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SEASONAL MIGRATION IN THARPARKAR DISTRICT OF SINDH PROVINCE, PAKISTAN: An In-depth Empirical Analysis

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Abstract

This study thoroughly investigates the influence of poverty-related characteristics of poor households, such as socioeconomic, livelihood and distance characteristics, on their decision to seasonally migrate from the Tharparkar district of Sindh province to nearby districts where seasonal livelihood and employment opportunities exist in irrigated agriculture. The study was carried out using multi-stage cluster sampling and data was collected through face-to-face interviews using a questionnaire. We estimated a binary logit model and subsequently tested hypotheses about the influence of those poverty-related characteristics on poor households' seasonal migration. Our hypotheses testing results exhibit that poverty among the households, existing in their low household income, indebtedness, child labour, lack of access to drinking water and health services, are the major factors behind seasonal migration. To encounter the adverse effect of poverty on seasonal migration, we suggested several policy measures overall related to food security, water availability and economic opportunities, such as access to interest-free credit, livestock marketing, and promotion of handicrafts.

Keywords: Seasonal Migration, Socio-economic, Livelihood, Distance Characteristics, Binary Logit Model, Poverty.
JEL Classification: O15, P25, R23, C01, C12.

I. Introduction

Migration can be defined as the relocation of people from one area to another with the purpose of their resettlement in the new area, where they migrated either permanently or temporarily in search of livelihood and employment opportunities [Kesheri and Bhagat (2010) and Brauw (2007)]. In historical and human evolution perspectives, migration has stemmed from many factors but it is not limited to social, economic, legal, political, cultural and educational factor, which are by, and large divided into 'push' and 'pull' factors, initially discussed in a comprehensive theory of migration, proposed by Everett Lee in 1966, and later expanded by Castelli (2018) and Van Hear,

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et al., (2017). Push factors involve those disappointing situations, like war, natural catastrophe, famine, etc., for the local people to migrate either temporarily or permanently to other areas where their lives sustain. Nevertheless, pull factors are those appealing situations, like better economic, social, political, and educational opportunities, in the areas of destination that attract people to migrate to from their areas of origin, as Lee (1966) briefly discussed in his theory of migration, to the regions with these prospects [Kline (2003) and Castelli (2018)]. Also, the difference of wages between the place of origin and destination, including travel costs, affect seasonal migration, according to the neoclassical theory of migration [Massey, et al., (1993)].

The Permanent migration of people takes place to the new area where they migrate forever like emigration to a country. In contrast, the temporary migration of people can be both internal and external; in external migration, people temporarily migrate internationally, regionally or provincially, from one country to another or province for employment, business and asylum. The internal migration can be both inter-provincial, for instance, the migration that takes place between the two provinces and in intra-provincial within the same province moving from one district or another characteristically [Deshingkar (2006)]. Whether it is inter-provincial and intra-provincial migration, there is another type of temporary migration, called seasonal or return migration, which people do for a short period intending to be back to their place of origin. In other words, seasonal migration is a temporary migration[1] which involves economic mobility of labour seasonally [Kesheri and Bhagat (2010)].

Seasonal migration is a common phenomenon all over the world, specifically in the remote (drought-prone) areas of South Asian and African countries where poverty-related characteristics such as low household income, indebtedness, child labour, livestock mortality, lack of access to drinking water and health services force the poorer adult labourers to move towards the areas. They could find livelihood and subsistence opportunities like seasonal labour in irrigated agriculture in specific crop seasons. Following a comprehensive theory of migration, Lee (1966), Castelli (2018) and Bhagat (2010) define seasonal migration as a form of migration, whereby people move to the area of destination for a specific period intending to earn income and then come back to their area of origin once crop season is over. In this context, seasonal migration is also a widespread trend in the Tharparkar district of Sindh province in Pakistan due to recurrent spells of droughts, high variations in monsoon rains and the resulting poverty among households over the last few decades [Sattar (2014)]. As a result, local communities in the Tharparkar desert, confronted with the loss of rain-fed livelihood opportunities, such as crop failures, lack of drinking water and livestock morbidities and mortalities in addition to their indebtedness the increasing burden of informal credit,

[1] In the literature, temporary migration term is used interchangeably with circular, seasonal and short-term migration and explained as a moved labour activity of a migrating person from less economically active area to more economically active one [Kesheri and Bhagat (2010)]. In our study, we preferably used 'seasonal migration' as compared to other terms.

seasonally migrate to the nearby districts where they could find seasonal livelihood opportunities in terms of the agricultural labourer, fodder for livestock, and access to water and health services during a particular crop season. According to FRDP (2018), there are mainly two types of seasonal migration across district Tharparkar due to drought-related poverty: (i) the households who migrate with their livestock and (ii) some adults of the households who migrate with livestock while other family members stay at home. In the recent past, this seasonal migration trend has increased in manifold due to the development of roads and communication network across the district [Sattar (2014)].

According to Parida and Madheswaran (2015), the main reason behind seasonal migration is the lack of livelihood alternatives in rural areas. For instance, the threatening factors, joblessness, indebtedness, low wages, irregular and lower-income, and food insecurity within the households push individuals to seasonally migrate [Castelli (2018)]. Cristina (2015) further clarifies not only the socioeconomic characteristics of the affected households who seasonally migrate to irrigated areas of Sindh province, which offer temporary employment and income, but other factors, such as indebtedness and distance to nearby towns, force these households to escape their vulnerability to drought-related poverty resulting from hunger, malnutrition, diseases, livestock mortality, and more.

