American Journal of Theoretical and Applied Statistics
2025, Vol. 14, No. 3, pp. 99-108
https://doi.org/10.11648/j.ajtas.20251403.11

Research Article

Socio-Economic and Demographic Drivers of Irregular Migration to South Africa: A Bayesian and Logistic Regression Analysis

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Abstract

Human trafficking negatively impacts individuals and national development, yet its root causes are poorly understood. This study aimed to investigate the socioeconomic and demographic factors influencing irregular migration from Shashogo Woreda, Hadiyya Zone, Central Ethiopia to South Africa. Data from 346 respondents across eight Kebeles were analyzed using bivariate and Bayesian logistic regression models. The findings revealed that about 50L. 57% of household heads plan to send a family member abroad, while 49.42% do not. Female-headed households are significantly less likely to plan irregular migration than male-headed ones (Coeff = -1.527, OR = 0.217, P = 0.001). The odds of planning migration rise by 45.7% per additional household member (Coeff = 0.784, OR = 1.457, P = 0.000) and by 21.2% for each year increase in the household head's age (Coeff = 0.193, OR = 1.212, P = 0.000). Education negatively correlates with migration plans, as those with primary education (Coeff = -2.652, OR = 0.816, P = 0.001) or a diploma and above (Coeff = -3.228, OR = 0.040, P = 0.001) are less likely to plan migration compared to those with secondary education, while uneducated respondents show no significant difference. Non-agricultural employment such as trade (Coeff = -2.781, OR = 0.062, P = 0.001), formal jobs (Coeff = -1.549, OR = 0.212, P = 0.020), or other work (Coeff = -2.453, OR = 0.086, P = 0.002) also lowers migration plans compared to agricultural work. Urban residents are more likely to plan migration than rural ones (Coeff = 1.309, OR = 3.704, P = 0.001), and those unaware of migration risks are significantly more likely to plan migration than those who are aware (Coeff = 1.623, OR = 5.066, P = 0.001). In conclusion, irregular migration from Shashogo Woreda is driven by structural socio-economic challenges and the allure of better opportunities abroad. Key predictors include age, sex, family size, education, employment type, residence, and risk awareness. Despite awareness of migration risks, economic hardships remain dominant drivers. Effective policy responses should focus on rural development, youth employment, education access, and safe migration alternatives to address the root causes.

Keywords

Irregular Migration, Drivers, Hadiyya, Outcomes, Pull Factors, Push Factors

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Received: 10 May 2025; **Accepted:** 29 May 2025; **Published:** 23 June 2025

1. Introduction

Migration refers to the relatively permanent change of residence or address, often crossing administrative or political boundaries. It involves the movement of individuals or groups, either across international borders or within a country. As a population phenomenon, migration encompasses all forms of human movement, regardless of its duration, composition, or causes. Migration is broadly classified into two types: internal and international. Internal migration, or domestic migration, occurs within a country and is often motivated by educational opportunities, economic improvement, natural disasters, or civil disturbances. On the other hand, international migration involves movement across national borders, driven by factors such as employment, safety, and family reunification [1].

While international migration often captures more attention, internal migration remains the dominant form globally. Migration is closely tied to improved human capital and access to networks that can facilitate subsequent relocations. Globally, the number of international migrants reached 272 million in 2019, accounting for 3.5% of the world's population. Of these, 52% were male, 48% female, and 74% were of working age (20–64 years). In Africa, migration patterns reveal significant intra-regional movement, with over 21 million Africans living in another African country in 2019, an increase from 18.5 million in 2015 [2]. Similarly, the number of Africans residing outside the continent rose from 17 million in 2015 to nearly 19 million in 2019. Economic aspirations and regional integration efforts, such as ECOWAS regulations promoting visa-free entry and the right to residence, have further enhanced mobility within Africa. Migration continues to serve as a pathway for economic and social advancement [2, 3].

