the significance level (i.e., $Sig^-$) assumes that the true treatment effects are underestimated. The upper bound of the significance level (i.e., $Sig^+$) assumes that the true treatment effects are overestimated. If both the lower and upper bounds of significance are significant at small gamma values, it can be claimed that there is a relatively high probability of an unobserved variable influencing the results regarding the effect of receiving credits on household migration inclination; therefore, in this case, the estimated effects are sensitive to the presence of unobserved variables. The results indicate that the inference regarding the impact of credit interventions on the migration inclination index variable does not change through unobserved variables, and households are allowed to vary in their chances for treatment by up to 300% ((4-1)*100) =300) at $\Gamma$=4 concerning unobserved auxiliary variables. Therefore, it can be concluded that the ATT impact estimates in this study are not sensitive to unobserved hidden bias for all output variables, and they represent a net effect of using rural credits.

**Table 6.** Sensitivity Analysis of the Effect of Hidden Bias on the Inclination to Migrate Among Rural Households

| Gamma | Sig+ | Sig- |
|---|---|---|
| 1 | 0.000 | 0.000 |
| 1.2 | 0.000 | 0.000 |
| 1.4 | 0.000 | 0.000 |
| 1.6 | 0.000 | 0.000 |
| 1.8 | 0.000 | 0.000 |
| 2 | 0.000 | 0.000 |
| 2.2 | 0.000 | 0.000 |
| 2.4 | 0.000 | 0.000 |
| 2.6 | 0.000 | 0.000 |
| 2.8 | 0.000 | 0.000 |
| 3 | 0.000 | 0.000 |
| 3.2 | 0.000 | 0.000 |
| 3.4 | 0.000 | 0.000 |
| 3.6 | 0.000 | 0.000 |
| 3.8 | 0.000 | 0.000 |
| 4 | 0.000 | 0.000 |

Sig+: Upper bound of the significance level (true treatment effects are overestimated).
Sig-: Lower bound of the significance level (true treatment effects are underestimated).
Source: Research Findings

## CONCLUSIONS

This study finds that rural migration is a multidimensional phenomenon influenced by complex socioeconomic factors, and that access to microcredit can play a decisive role in mitigating it. The empirical analysis, based on field data from the Sistan region, was conducted using a seven-stage propensity score matching (PSM) methodology. In the first stage, a probit model was employed to estimate the propensity score by evaluating the determinants of household investment and participation in rural credit programs.

The results indicate that changes in household age and savings have a significant negative effect on the probability of accessing rural credit. Conversely, household size, crop area, livestock units, and the frequency of visits from agricultural extension services all have significant positive effects on the likelihood of accessing credit.

The findings indicate that an increase in either crop area or livestock units raises the likelihood of a household accessing rural credit. Furthermore, households that consult agricultural extension services are more likely to receive credit. In the second stage, the propensity score matching (PSM) approach was evaluated for covariate balance, selection bias, and common support. The results confirmed that the balancing property was satisfied, as the percentage bias of the covariates was significantly reduced. The analysis also demonstrated strong common support between the control and treatment groups, validating the use of the PSM approach. In the third stage, the impact of credit on the rural migration index was estimated using the PSM method with multiple matching algorithms.

The results showed that credit access had a negative effect on the migration index. Specifically, the Average Treatment Effect on the Treated (ATT) rate—which measures the impact of credit received by the treatment group—indicated that the migration tendency index of households receiving rural credit was, on average, 24.22 to 24.25 points lower than that of non-recipient households across the three matching algorithms. This suggests that receiving rural credit reduced the migration propensity of recipient households by approximately 34.31% to 34.29% compared to non-recipient households. Finally, the robustness analysis of the Propensity Score Matching (PSM) confirmed that the inference regarding the effect of credit interventions on households' migration propensity was not affected by unobserved variables. The analysis allowed for households to differ in their likelihood of treatment by up to 300% in terms of complementary treatments. Therefore, it can be concluded that the ATT results of this study are not sensitive to latent bias and represent a genuine effect of rural credit use.

In conclusion, this study demonstrates that rural credit can become an effective tool for stabilizing rural populations only when implemented as part of a comprehensive rural development program. Such a program must integrate other critical components, including extension services, agricultural insurance, and infrastructure development. This integrated approach addresses the root causes of migration by fostering an entrepreneurial ecosystem and generating sustainable rural employment, thereby making a significant contribution to balanced regional development.

## REFERENCES

1. Anabastani, A.A., &Anabastani, Z. 2011. The process of income generation and its role in rural-urban migration to Sabzevar. *Urban Res. and Plan.*, **2(5):** 133-146.
2. Bauer, S. 2016. Does credit access affect household income homogeneously across different groups of credit recipients? Evidence from rural Vietnam. *J. rural stud.*, **47**: 186-203.
3. Etezadi, S. K., Daneshvar-Kakhaki, M., & Mohammadi, H. 2021. The effects of access to formal and informal financial credits on migration in Khorasan Razavi province. *J. of Rural Dev.*, **2(24):** 121-156.