Although various research studies have been conducted worldwide on the factors affecting seasonal migration, very limited empirical evidence exists on this essential issue in Pakistan. To fulfil this research gap, our study, is the first research that investigates different socioeconomic, livelihood and distance characteristics affecting seasonal migration in the Tharparkar district of Sindh province in Pakistan. Therefore, this study empirically analyses to what extent these different characteristics during the droughts influence the seasonal migration of poor households living across the Tharparkar desert in Sindh province.

The rest of the study is organised as follows: Section II presents the literature reviews analysing seasonal migration in detail. Section III describes the case study area, the survey design and its implementation, while Section IV specifies the econometric modelling framework. Section V presents descriptive statistics, models results, robustness analysis and hypotheses testing. Lastly, Section VI demonstrates the conclusion followed by policy recommendations.

II. Review of Literature

Most studies have been carried out on socioeconomic and livelihood characteristics and their impact on seasonal migration. A study conducted by Samita (2008) in India discloses that households seasonally migrate largely due to non-availability of employment opportunities in Maharashtra, Karnataka and Utter Pradesh provinces, and drought in Rajasthan and Gujarat provinces, respectively. Her study concluded that the migrant families having higher levels of education also migrate seasonally but only

to urban areas to seek employment, whereas less educated families migrate temporarily to the nearby areas with the lower distance. Likewise, in their study, Wand Schneider and Mishra (2003) analysed that people seasonally migrate from drought-prone areas to nearby developed towns in India to access employment, credit, agricultural inputs, livestock marketing, education, and health services.

Gorlich and Trebesch (2006) research specifically addresses a trend of international seasonal migration in Moldova, Africa. Using a binary logit model, the researchers found that some household characteristics of seasonally migrant communities, such as household size, education levels, poverty, and migration experience, positively and significantly encourage seasonal migration, whereas age and the number of dependents negatively affect seasonal migration. They concluded that increased labour population and collapsed rural economy were the main causes behind seasonal migration in Moldova. Shahriar et al., (2006) applied a logit model using a cost-benefit approach of the poor households' decision regarding their seasonal migration from Kurigram district in Northern Bangladesh. For example, if poor households' migration decision will benefit them, they migrate, otherwise not. The authors found that economic determinants, ecological vulnerability and individual characteristics have significant influence on seasonal migration.

Rademacher-Schulz, et al., (2014) assessed that the subsequent food insecurity resulting from low crop production compel poor households to leave their agro-based work and migrate seasonally towards places where non-agro-based work is offered. Households migrate to earn money and buy food to fulfil their basic needs. Most of the farming households in Ghana believe that without temporary or seasonal migration, fulfilling necessities is difficult [Geest (2011)]. In Tanzania, political uncertainty, high population growth, land ownership, and non-availability of irrigated water encourage the internal seasonal migration [Msigwa (2013)].

Seasonally migrant families living in Northern Bangladesh are mostly farmers and crop variability compel them to vacate their homes because after plantation during the autumn season, there is no availability of work in their areas, and they become unemployed [Shahriair, et al., (2006)]. Thus, inadequate employment opportunities pressurise their family members to migrate to areas where work and financial resources are accessible. In one of the earlier studies, Chaudhry (1978) analysed that the socioeconomic and livelihood characteristics such as gender, age, education, type of work, assets, land cultivation and irrigation services are significant factors affecting seasonal migration. The study further demonstrated that less educated households choose to migrate for smaller distances with limited time so that they could come back securely to their area of origin. Socioeconomic differences are the main reason behind temporary migration in Bangladesh [Khan (1982)]. Hossain (2001) studied that poverty among the migrating households in terms of their lower household income, the labour needs work and roads network connecting their villages to the cities that lead them to reach their destination areas are the 'push' factors for seasonal migration.

Kesheri and Bhagat (2012) used National Sample Survey data carried out in India from 2007–2008 and studied characteristics influencing seasonal or temporary migration throughout all provinces of India. Using binary logit models, they found that characteristics, including monthly per-capita expenditure, household size, gender, age, marital status, education levels, land holdings, social groups and provinces of India, positively and significantly affect seasonal migration across India. In Pakistan, majority of the households migrate seasonally to seek employment, get financial assistance and improve their living standard [Gazdar (2003)].

III. Case Study, Survey Design and Implementation

Thar Desert is spread from the Cholistan in Punjab to Nagarparkar in the Sindh provinces of Pakistan and from Haryana to Rajasthan provinces in India, respectively. Located within the Thar Desert, the Tharparkar district in the Sindh province of Pakistan is one of the most densely populated deserts globally, with 1.65 million inhabitants [PBS (2017)]. With its adverse demographic and environmental conditions, Tharparkar district has very limited economic and livelihood opportunities, which consistently make the survival of communities extremely challenging, specifically during the consecutive drought spells. Locally, livelihood sources are confined to only rain-fed agriculture and livestock rearing. Due to lack of rainfalls, even in monsoons periods, drought spells endlessly occur year after year, which results in increased food insecurity, infant mortality, and livestock morbidity and mortality. As a result, Tharparkar is regarded among the most vulnerable districts of Sindh province because of its food insecurity and poverty [Akbar (2014)]. According to FDRP (2015) survey, around 90 per cent of households' livelihood depends upon rain-fed agriculture and livestock, 8 per cent are workers and run their businesses (e.g. small shops), and only 2 per cent of people have government and private jobs.