Most of the young adults who migrate to the Republic of South Africa (RSA) are economically active, driven by the desire for better employment opportunities [4]. In 2009, it was estimated that more than 10,000 Ethiopian migrants were smuggled annually from Ethiopia to South Africa along irregular migration routes, although more recent statistics are unavailable [5]. Migrating through these illegal channels often involves smuggling or trafficking, a perilous process that exposes migrants to severe human rights abuses and even death [6]. In recent years, tragic stories of young Ethiopian men and women found dead in overcrowded containers or heavy-duty trucks have become a regular occurrence in the media, both locally and across Africa [7, 8].

Irregular migration has become a growing concern globally, particularly in contexts where governments fail to establish legal migration systems despite strong demand for workers, leaving migrants vulnerable to exploitation and high levels of risk. Smuggling, trafficking, bonded labor, and a lack of basic human and worker rights have become the harsh realities for millions of migrants. Policy approaches to address these issues have often been insufficient, lacking a comprehensive understanding of migration's drivers. Simplistic solutions tend to have unintended negative consequences. Additionally, factors such as information flow and personal networks including kinship and friendship connections are crucial in shaping migration patterns, as migrants often rely on these networks for information about potential destination areas [9]. Irregular migration presents significant challenges for countries of origin, transit, and destination, as well as for the migrants themselves. Migrants in irregular situations face severe risks of discrimination, exploitation, and abuse, and are particularly vulnerable to being exploited by criminal organizations involved in human trafficking and migrant smuggling, which constitutes a serious violation of human rights. Even refugees and asylum seekers, despite international legal protections, face numerous challenges in their migration journey, especially as the process of obtaining refugee status becomes increasingly difficult and finding countries willing to accept refugees becomes more complex [10, 11].

The issue of illegal migration from Ethiopia to South Africa is particularly prevalent in the southern regions, especially in Hadiya Zone. This migration journey is fraught with risks, leading to numerous human rights violations and fatalities. Migrants often face life-threatening dangers, such as being attacked by wild animals, succumbing to starvation, famine, and other natural disasters. Many also endure harrowing conditions, such as being transported in sealed containers, selling or borrowing assets to fund the journey, and losing contact with their families and loved ones. While existing literature offers valuable insights into the socio-demographic and economic factors influencing international migration, studies focusing on Hadiya and Kembata-Tembaro zones in Southern Ethiopia, using models like the Logistic Mixed Model, have contributed significantly to understanding these migration dynamics [12].

This study explores the growing difficulties of illegal migration in Shashogo Woreda, an area with a high proportion of international migrants. While previous research has largely focused on past migration trends, this study examines the future migration intentions of household heads, specifically investigating how past migration experiences influence decisions to send family members to South Africa. Using Bayesian logistic regression models, the study identifies significant factors affecting these migration plans. Shashogo Woreda, Hadiyya zone, characterized by a dense population and significant youth migration, has seen many individuals abandon education, family, and home to pursue dangerous and illegal migration. The study aimed to investigate the socioeconomic and demographic factors influencing irregular migration from Shashogo Woreda, Hadiyya Zone, and Central Ethiopia to Republic of South Africa.

2. Data and Methodology

2.1. Study Area and Target Population

The study was conducted in Hadiya zone of the Shashogo woreda, which is located in the central eastern part of the central region of Ethiopia. Geographically it ties between 70 24'-7 0 40'N and 370 54`-380 12` E. The study area covers about an estimated area of 1,681.72 km^2. It is situated about 226km far from south of Addis Ababa and 54km north east of Hosanna. The study area is in the rift valley floor bounded to the west by Mount Hambaricho (Kambata zone), to the north east by hill of Aambaricho (Silte zone) [13].

2.2. Sampling Design

This study employed a multi-stage sampling design. When the number of small areas is large, surveying all units in every area may not be feasible due to travel costs and time constraints. Therefore, a more efficient approach involves selecting a subset of small areas for the survey [14]. In this study, the sampling frame consisted of 32 kebeles. A three-stage sampling technique was implemented: in the first stage, a sample of kebeles was selected as the primary sampling units; in the second stage, villages were sampled within each selected kebele; and in the third stage, households were chosen within each selected village. To ensure accuracy, a relisting of all households in the sampled villages was conducted, as recommended by Longford [15].