4. Ghanbari, Y., & Noori, R. 2017. Evaluating the impact of micro-credits from the Imam Khomeini Relief Foundation on population retention in rural areas: A case study of Khomain County. *Eco. Res. J.*, **17(65):** 177-198.
5. Gitonga, Z. M., De Groote, H., Kassie, M., & Tefera, T. 2013. Impact of metal silos on households' maize storage, storage losses and food security: An application of a propensity score matching. *Food Policy.*, **43:** 44-55.
6. Luan, D. X., & Bauer, S.  2016. Does credit access affect household income homogeneously across different groups of credit recipients? Evidence from rural Vietnam. *J. Rural Stud*, **47**: 186-203.
7. Lyu, H., Dong, Z., Roobavannan, M., Kandasamy, J., & Pande, S. (2019). Rural unemployment pushes migrants to urban areas in Jiangsu Province, China. *Palgrave Comm.*, **5(1)**: 1-12.
8. Mehmandoost, H., Sargazi, A., Keikha, A., Ziaee, S., & Sani Heidary, A. 2025. The effective factors influencing entrepreneurship development in rural areas: A case study of Hamun County. *J. Agric Econ Dev*., **39(3)**, 225-244.
9. Phan, D. 2012. Migration and credit constraints: Theory and evidence from Vietnam. *Rev. of Dev. Econ.*, **16(1)**: 31-44.
10. Saha, S., Alam, M. J., Al Abbasi, A. A., Begum, I. A., Rola-Rubzen, M. F., Parikh, P., & McKenzie, A. M. 2025. Can credit promote rural transformation? Evidence from district-level data in Bangladesh. *Hum. and Soc. Scie. Com.*, **12(1)**: 310.
11. Sani Heidary, A. R., Daneshvar Kakhki, M., Shahnoushi, N., & Sabouhi Sabouni, M. 2019. The Role of Microcredit in Sustainable Rural Development: A Case Study of Selected Villages of Torbat-e-Jam County of Iran. *Vill and Dev*., **22(3)**: 125-154.
12. Story, W. T., & Carpiano, R. 2015. Household social capital and socioeconomic inequalities in child undernutrition in rural India: Exploring institutional and organizational ties. *Ann. Glob. Health* ., **81(1)**: 119-120.
13. Turkkan, C. 2025. Entrepreneurial Back-to-Landers: How Neo-Farmers in Turkey Choose Where to Settle. *Pop., Space and Place*., **31(1):** e2863.
14. World Bank. 2020. Rural-Urban Migration in Developing Countries: Lessons from the Literature. Policy Research Working Paper 9662.

15. Zhou, J., Zhang, X., Korkmaz, A. G., Ding, X., & Yue, P. 2024. Mirroring the urban exodus: The impact of return migration on rural entrepreneurship. *Fin. Research Lett.*, **66**, 105619.

## تأثیر اعتبارات خرد بر مهاجرت خانوارهای روستایی (مورد مطالعه منطقه سیستان)

**مهتاب سارانی، علیرضا سرگزی، علیرضا کیخا، و محمود احمدپور برازجانی**

**چکیده**

این مطالعه به بررسی تأثیر اعتبارات روستایی بر مهاجرت خانوارها در منطقه سیستان می‌پردازد. داده‌ها از طریق پرسشنامه‌های توزیع شده بین ۵۲۲ خانوار در مناطق روستایی سیستان جمع‌آوری و از روش جورسازی برپایه نمره تمایل، (PSM)برای تجزیه و تحلیل استفاده شد. نتایج این مطالعه نشان می‌دهد که اعتبارات دریافتی در هر سه الگوریتم تطبیق (هسته، نزدیکترین همسایه و شعاعی) تأثیر منفی بر شاخص تمایل به مهاجرت خانوارهای روستایی داشته است. در واقع، شاخص میانگین اثر درمان بر روی درمان‌شده (ATT) تمایل به مهاجرت خانوارهای دریافت‌کننده اعتبارات روستایی در سه الگوریتم تطبیق به طور متوسط 24/25-24/22کمتر از خانوارهای غیردریافت‌کننده (گروه کنترل) بوده است. این بدان معناست که دریافت اعتبارات روستایی، تمایل به مهاجرت خانوارهای دریافت‌کننده را به طور متوسط 34/31-34/29 درصد در مقایسه با خانوارهای غیردریافت‌کننده کاهش داده است. این یافته ها نشان می‌دهد که اعتبارات روستایی نقش مؤثری در توسعه کسب وکارهای کشاورزی خانوارها و همچنین هزینه‌های مصرفی آنها ایفا می‌کند. بنابراین افرادی که به این اعتبارات روستایی دسترسی دارند، تمایل دارند مدت بیشتری در روستا بمانند. در واقع، اعتبارات دریافتی از طریق سرمایه‌گذاری در کسب‌وکارهای اقتصادی خانوار، جریان‌های درآمدی پایدار ایجاد کرده و قدرت پس‌انداز را افزایش می‌دهد و ظرفیت‌ها و قابلیت‌های معیشتی روستایی را نیز گسترش می‌دهد. با توجه به این یافته‌ها، پیشنهاد می‌شود نهادهای دولتی تخصیص اعتبارات به ساکنان روستایی را در اولویت قرار دهند و برنامه‌ریزی لازم را برای تخصیص منابع کافی انجام دهند.