The land of Tharparkar district is classified into three main terrains: socioeconomic, livelihood and environmental characteristics are diversified: (i) the desert area, Chachro, Dahli and Islamkot Talukas, which entirely relies on rain-fed agriculture. According to Gazdar (2003), it is that part which is always prone to the high risk of droughts that leads to the seasonal migration of households, ensuring their food and livestock security to the nearby irrigated areas, including Umerkot, Mirpurkhas and Badin districts in Sindh province of Pakistan. (ii) the semi-desert area, Kaloi, Diplo and Mithi Talukas, where the ground water and even in some parts, specifically in Diplo and Kaloi Talukas, the river water are slightly accessible for cultivation, and (iii) the hilly-desert area, Nagarparkar Taluka, which borders with the Kutch (Sindh) district of Gujarat province in India, where the groundwater is mostly sweet, ensuring its substantial availability for households, agriculture and livestock (Figures 1 and 2).

To assess the impact of socioeconomic, livelihood and distance characteristics on seasonal migrant households, we selected a sample of 440 households living in

FIGURE 1

Tharparkar district (Case study area) and its location in the Sindh province of Pakistan

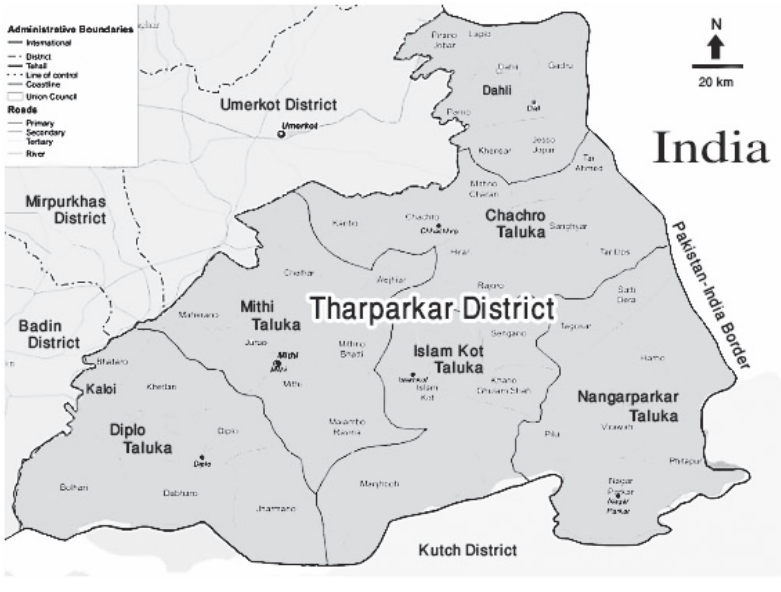

FIGURE 2

Tharparkar district and location of its Talukas (or Sub-districts)

the five different villages of Mithi, Diplo, Chachro, Islamkot and Nangarparkar Talukas (sub-districts)[2]. Using multi-stage cluster sampling, we first selected these Talukas. Using a statistical sample-size formula,[3] the villages were randomly selected from the different union councils (UCs) of these Talukas . In each village, some households were randomly selected for the final interview. The households heads or the adult individual interviewed if the head was absent. A questionnaire was designed and pretested during the focus group interviews and preliminary surveys. The field surveys were implemented to collect data using the above sampling approach using these questionnaires.

IV. Econometric Model

The binary dependent variable takes the values of 1 and 0. Now, suppose that this binary variable y_{ik} is observable by a latent random variable y^*_{ik} with its probabilities $P(y^*_{ik} > 0)$ if an individual (or the head of the household) has migrated seasonally, and $P(y^*_{ik} \leq 0)$ if otherwise, respectively, when they were interviewed during the field surveys.

$$y_{ik} = \begin{cases} 1 = \text{if } i^{th} \text{ individual migrated seasonally}, & y^*_{ik} = x'_{ik}\,\beta_k > 0 \\ 0 = \text{otherwise}, & y^*_{ik} = x'_{ik}\,\beta_k \leq 0 \end{cases}$$

Considering that $P(y_{ik} = 1)$ is a linear function of covariates or independent variables (Greene, 2018; Hosmer and Lemeshow, 2000), whereas x'_{ik} are the *k* number of observable independent variables for *i* number of sampled individuals, β_k is a deterministic part, i.e. vector of the *k* number of coefficients to be estimated, including a constant (or intercept), and ε_{ik} is a stochastic part in Equation (1).

$$P(y_{ik} = 1) = x'_{ik}\,\beta_k + \varepsilon_{ik} \quad (1)$$

We apply a binary logit model to investigate the influence of independent variables, such as socioeconomic, livelihood and distance characteristics, on individuals decisions to migrate seasonally. We first attempt to move from the linear probability expressed in Equation (1) towards odds or odd-ratios as in Equation (2).