2.3. Sample Size Determination

Sample size is determined by considering various factors, such as the research objective, study design, cost constraints, and the required degree of precision. Taking these key aspects into account, the sample size for this research is determined using the method outlined in reference [16] as follows:

$$n = \frac{p(q)(Z_{\alpha/2})^2}{e^2} \tag{1}$$

Where n_c = the size of the sample, $z_{\alpha/2}$ is the confidence interval at 95% is assumed ($z_{\alpha/2} = 1.96$), P is proportion of migrant which is 0.350 (12), q = 1- p is proportion of non-migrant, ϵ = Margin of error, ϵ = 5% is accepted by assumption.

$$n = \frac{0.350(0.650)(1.96)^2}{0.05^2} = 349$$

Using the above equation, 8 kebeles were selected from a total of 32, and a sample size of 350 was determined. The selected kebeles Shayambe-Wanchikota, Biramora, Ajecho-Boyo, Bidika, Ushegola, Alage-Gimbicho, Doisha-Belaya, and Bacha-Gola were chosen using a simple random sampling technique (lottery method). Households from each selected kebele were then sampled systematically, with a random starting point, following a quick survey of the population in each village (Goti). The sampling interval for households in each selected kebele was determined by dividing the total number of households by the allocated sample size. The final required sample size for the study was 349 households.

2.4. Data Sources and Methods of Data Collection

In this study, primary data was collected from households using a structured questionnaire, while secondary data from relevant literature and local administrative documents was used for sample size determination. The questionnaire included quantitative variables, with slight modifications to assess migration to the Republic of South Africa. Data collection was carried out by trained enumerators and the investigator, with proper training provided to minimize errors and ensure accurate understanding of the questionnaire.

2.5. Variables in the Study

Dependent Variable

It analyzes two dependent variables: migration status (1 = Occurrence of Migrant in the household who ever migrated to Republic of South Africa (including returnees) and 0 = No migrant in the household who not ever migrated from Household, and future migration status, which reflects whether a household plans to send a member to South Africa in the future and 0 = household who have no plan to send any member of household to Republic of South Africa).

The independent variables are Age of household head, Sex of household head, marital status of head, Education Status of household head, Job/occupation of household head, Family Size of household, Family Pressure, Age of migrant, Education Status of migrant, farm land size, Average income of household head, Residence of household, Push factors (Likert scale), pull factors (Likert scale) and other variable, which are exhausted using self-structured questionnaires.

2.6. Statistical Model

Bayesian Logistic Regression Model

Logistic regression is a flexible statistical method for predicting a response variable using various types of independent variables. It evaluates predictor importance, interactions, and covariate effects while being robust against outliers. Preferred over probit models, it requires assumptions like proper variable coding, relevant predictors, low error, linearity in logits, independent sampling, no multicollinearity, and adequate sample size.

Let $Y_{n\times 1}$ be a dichotomous outcome random variable with categories 1 (household head who have plan to send any family member to RSA with irregular migration and migrants) and 0 (household head who have no plan any family member to leave the residential area with irregular migration to RSA). Let $X_{n\times(p+1)}$denote the collection of p-independent variables of Y.

