zef
Center for
Development Research
University of Bonn

ZEF-Discussion Papers on
Development Policy No. 355

Md. Sohel Rana and Amy Faye

Destination choices during internal temporary migration: Evidence from northern Bangladesh

Bonn, December 2024

Md. Sohel Rana and Amy Faye. Destination choices during internal temporary migration: Evidence from northern Bangladesh. ZEF – Discussion Papers on Development Policy No. [XX], Center for Development Research, Bonn, [December 2024], pp. 35.

ISSN: 1436-9931

Published by:
Zentrum für Entwicklungsforschung (ZEF)
Center for Development Research
Genscherallee 3
D – 53113 Bonn
Germany
Phone: +49-228-73-1861
Fax: +49-228-73-1869
E-Mail: zef@uni-bonn.de
www.zef.de

The authors:

Md. Sohel Rana, Center for Development Research (ZEF), University of Bonn, Germany. Contact: srana@uni-bonn.de

Amy Faye, Center for Development Research (ZEF), University of Bonn, Germany. Contact: afaye@uni-bonn.de

Acknowledgements

We are grateful to the German Academic Exchange Service (DAAD) and the Foundation Fiat Panis for funding this research. We also acknowledge the invaluable feedback provided by Professor Dr. Matin Qaim of the Center for Development Research (ZEF) and the Institute for Food and Resource Economics (ILR) at the University of Bonn, which greatly contributed to the design of this study.

Abstract

Whilst migration to urban areas is often understood through higher wage opportunities, it is not well understood why many rural poor often prefer rural destinations, particularly during temporary migration. This preference also calls for an investigation of the household-level income effects of different destination choices. Our study focuses on northern rural Bangladesh, where rural-bound temporary migration is common. We employ a multi-step conditional probit model with subsamples to analyze temporary migrant's destination choices, accounting for their self-selection into migration. Similarly, we apply a multi-step control function approach to address endogeneity in examining the income effects of different destination choices. Our results show that destination choices rely on migrants' individual characteristics, prior perceptions and subsequent experiences of the destination, and the influence of migrant networks. Although rural destinations often offer a better income-to-cost ratio, they are not necessarily better than urban destinations in increasing total household income. In fact, remittances from rural-bound temporary migration are lower than those from urban-bound migration. Yet, rural destinations offer greater utility maximization in the face of migrants' constraints, leading to a preference for this destination type among such migrants.

Keywords: Agricultural lean periods; Bangladesh; Destination choices; Temporary migration; Rural-to-rural migration

JEL Codes: J43, Q18, R23

1. Introduction

Globally, around 682 million people live in extreme poverty, of whom, around 75% reside in rural agrarian societies where they inevitably face livelihood fluctuations and seasonal hunger during agricultural lean periods (Christensen, 2023; Kharel et al., 2021). In northern Bangladesh, for example, a 2-3 months' lean period occurs twice a year during the two dominant cropping seasons, affecting around seven million rural poor from around two million agricultural labor-dependent households (BBS, 2022; Bryan et al., 2014; Khandker & Mahmud, 2012; Zug, 2006). Studies have identified temporary migration as a common strategy for the rural poor to cope with income seasonality and seasonal hunger during lean periods, when on-farm wage opportunities drastically drop in the origin villages (Bryan et al., 2014; Coffey et al., 2014; Khandker & Mahmud, 2012; Khandker et al., 2012; Kharel et al., 2021; Rana et al., 2024).

Existing migration theories predict such income-driven migration originating from the low-productive rural agricultural sector to follow higher-paying modern sectors in urban areas (De Haas, 2021; Lee, 1966; Lewis, 1954; Todaro, 1969). Consequently, the assumption of temporary migration from rural to urban destinations is common in the existing literature (Asefawu & Nedessa, 2022; Bryan et al., 2014; Coffey et al., 2014; de Brauw & Harigaya, 2007; Keshri & Bhagat, 2013; Lagakos et al., 2023; Liu & Xu, 2015; Tiwari et al., 2022; Wang et al., 2021). However, Meghir et al. (2022) find around 65% of temporary migrants from northern rural Bangladesh migrating to other rural destinations during their lean periods, despite the higher wage opportunities in Bangladeshi cities for migrant laborers in physical labor-based jobs like rickshaw-pulling, construction sites, among others (Bryan et al., 2014; Lagakos et al., 2023). Similar rural-to-rural temporary migration is also common in neighbouring Myanmar and India (Visaria & Joshi, 2021; Wang & Charles-Edwards, 2024). This raises a fundamental question as to why many temporary migrants prefer other rural destinations over urban, a topic not well understood in the existing literature.