[2] When survey was conducted, Kaloi and Dahli Talukas were not created. Therefore, Mithi, Diplo, Chachro, Islamkot and NangarparkarTalukas were included in the sample (Figure 2).

[3] We used $N = \frac{Z^2_{\alpha/2}\,(p)(1\text{-}p)}{e_2}$ formula to calculate sample size through the margin of error. Here, N is the sample size, $(Z_{\alpha/2})$ is the standard error at selected 95% confidence interval (i.e. 1.96), p (1 – p) is estimated percent (or standard deviation) in the population of union councils (UCs), and e is the margin of error under 5% level of significance (i.e. 0.05).

$$\text{Odds}_i = \frac{P(y_{ik} = 1)}{1 - P(y_{ik} = 1)} \tag{2}$$

Second, the logarithms of odds using the above Equation and calculate a binary logit model as expressed in Equation (3).

$$\text{Logit}\,[P(y_{ik} = 1)] = \text{Log}\left[\frac{P(y_{ik} = 1)}{1 - P(y_{ik} = 1)}\right] = \pi_i$$

or

$$\pi_i = \frac{\exp^{(x'_{ik}\,\beta_k)}}{1 + \exp^{(x'_{ik}\,\beta_k)}} \tag{3}$$

Equation (3) now form a binary logit model, where π_i is the probability of an 'event' if an individual or the head of the household has seasonally migrated from Tharparkar district to its adjacent districts in the Sindh province of Pakistan.

V. Results

1. Descriptive Statistics

During the survey, respondents were asked about their socioeconomic characteristics. Respondents' age is 42 years, on average which is larger than the national average that is 23 years; however, the average number of adults is 2.3 persons per household that is almost in line with our national statistics with an average of 3.6 adults per household in the country (Table 1). These statistics suggest that the decision to migrate seasonally is, on average, take the adults, who have a higher potential in doing labour work than the other age groups within the households.

Household income is around 1647 rupees per month, which is much lower than the national average, indicating that the poverty of households is high in the district. UNICEF (2010-11) report demonstrates that poor households, who are extremely poor and vulnerable to poverty, constitute 54.16 per cent of all households in the district, which is almost double our national average which is 27.8 per cent. This indicates that every second household is extremely poor and highly vulnerable to poverty in district Tharparkar. It becomes very common for farmers and poor households to get loans or informal credit to buy crop seeds and food and eventually become vulnerable to indebtedness for a long term if drought situation prevails for some years [FRDP (2018)]. Besides, children's primary education gets immensely affected because of poverty involving their children in child labour. For instance, the number of children who never went to school on average is 53.2 per cent, which is much higher than in Pakistan. Besides, children eventually involved in child labour are overall 76

per cent, which is on average much higher than the same in our country. This evidence is strongly supported by a highly significant positive correlation 0.363 (p-value < 0.000) between children who never went to school and child labour variables, indicating that the higher number of children out of schools, the higher the number of children is involved in child labour (Tables 1 and 2).

Similarly, even more, empirical evidence is in line with the above statistics. The household income has a negative-strong correlation significantly – 0.218 (p-value < 0), exhibiting that the higher the household income, the higher it is evident that fewer children are doing child labour. Besides, there is a positive but statistically and highly significant correlation 0.365 (p-value <0.000) between indebtedness (i.e. getting an informal loan) and household income, which reveals that indebtedness positively con-

TABLE 1

Variable Description and Descriptive Statistics

Variables	Variable names	Description	Tharparkar	Pakistan average*
Age	age	Respondent's age in years (average)	41.76	23
Number of adults	hsizead	Number of adult persons/household (average)	2.3	3.6
Household income	hhinc	PKR thousands/month (average)	1.647	35.662
Indebtedness	indebt	Dummy (1 = Yes, being in debt) (per cent)	36	---
Children never went to school	chnever	Number of children (per cent)	53.2	20.1
Children doing child labour	chwork	Number of children (per cent)	76	47.5
Type of house	hstruct	Dummy (1= Kutcha) (percent)	94.77	34.52
Landholdings	ldhold	Number of acres owned by the household (average)	8	25
Livestock animals	lstock	Number of animals owned (average)	9.53	---
Water distance	watdist	Distance from drinking water in kilometers (average)	0.6	---
Hospital/ Dispensary distance	hpdist	Distance from hospital in kilometers (average)	14.8	---
City distance	citydist	Distance from a nearby city in kilometres (average)	28.8	---

Source: Field survey (2016 – 2017).

* Pakistan Bureau of Statistics (2015). Only available national statistics are mentioned in the table.