Where $X = \begin{bmatrix} 1 \; x_{11} \; \dots \; x_{1p} \\ 1 \; x_{21} \; \dots \; x_{2p} \\ 1 \; x_{n1} \; \dots \; x_{np} \end{bmatrix}$ is called regression matrix and without the leading column of 1 is termed as independent data matrix. We use p_i to represent the probability that Y=1 and we define 1- p_i to the probability that Y=0. These probabilities are written in the following form:

$$p_i = P\left(Y = \frac{1}{X_i}\right) \quad (2)$$

$$1 - p_i = P\left(Y = \frac{0}{X_i}\right) \quad (3)$$

In Equation (4) we use the model for the natural logarithm of the odds (log odds) to favor Y = 1.

$$ln \frac{P(Y=1/X_j)}{1-P(Y=1/X_j)} = ln \frac{p_i}{1-p_i} = \beta_o + \sum_{j=1}^{n} \beta_j X_j \quad (4)$$

Using the inverse of the logit transformation of Equation (4) we arrive at the following:

$$P(Y = 1/X_j) = \frac{e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}{1+e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}} = \frac{1}{1+e^{-(\beta_o + \sum_{j=1}^{n} \beta_j X_j)}} \quad (5)$$

The Bayesian approach treats model parameters as random variables and requires prior distributions to be specified, while data are considered fixed. Bayesian logistic regression is used to infer parameters of a logistic regression model, following the standard Bayesian framework: specifying the likelihood function, prior distributions, and posterior distribution [19].

Likelihood Function

In logistic regression, the likelihood function for independent observations is the product of individual Bernoulli probabilities. For subject ith, the likelihood contribution is:

$$l(y_i/\beta) = \prod_{i=1}^{n} p_i^{y_i}(1-p_i)^{1-y_i} \quad (6)$$

Where, p_i represents the probability of the event for subject i who has covariate vector Xi, yi indicates the presence, yi=1, or absence yi=0 of the event for that subject. We know that, in equation (6) logistic regression the probability of success written as:

$$p_i = \frac{e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}{1+e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}} \quad (7)$$

Since individual subjects are assumed independent from each other the likelihoods function over a data set of subjects is:

$$l(y_i/\beta) = \prod_{i=1}^{n} \left(\frac{e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}{1+e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}\right)^{y_i} \left(1 - \frac{e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}{1+e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}\right)^{1-y_i} \quad (8)$$

Prior Distribution

Bayesian estimation requires specifying priors for all parameters. When prior knowledge is limited, non-informative priors are commonly used. For this purpose, the most common priors for logistic regression parameter is normal has the form: $\beta_j \sim (\mu_j, \sigma_j^2)$. Hence, the prior distribution of logistic regression coefficient is given as:

$$p(\beta_j) = \frac{1}{\sqrt{2\pi\sigma_j^2}} exp\left\{-\frac{1}{2}\left(\frac{\beta_j - \mu_j}{\sigma_j}\right)^2\right\} \quad (9)$$

In Bayesian analysis the precision is often specified instead of variance. The most common choice for $\mu_j$is zero, and $\sigma_j$is usually chosen to be large enough to be considered as non-informative, common choices being in the range from $\sigma_j = 10$ to $\sigma_j = 1000$ [20].

Posterior Distribution

The posterior distribution combines the likelihood function and priors:

P(β｜data)∝l(data｜β)·p(β)

or

$$p(\beta/data) = \prod_{i=1}^{n} \left(\frac{e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}{1+e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}\right)^{y_i} \left(1 - \frac{e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}{1+e^{\beta_o + \sum_{j=1}^{n} \beta_j X_j}}\right)^{1-y_i} * \frac{1}{\sqrt{2\pi\sigma_j^2}} exp\left\{-\frac{1}{2}\left(\frac{\beta_j - \mu_j}{\sigma_j}\right)^2\right\} \quad (10)$$

Due to its complexity, the posterior is often approximated using Markov Chain Monte Carlo (MCMC) methods, such as the Gibbs sampling algorithm implemented in Win BUGS.

Bayesian inference relies on posterior distributions of model parameters, but evaluating these distributions often involves complex, high-dimensional integrations. Markov Chain Monte Carlo (MCMC) methods, particularly the Gibbs sampling algorithm, address these challenges by approximating posterior distributions.

The Gibbs sampler, introduced by Geman and Geman (1984), is a specific case of the Metropolis-Hastings algorithm where proposed moves are always accepted (α=1\alpha = 1α=1). It generates samples iteratively by sampling each parameter from its full conditional distribution, allowing inference from multivariate distributions.