TABLE 2

Pairwise Correlation Coefficients (Matrix)

	age	hsizead	hhinc	indebt	chnever	chwork	hstruct	ldhold	lstock	watdist	hpdist	citydist
age	1											
hsizead	0.093*	1										
hhinc	0.153***	0.073	1									
indebt	-0.059	- 0.107**	0.365***	1								
chnever	0.047	0.191***	-0.005	-0.237***	1							
chwork	-0.047	-0.014	-0.218***	-0.137***	0.363***	1						
hstruct	-0.017	0.018	-0.282***	-0.097**	0.102**	0.231***	1					
ldhold	-0.06	-0.015	-0.028	-0.05	0.028	0.093*	0.015	1				
lstock	0.092*	0.013	0.308***	0.134***	0.035	-0.066	-0.096**	-0.046	1			
watdist	0.073	0.067	0.127***	-0.011	-0.041	-0.222***	-0.113**	-0.063	0.033	1		
hpdist	0.005	0.006	0.009	0.032	0.108**	-0.063	-0.028	-0.026	-0.093**	-0.171***	1	
citydist	-0.018	-0.137***	-0.115**	0.005	-0.068	-0.069	-0.026	0.198	0.096*	-0.300***	0.456***	1

Source: Authors' estimation.

Note: Akaike Information Criteria (AIC), statistical significances at 1% , 5% and 10% levels are indicated by ***,** and *.

tributes to an increase in the household income. The same indebtedness variable influences negatively and highly significantly children who never attended schools and child labour variables (Table 2).

Furthermore, we collected data on livelihood characteristics; each household has 8 acres of land holdings, whereas each household has on average 9 livestock animals. Table 2 shows that livestock is one of the main sources of livelihood for poor households, with evidence of a highly significant strong correlation of 0.308 (p-value < 0.000) between average monthly household income and the average number of livestock animals per household. We also included distance characteristics influencing seasonal migration. Access to drinking water, on average, was found at 0.62 kilometers. In contrast, the distance to the hospitals (or dispensaries) in nearby towns and the city on average was 14.8 and 28.8 kilometres, respectively (Table 1). The distance to the city is larger than the hospitals because in Nangarparkar Taluka, people consider Mithi Taluka a city; for Chachro and Islamkot, Umerkot is considered a city and for Mithi and Diplo, both Mirpurkhas and Badin are considered as cities. The average monthly household income have statistically significant positive and negative correlations 0.127 (p-value < 0.000) and -0.115 ((p-value < 0.015) with water distance and city distance variables, respectively. Therefore, households with relatively higher or stable monthly incomes travel more to fetch drinking water. They travel less to the nearby cities indicating that these are the households whose adults migrate with their livestock to irrigated agriculture areas and send income to their household members who stay in villages. Household construction has significant positive correlations of 0.102 (p-value < 0.05) and 0.231 (p-value < 0.001) with children who never attended school and child labour, respectively.

Also, household construction has a negative but statistically significant correlation –0.096 (p-value <0.05) with livestock animals. These correlation results reveal that the number of livestock is small, and children do not go to schools but are involved in child labour if household poverty is high.

Additionally, we perform non-parametric Kruskal-Wallis (χ^2) tests to assess further the sample differences in socioeconomic, livelihood and distance characteristics of poor households living across five Talukas of district Tharparkar (Appendix, Table A-1). The results verify that the differences except in age and indebtedness variables are statistically significant for all the variables across five Talukas of the district at different levels of statistical significance. The terrain or landscape of the Tharprkar district is classified into three main distinct areas, including desert, semi-desert and hilly areas. We also examine the differences in socioeconomic, livelihood and distance characteristics between these three individual areas, including desert versus semi-desert and hilly, semi-desert versus desert and hilly, and hilly versus desert and semi-desert areas using non-parametric Mann-Whitney U tests [Talpur, et al., (2018)] (Appendix, Table A-2). For most socioeconomic variables except age and indebtedness, livelihood and distance characteristics, there are statistically significant differ-

ences at 1 per cent, 5 per cent and 10 per cent levels between the desert area, Chachro and Islamkot and semi-desert and hilly areas, more specifically, those between livelihood and distance characteristics. Therefore, these results suggest that the differences in these poverty-related characteristics affect poor households relatively more than counterparts in other areas, including semi-desert and hilly areas, in the district.

TABLE 3

Estimated Binary Logit Models

Variables	Model – 1 Coefficient (St. Error)		Model – 2 Coefficient (St. Error)		Model – 3 Coefficient (St. Error)	
Socioeconomic characteristics						
Constant (Intercept)	-1.622	(1.299)	-3.072**	(1.454)	-2.734	(1.791)
Age	0.063***	(0.019)	0.068***	(0.019)	0.069***	(0.021)
Number of adults in household	-0.724**	(0.314)	-0.642***	(0.320)	-0.969***	(0.365)
Household income	0.0005***	(0.0001)	0.0005***	(0.0001)	0.0005***	(0.0001)
Indebtedness	-2.730***	(0.469)	-2.820***	(0.481)	-2.921***	(0.526)
Children never went to school	-1.144***	(0.288)	-1.391***	(0.321)	-1.498***	(0.338)
Children doing child labour	-3.243***	(0.437)	-3.281***	(0.445)	-3.492***	(0.520)
Type of house (Kutcha)	-2.268***	(0.727)	-2.189***	(0.734)	-1.894**	(0.848)
Livelihood characteristics						
Landholdings			-2.192*	(1.147)	-2.242**	(1.103)
Livestock animals			0.110**	(0.048)	0.139***	(0.052)
Distance characteristics						
Water distance					0.689***	(0.227)
Hospital/Dispensary distance					0.043**	(0.021)
City distance					-0.045***	(0.015)
Model-Fit statistics						
Pseudo R^2	0.55		0.57		0.62	
Log Likelihood (Unrestricted)	-235.822		-235.822		-235.822	
Log Likelihood (Restricted)	-105.618		-100.803		-89.564	
Probability (χ^2)	0		0		0	
AIC	227.237		221.607		205.129	
Observations (N)	440		440		440	

Source: Authors' estimation.
Note: Akaike Information Criteria (AIC), statistical significances at 1% , 5% and 10% levels are indicated by ***, ** and *.