The algorithm begins with initial parameter values and iteratively updates each parameter until convergence is achieved. Convergence ensures that the sampled values represent the target posterior distribution, making Gibbs sampling a key tool for Bayesian analysis [18, 19].

3. Results and Discussion

The primary objective of this study was to investigate the socio-economic and demographic causes and consequences of irregular migration from Central Ethiopia to the Republic of South Africa, with a focus on Shashogo Woreda in Hadiya Zone. Data was collected from households that either had plans to send a member of their household to South Africa or had already sent a member. Data collection took place from June to August 2024. A sample size of 346 was initially determined for the study; however, 4 respondents were unavailable, resulting in the analysis being based on the data from 346 respondents. Among the 346 households, 50.57% (175 household) had plans to send a member to South Africa, while the remaining 49.42% (171 households) had not yet made such plans.

3.1. Descriptive Analysis of Results

Table 1 presents the descriptive statistics for the continuous independent variables. Family size ranged from 1 to 12, with a mean of 7.06 and a standard deviation of 3.13. The average age of household heads was 46.43 years (SD = 12.64), while the mean household farmland size was 2.07 hectares (SD = 1.93).

Table 1. *Descriptive Statistics of Continuous Independent Variables (Shashogo Woreda, 2024).*

Continuous Variables	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Dev**
Family size	346	1	12	7.06	3.134
Age of household head (in year)	346	26	80	46.43	12.641
Farmland size (in hectare)	346	0.00	9.00	2.0684	1.92925

3.2. Bivariate Analysis Results

This section explores the relationship between future migration status and various independent variables using descriptive statistics, chi-square, and likelihood ratio tests. Frequency distributions were also provided for each variable category. The analysis identified significant associations with future migration status for variables such as the sex and education level of the household head, current residence, workplace, awareness of illegal migration, and whether the household experienced negative consequences of illegal migration. Conversely, no significant associations were found for the household's experience of specific negative migration consequences, deportation history of members from transit countries, or how migration costs were covered, as indicated by significance values above the 5% threshold (table 2).

Table 2. *Test of Association between dependent and Explanatory Variables (Shashogo Woreda, 2024).*

Variable	**Category**	**Plan to send any member of household to RSA?**						**Chi-square (Sig.)**	**LR (Sig.)**
		Have plan		**Have no plan**		**Total**			
		Count	**%**	**Count**	**%**	**Count**	**%**		
Sex of HH	Male	95	38.15%	154	61.8%	249	71.4%	58.896 (0.000)	62.634 (0.000)
	Female	80	82.5%	17	17.5%	97	28.6%		
Education Level of HH	Uneducated	18	31.03%	40	68.96%	58	16.76%	41.824 (0.000)	43.388 (0.000)
	Primary	64	70.3%	27	29.7%	91	26.8%		
	Secondary	50	39.1%	78	60.9%	128	37.8%		
	College Diploma &	43	62.3%	26	37.7%	69	20.4%		