2. Model Results

All estimated binary logit models capturing the influence of socioeconomic, livelihood and distance characteristics on a dummy dependent variable of seasonal migration in the Tharparkar district are demonstrated in Table 3. For data analysis, we used Stata – 14 software and estimated Model-1 to capture the socioeconomic characteristics of households influencing their seasonal migration. In Model-1, age, household income and livestock animal variables affect seasonal migration positively, however, less severally at statistically 5 per cent and 1 per cent levels of significance, respectively. It indicates that an increase in age and household income encourage seasonal migration. Besides, the number of adults in a household, indebtedness, children who never went to school and children doing child labour characteristics have negative but the larger coefficients statistically significant at 5 per cent and 1 per cent levels, respectively. It indicates that households do not migrate seasonally as they have high debts or loans to pay back; their children's work contributes substantially to household income, although living in Kutcha[4] houses.

Subsequently, Model-2 performs better than Model-1, as presented in Table 3. Model-2 is extended by including livelihood characteristics, such as landholdings and the number of livestock animals. Both livelihood characteristics are statistically significant at 10 and 5 per cent levels, respectively. The landholdings have a negative and larger coefficient; during the surveys, landholdings provide subsistence crops to the households and fodder to their livestock during the rainy season and the less severe drought situations, which ultimately discourage seasonal migration. On the contrary, the increase in number of livestock animals has a positive but smaller coefficient, avoiding livestock morbidity and mortality; during the surveys, poor households migrated with livestock to the irrigated areas, where they find both water and fodder for their animals.

Finally, we included distance characteristics to extend estimate Model-3 (Table 3). Pseudo R^2 is higher, and both log-likelihood and Akaike Information Criteria (AIC) of Model-3 are lower than the model-fit statistics of Model-1 and Model-2, respectively. The coefficients for distances to both water and health services appear statistically significant at 1 per cent and 5 per cent levels, respectively. However, both variables have positive signs and relatively lower magnitudes, suggesting that the unavailability of safe drinking water for the people and their livestock animals and health services in the nearby areas put additional pressure on the poor household to migrate seasonally. The distance to the city, which is statistically highly significant at 1 per cent level, and has a negative and even smaller coefficient, suggests that an increase in the distance between the cities, from where the migrating households further move to the nearby districts and locations of households' homes discourage their seasonal migration. It becomes difficult for those households living in the remote areas of the desert and semi-desert to seasonally migrate to the areas of their destination.

[4] The households living in Kutcha houses are made of mud and other natural raw material.

3. Robustness Analysis

Using the binary logit model, Kesheri and Bhagat (2012) also studied characteristics, including monthly household size and household expenditures, gender, age, marital status, education levels, land holdings, and social groups across provinces of India, affect seasonal migration. For robustness analysis, including household size

TABLE 4

Estimated Robust Binary Logit Model

Variables	Model - 3 Coefficient (Robust St. Error)	
Socioeconomic characteristics		
Constant (Intercept)	2.723*	(1.532)
Age	0.058***	(0.021)
Household size	-0.355**	(0.160)
Household expenditures	0.0005***	(0.0001)
Indebtedness	-1.863***	(0.481)
Children never went to school	-1.287***	(0.392)
Children doing child labour	-3.065***	(0.540)
Type of house (Kutcha)	-1.929**	(0.789)
Livelihood characteristics		
Landholdings	-1.235**	(0.565)
Livestock animals	0.140***	(0.048)
Distance characteristics		
Water distance	0.779***	(0.225)
Hospital/Dispensary distance	0.047**	(0.019)
City distance	-0.037***	(0.014)
Model-Fit statistics		
Pseudo R^2	0.56	
Log-Likelihood (Unrestricted)	-235.822	
Log-Likelihood (Restricted)	-104.274	
Probability (χ^2)	0.000	
AIC	234.549	
Observations (N)	440	

Source: Authors' estimation.
Note: Akaike Information Criteria (AIC), statistical significances at 1% , 5% and 10% levels are indicated by ***, ** and *.

and expenditures were included as proxy characteristics for household size adults and household income to estimate the influence of these variables on seasonal migration, as shown in Table 4. Using the binary logit model with robust standard errors, we have noticed that the magnitudes of coefficients relating to socioeconomic, livelihood, and distance variables have substantially decreased with their signs and statistical significances remaining the same. Also, Pseudo R2 has declined when using the robust logit model (Table 4). These empirical findings confirm that household size adults and household income have a comparatively stronger influence on seasonal migration as compared to their proxy variables, such as household size and expenditures.

4. Hypotheses Testing

We developed three hypotheses to investigate the influence of socioeconomic, livelihood and distance characteristics on households' decision of seasonal migration. These null hypotheses are mentioned as follows:

Hypothesis–1: The household socioeconomic characteristics do not influence seasonal migration.

Hypothesis–2: The livelihood characteristics do not influence seasonal migration.

Hypothesis–3: The distance characteristics do not influence seasonal migration.

We used both the Wald and the Log-Likelihood Ratio (LR) tests to test the above null hypotheses. The Wald test, which is a one model test roughly approximating the LR test, statistically finds that the explanatory variables affecting seasonal migration are significant as the coefficients are not equal to zero, whereas the LR test statistically compares the goodness of fit measures, i.e. log-likelihood (LL), of the restricted and the unrestricted models to confirm that adding some explanatory variables in the extended model is significant. The LR test finds that including socioeconomic, livelihood and distance characteristics in the extended models significantly influences seasonal migration.

To test our Hypothesis 1, we first applied the Wald test: $\beta_{age} = \beta_{hsizead} = \beta_{hhinc} = \beta_{indebt} = \beta_{chnever} = \beta_{chwork} = \beta_{hstruct} = 0$.

The critical value of Chi-square with 7 degrees of freedom is 14.31, whereas the estimated Wald statistic is 75.90. We do not accept our null hypothesis at the 5 per cent level of significance. Simultaneously, we also applied the LR test: LR = – 2 (LL Restricted model – LL Unrestricted model), is 266.42 at a 5 per cent level of significance. Based on these test statistics, we rejected our first null hypothesis and concluded that household socioeconomic characteristics significantly influence seasonal migration (Table 5).

Similarly, we applied the Wald test:$\beta_{ldhold} = \beta_{nlstock} = 0$ to test Hypothesis 2. The critical value of Chi-square with 2 degrees of freedom at a 5 per cent level of significance is 5.99, whereas the Wald statistic is 10.26 and the LR statistic is 9.63. Once again, based on both the Wald and the LR tests, we do not accept the null hypothesis

which confirms that the livelihood characteristics and socioeconomic characteristics of the households affect individuals (or the heads of the households) to migrate seasonally (Table 5).

Finally, we tested Hypothesis 3 to assess the influence of distance characteristics on seasonal migration. As usual, we applied both the Wald test: $\beta_{watdist} = \beta_{hpdist} = \beta_{citydist} = 0$, and the LR test, respectively. At a 5 per cent level of significance with 3 degrees of freedom, the critical value of Chi-square is 7.81, whereas the estimated Chi-square value of Wald test is 19.65 and the LR test is 22.48, respectively (Table 5). As a result, we do not accept our third null hypothesis and conclude that distance characteristics, socioeconomic and livelihood characteristics influence the decision of the households whether or not to migrate seasonally.

VI. Conclusion and Policy Recommendations

This study investigated the influence of socioeconomic, livelihood and distance characteristics of poor households living in district Tharparkar of Sindh province on their decision to migrate seasonally. The migrant households living in the different areas of the district seasonally migrate to the adjacent districts where the availability of irrigated agriculture provide them temporary employment, food security and livestock safety, most often during the period of drought. The study was conducted using multi-stage cluster sampling, and data were collected through interviews. Binary logit models were estimated to assess the influence of different socioeconomic, livelihood and distance characteristics of poverty on a dummy dependent variable of seasonal migration. All models performed well; however, Model 3 performed better than the other models demonstrating the statistical significance of all characteristics affecting

TABLE 5

Hypothesis Testing Results

Hypotheses	Wald test (p-value) $\beta i = 0 \quad \forall i = 1, 2, 3, ... , n$	LR test (p-value) LR = – 2 (LL Restricted model – LL Unrestricted model)
Hypothesis – 1	Wald = 75.90 (0.000)***[1]	LR = – 2 [– 235.82 – (– 105.63)]= 266.42 (0.000)***[1]
Hypothesis – 2	Wald = 10.26 (0.000)***[2]	LR = – 2 [– 105.63 – (–100.80)] = 9.63 (0.000)***[2]
Hypothesis – 3	Wald = 19.65 (0.000)***	LR = – 2 [– 100.80 – (– 89.56)]= 22.48(0.000)****[3]

Source: Authors' estimation.

[1]Chi-square ($\chi 2$) critical value with degrees of freedom = 7at 5% significance level is 14.07.

[2]Chi-square critical value with degrees of freedom = 2 at 5% significance level is 5.99.

[3]Chi-square critical value with degrees of freedom = 3 at 5% significance level is 7.81.

Note: Asterisk (***) presents statistical significances at 1% level.Furthermore, compared to the Wald test, which is one model test, the LR test is based on two models, so we used the restricted (with a constant only) model and the unrestricted models as the extended models to test our hypotheses.

seasonal migration. We also performed a robustness check by applying a binary logit model with robust standard errors. The original models still performed better, suggesting the variable selection for the original models was not counter-intuitive in terms of their signs, magnitudes, and statistical significances with overall superior model-fit statistics.

For hypotheses testing, we applied both the Wald and LR tests. Both tests confirmed that households' decision to seasonally migrate is significantly influenced by all factors, including their socioeconomic, livelihood and distance characteristics. Based on our model and hypotheses testing results, we conclude that poverty among the households, which exists in terms of their low income, expenditures, indebtedness, child labour, livestock mortality, lack of access to drinking water and health services, is the major factor behind seasonal migration.