Variable	Category	Plan to send any member of household to RSA?						Chi-square (Sig.)	LR (Sig.)
		Have plan		Have no plan		Total			
		Count	%	Count	%	Count	%		
	Above								
Working organization of HH	Agriculture	56	41.8%	78	58.2%	134	39.4%		
	Trade	46	48.4%	49	51.6%	95	28.0%	8.111 (0.044)	8.158 (0.043)
	Employee	56	63.63%	32	36.36%	88	25.43%		
	Other	17	58.6%	12	41.4%	29	8.6%		
Current residence place of HH	Rural	112	51.4%	106	48.6%	218	64.3%	8.08 (0.036)	8.09 (0.036)
	Urban	63	49.22%	65	50.78%	128	37.0%		
Negative consequence of illegal migration in household	Yes	110	49.3%	113	50.7%	223	65.8%	0.014 (0.906)	0.014 (0.906)
	No	65	52.84%	58	45.31%	123	35.5%		
Negative consequence of illegal migration faced on household	No	61	41.6%	57	48.3%	118	34.8%		
	Arrest	48	46.2%	37	43.5%	85	25%		
	Death	19	57.6%	14	42.42%	33	9.53%	4.262[a] (0.372)	4.278 (0.370)
	Disability	10	56.5	11	52.4%	21	6.2%		
	facing a financial crisis	37	41.6%	52	58.4%	89	26.3%		
Household members ever deported from transit countries	No	77	49%	80	51.0%	157	46.3%		
	Mozambique	27	58.7%	19	41.3%	46	13.6%		
	Malawi	19	50%	19	50%	38	11.2%	4.861 (0.302)	6.715 (0.297)
	Tanzania	35	59.3%	24	40.67%	59	17.05%		
	Other	17	37.0%	29	63%	46	13.6%		
The migrants cost cover	From abroad	64	46.0%	75	54.0%	139	41.0%		
	In the country	38	44.7%	47	55.3%	85	25.1%	4.31 (0.116)	4.322 (0.115)
	From both	73	59.83%	49	40.16%	122	35.26%		
Awareness about illegal migration	Yes	141	61.0%	90	39%	231	68.1%	38.236 (0.000)	36.808 (0.000)
	No	34	29.60%	81	70.40%	115	33.23%		
Migrant in household	Yes	102	52.3%	93	47.7%	195	57.5%	1.389 (0.023)	1.390 (0.022)
	No	73	48.34%	78	54.2%	151	43.64%		

The results in Table 2 indicate that 71.4% of the respondents are male, while the remaining 28.6% are female. There is a significant gender difference in terms of plans to send a household member to the Republic of South Africa (RSA). A greater proportion of male household heads (61.8%) reported having no such plans, whereas 82.5% of female household heads reported having plans to send a household member. This suggests that female-headed households are more likely to plan for migration to RSA than their male counterparts. In terms of educational status, 37.8% of respondents had attended secondary school, 26.8% had completed primary school, 16.76% were uneducated, and 20.4% held a college diploma or higher. Among these groups, the highest proportion of those planning to send a household member to RSA were individuals with primary education (70.3%), followed by those with a college diploma or higher (62.3%), and those with secondary education (39.1%).

Out of the 346 sampled households, a higher percentage of rural households (51.4%) reported plans to send a member to RSA compared to urban households (49.2%). Among those who did not plan to send a household member, 64.3% resided in rural areas, while 35.7% lived in urban areas. Regarding the source of migration costs, 41.0% of respondents reported receiving financial support from relatives abroad, 25.1% from within the country, and 35.26% from both domestic and international sources. Furthermore, 68.1% of respondents indicated they were aware of the risks and realities of illegal migration, while the remaining 31.9% lacked such awareness (table 2).

3.3. Descriptive Statistics of Push–Pull Factors

This study presents the push–pull factors influencing migration from shashogo Woreda, Hadiya Zone, using a five-point Likert scale for each respondent. Push factors refer to reasons that compel individuals to leave their home country, while pull factors refer to the reasons that attract. individuals or groups to the destination country.

In general, the push–pull factors for migration from Hadiya Zone in shashogo Woreda primarily reflect economic-related reasons such as unemployment, poverty, lack of job opportunities, farmland shortage, large family size, better quality of life, availability of infrastructure, high job opportunities, better economic opportunities, and better wage rates.

Table 3. *Push Factors of Migration (Shashogo Woreda, 2024).*

Push Factors	Strongly Disagree		Disagree		Neutral		Agree		Strongly agree	
	Fr	%	Fr	%	Fr	%	Fr	%	Fr	%
Unemployment	21	6.2	57	16.8	35	8.6	180	53.1	52	15.3
Poverty	27	8	60	17.7	60	17.7	145	42.3	62	18.3
Lack of Job opportunity	13	3.8	36	10.6	32	9.4	182	53.7	83	25.4
Farm Land shortage	23	6.8	72	21.2	40	11.8	142	41.9	69	21.3
Large family size	39	11.5	73	21.5	55	16.2	132	38.9	47	19.9

As shown in Table 3, the analysis revealed that the primary push factors driving migration from Shashogo Woreda were economic in nature, including unemployment, poverty, lack of job opportunities, farmland shortage, and large family size. These factors were identified as push factors by 68.4%, 60.6%, 79.1%, 63.2%, and 58.8% of respondents, respectively. Conversely, 23%, 25.7%, 14.4%, 28%, and 33% of respondents disagreed with these reasons being push factors. To further elaborate on the results, the five-point Likert scale responses were grouped into three categories: "Disagree" (combining strongly disagree and disagree), "Agree" (combining strongly agree and agree), and "Neutral."

Table 4. *Pull Factors of Migration (Shashogo Woreda, 2024).*

Pull Factors	Strongly Disagree		Disagree		Neutral		Agree		Strongly agree	
	Fr	%	Fr	%	Fr	%	Fr	%	Fr	%
Better quality of life	13	3.8	39	11.5	31	9.1	194	57.2	62	18.3
Availability of infrastructure	11	3.2	38	11.2	35	10.3	175	51.6	80	23.6
High Job opportunity	7	2.1	30	8.8	19	5.6	184	54.3	99	29.2
Better wage rate	14	4.1	36	10.6	35	10.3	181	53.4	73	21.5
The better economic opportunities	7	2.1	30	8.8	16	4.7	186	54.9	100	29.5

As shown in Table 4, the proportions of respondents for key migration pull factors are as follows: 75.7% agree that better quality of life is a key pull factor, while 15.3% disagree. Similarly, 75.2% agree that the availability of infrastructure is a pull factor, with 15.4% disagreeing. For high job opportunities, 74.9% of respondents agree, while 10.9% disagree. Regarding better economic opportunities and better wage rates, 14.7% and 10.9% of respondents, respectively, disagree. In contrast, 83.5% and 84.4% agree that these factors are significant migration pull factors in the study area, attracting people to migrate abroad.

3.4. Bayesian Logistic Regression Model

The Bayesian logistic regression model, estimated using the Gibbs sampler in Win BUGS, produced reliable posterior statistics, with MC errors below 5% of standard errors, confirming model convergence and accuracy [17].

Table 5. Summaries of Posterior parameters (shashogo Woreda, 2024).

Node	Variable name	Mean ($\hat{\beta}$)	$s.d$	MC error	CI at 95%	
					Lower	Upper
Beta [1]	Age of HHH	-0.1367	0.02517	8.418E-4	-0.1869	-0.08858
Beta [2]	Sex of HHH	2.176	0.3702	0.007897	1.476	2.919
Beta [3]	family size	0.6218	0.09402	0.002376	0.4445	0.8127
Beta [4]	Education Level of HH	0.2431	0.2701	0.007941	0.2913	0.8127
Beta [5]	Working organization of HHH	0.8075	0.2209	0.003557	0.3861	0.7695
Beta [6]	current residence place of HHH	-1.027	0.3667	0.005553	-1.759	-6.232E-5
Beta [7]	awareness	-1.752	0.3581	0.006332	-2.478	-0.3276
Beta [8]	land size	-0.01082	0.08346	9.573E-4	-0.1746	0.1534

As shown in Table 5, eight variables age, sex, family size, education, working organization, residence, and awareness were significant predictors of irregular migration, with 95% credible intervals excluding zero. Monthly income and land size were not significant, as their intervals included zero. Lag-4 autocorrelation showed some post burn-in correlation, which is typical but warrants attention.

4. Discussion

This study aimed to investigate the socio-economic and demographic factors influencing (driving) irregular migration from Hadiya Zone, Shashogo Woreda, to the Republic of South Africa. The analysis, based on data from 346 respondents, revealed that 50.57% of households had plans to send a member to South Africa, while 49.42% had no such plans.