Based on our in-depth empirical analysis of household poverty characteristics and its adverse influence on seasonal migration, we have identified several recommendations for policy-makers dealing with rural development, particularly district Tharparkar of Sindh in Pakistan. During the drought spells, the free food supply like wheat flour should be ensured by the government authorities and the easy and reliable accessibility of drinking water for the poor households and their livestock. The installation of sweet water plants and transportation of water through pipelines and portable water tanks in distant areas is highly needed. To discourage indebtedness, interest-free credit must be available for the poor households to fulfil their necessities and buy crop seeds and fodder for their livestock. School enrolments are encouraged through provisions of free meals to children. Economic opportunities, such as the promotion of handicrafts, marketing of livestock, job quotas in education, provision of health services, promotion of tourism, need to be provided to poor residents. Nutritional programmes for pregnant mothers and infants must be initiated together with water and sanitation projects. Rain-harvesting and vegetation management projects are encouraged and deforestation is discouraged by both local and government interventions. Benazir Income Support Programme (BISP) has expanded the royalty of the Thar Coal project, must be allocated to have adequate financial support for the policy recommendations.

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APPENDIX

TABLE A-1

Respondents' Socioeconomic, Livelihood and Distance Characteristics by Talukas (Sub-districts)

Variables	Talukas					KW statistic (p-value)[2]
	Mithi	Islamkot	Nan-garparkar	Diplo	Chachro	
Age (years)	41.5	41.6	41.3	41.5	42.9	0.520 (0.973)
Number of adults/ household	2.3	2.4	2.2	2.1	2.3	8.297 (0.081)*
Household income (PKR/month)	1726.7	1562.4	1651.1	1561.5	1710.6	1.653 (0.799)
Indebtedness (%)	0.4	0.3	0.3	0.3	0.4	0.540 (0.969)
Children never went to school (average)	0.8	1.3	0.7	0.5	1	17.513 (0.001)***
Children doing child labour (per cent)	0.7	0.8	0.6	0.7	0.8	12.584 (0.014)**
Landholdings/ household (average)	8.6	8.3	7.5	8.8	6.8	13.736 (0.008)***
Livestock animals/ household (average)	10.3	11	8.6	8.9	8.6	32.458 (0.000)***
Water distance (Kilometers)	0.4	1.1	0.4	0.6	0.6	26.227 (0.000)***
Hospital/Dispensary distance (Kilometers)	3.8	18.4	25.2	11.9	14.2	231.653 (0.000)***
City distance (Kilometers)[1]	24.7	18.4	45	41.8	15	267.041 (0.000)***
Total number of respondents (N = 440)	94	90	92	79	85	

Source: Authors' estimation.

[1]City distances, and so their locations in terms of distance (and roads), for each Taluka are different. For instance, Mirpurkhas city is nearby in terms of distance (or roads) to Mithi Taluka, Mithi city is near to Islamkot and Nangarparkar, Badin city to Diplo and Umerkot city is near to Chachro Taluka.

[2]KW statistic refers to Kruskal-Wallis Chi-square (χ^2) test value at 4 degrees of freedom, whereas asterisks *, **, *** refer to 1%, 5% and 10% statistical significances of KW test.

TABLE A-2

Respondents' Socioeconomic, Livelihood and Distance Characteristics by Terrains (Landscapes)

Variables	Areas (terrains)[1]					
	Desert versus Semi-desert & Hilly (MW statistic)[2]		Semi-desert versus Desert & Hilly (MW Statistic)		Hilly versus Desert & Semi-desert (MW Statistic)	
Age (years)	42.2	(-0.341)	41.5	(0.167)	41.3	(0.210)
Number of adults/ household	2.4	(-2.746)***	2.2	(1.462)	2.2	(1.549)
Household income (PKR/month)	9917	(-1.844)*	9630	(-0.015)	9075	(2.237)**
Indebtedness (%)	0.4	(-0.397)	0.3	(0.061)	0.3	(0.404)
Children never went to school (average)	1.1	(-3.591)***	0.7	(2.374)**	0.7	(1.469)
Children doing child labour (per cent)	0.8	(3.209)***	0.7	(1.037)	0.7	(2.617)**
Landholdings/household (average)	7.6	(2.255)**	8.7	(-3.069)***	7.5	(0.972)
Livestock animals/household (average)	9.8	(-2.956)***	9.7	(0.317)	8.6	(0.972)
Water distance (Kilometers)	0.8	(-3.884)***	0.5	(1.895)*	0.4	(2.399)**
Hospital/Dispensary distance (Kilometers)	16.4	(-2.367)**	7.5	(11.907)***	5.6	(-11.442)***
City distance (Kilometers)	16.7	(12.405)***	32.5	(-2.991)***	45.0	(-11.338)***
Total number of respondents (N = 440)	175		173		92	

Source: Authors' estimation.

[1]Tharparkar district has three main terrains (landscapes): a desert area (Chachro and Islamkot Talukas), a semi-desert area (Mithi and Diplo Taluka) and mostly a hilly terrain (NangarparkarTaluka).

[2]MW statistic refers to **Mann-Whitney U test value**, whereas asterisks *, ** and *** refer to 1%, 5% and 10% statistical significances of KW test.