Main factors contributing to irregular migration in the study area were identified as unemployment, poverty, lack of job opportunities, farm land shortage, Influence and pressure from friends and families and large family size. Such reasons have also been mentioned and discussed by numerous previous related studies in detail. These economic motivations emerged as significant drivers forcing migration. Notably, lack of job opportunities played the most substantial role, followed by unemployment, farm land shortage, large family size, and poverty, aligning with findings from previous studies [21].

Our study aligns with findings from various studies on factors influencing return migration and intentions for re-migration. Influential determinants such as marital status, economic deprivation, and unemployment significantly impact both the initial decision to migrate and considerations for future migration. For instance, a study by Ebrahim and Biru (2022) examined the drivers of migration, challenges faced by returnee migrants, and their future intentions in the Amhara region of Ethiopia. The research found that current marital status positively influenced returnees' intentions to remain in their homeland, while economic hardships and joblessness were significant factors contributing to considerations of re-migration [22].

Both family size and the age of the household head have a positive association with future migration status. The odds ratio indicates that the plan to send any member of the household to RSA increases by 45.7% for every one-unit increase in family size. Similarly, the odds ratio for the age of the household head shows that the plan to send any member of the household to RSA increases by 21.2% for every one-unit increase in age. This result aligns with other findings [12].

Current residence place is an important variable that helps us understand the association between residence and irregular migration. The variable is found to have a significant association with the plan to send any member of the household to RSA. Our study revealed that rural household heads have more plans to send any member of the household than urban household heads. This finding is consistent with other related studies [23].

This study's findings that sex, age, family size, educational level, working organization, and current residence place significantly influence future migration intentions align with existing research. For instance, a study by Teshome et al. (2013) on young adult migration from southern Ethiopia to South Africa found that factors such as age, marital status, occupation, and education level significantly affect migration decisions [23].

5. Conclusion

This study explored the socio-economic and demographic determinants and consequences of irregular migration from Central Ethiopia, specifically Shashogo Woreda in Hadiya Zone, to the Republic of South Africa. The findings reveal that irregular migration is deeply rooted in both structural push factors such as unemployment, poverty, lack of job opportunities, farmland scarcity, and large family sizes and powerful pull factors, including the attraction of better wages, job opportunities, infrastructure, and improved quality of life abroad.

Descriptive and bivariate analyses identified significant associations between migration intentions and variables such as sex, education level, occupation, place of residence, and awareness of the risks associated with illegal migration. Remarkably, female-headed households and those with primary-level education were more inclined to plan migration. Moreover, the Bayesian logistic regression analysis confirmed that demographic and socio-economic factors specifically age, sex, family size, education, employment type, residence, and awareness are strong predictors of irregular migration intentions. In contrast, household income and landholding size showed no significant effect.

Despite increased awareness of the risks of irregular migration, including arrest, disability, or even death, these constraints have not significantly changed migration plans. This highlights the persistent economic pressures and perceived lack of feasible alternatives within the local context.

In general, irregular migration from the study area is driven more by a complex relationship of local vulnerabilities and external economic promises than by a lack of awareness. Thus, policy interventions should prioritize rural development, youth employment, access to education, and legal migration pathways. Strengthening local livelihoods and increasing awareness campaigns may moderate the root causes driving irregular migration trends in central Ethiopia.

Abbreviations

RSA	Republic of South Africa
HH	Household Head
OR	Odds Ratio
IRB	Institutional Review Board
CSA	Central Statistical Agency
MCMC	Markov Chain Monte Carlo
Win BUGS	Windows Bayesian Inference Using Gibbs Sampling

Acknowledgments

Our heartfelt thanks go to the data collectors (enumerators), supervisors, and all the households who willingly provided accurate information that made this migration research a reality. We also extend our appreciation to all the officials who guided and supported us throughout the study.

Conflicts of Interest

The authors declare no conflicts of interest.

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