Several studies explain the destination choices for internal migration, but this is mostly for permanent or longer-term migration types, where the migrants often maintain a weakened connection to their places of origin (Aydemir & Duman, 2021; Chamberlin et al., 2020; De Weerdt et al., 2021; Fafchamps & Shilpi, 2012; Thiede, 2023). To our knowledge, there is only one study by Rana & Qaim (2024) that explains the destination choices for temporary migration, employing an explorative qualitative methodology. Their study highlights the importance of migrant's individual characteristics such as, age, skills, and education, and perceptions such as prior negative perception of cities, in destination decision-making during temporary migration. Furthermore, the influence of migrant networks, and destination characteristics such as, comparative income-to-cost ratio, physical comfort, and wage opportunities are also found crucial in such decision-making.

We build our study on this existing knowledge, employing a quantitative methodology that helps us further enhance our understanding of temporary migrants' destination decision-making. For instance, although distance is an important factor in the destination decision-making during permanent migration (Aydemir & Duman, 2021; De Weerdt et al., 2021; Fafchamps & Shilpi, 2012; Lee, 1966; Lucas, 2015), Rana & Qaim (2024) could not corroborate this for temporary migration. Our paper re-evaluates this potentially ambiguous aspect using quantitative data. Additionally, Rana & Qaim (2024) conclude that rural destinations often offer better income-to-cost ratio than urban destinations, which questions the widely held beliefs about urban destinations offering greater income gains. Similarly, a recent study in Peru finds positive welfare gains from temporary labor mobilities irrespective of the destination type (Fabry & Maertens, 2024). Our study examines the comparative income effects of destination choices during temporary migration from different geographical contexts to contribute to this emerging literature on temporary migration.

In brief, we aim to achieve two objectives: 1) identifying factors for temporary migration decisions to rural versus urban destinations, and 2) investigating the household-level income effects of such destination choices. We organize this article as follows: Section 2 presents the data and specified models used to achieve our research objectives. The empirical results are presented and discussed in Section 3. Finally, we conclude the article and outline its policy implications in Section 4.

2. Materials & methods

2.1 Data

We conduct the study in Rangpur Division of Bangladesh–the poorest division in the country, where agricultural seasonality is more pronounced and temporary migration is more common than in other parts of the country (Hossain & Hossen, 2020; Khandker & Mahmud, 2012; Khandker et al., 2012). Around 47% of rural households from this region send migrants temporarily (Kharel et al., 2021) and many of them migrate to other rural destinations in search of temporary farm jobs (Bryan et al., 2014; Meghir et al., 2022).

Rangpur division consists of eight districts. Among them, we select the two poorest districts, namely, Dinajpur and Kurigram with the highest proportion of agricultural labor-dependent households that are more vulnerable to agricultural seasonality thus more prone to temporary migration during lean periods (BBS, 2022; Hossain & Hossen, 2020; Khandker et al., 2012). Dinajpur district comprises of 2,131 villages, and Kurigram of 1,872 (BBS, 2014). Following stratified random sampling, we select a total of 30 villages- 16 from Dinajpur and 14 from Kurigram.

Following the village selection, we collect household lists for the selected villages from the respective local government offices, known as the *union parishad* office. The selected 30 villages have a total of 7,441 households, as calculated from the lists. At 99% confidence level and 5% margin of error, we estimate to survey a minimum of 612 households. We randomly select 10% of households from each village for the survey, with an additional 6% as replacements in case of non-response. We survey a total of 878 households from the lists. The surveyed households include approximately 10-14% of total households from each village.

There are two dominant agricultural lean periods in northern Bangladesh: the *Aman* lean in September-November between planting and harvesting the *Aman* seasonal crops, and the *Boro* lean in February-April between planting and harvesting the *Boro* seasonal crops (Bryan et al., 2014; Gill et al., 2003; Rana et al., 2024). The rest of the year are considered normal periods with normalized wage opportunities in the origin villages (Rana & Qaim, 2024). We conduct the survey during the *Boro* post-harvest period, June-August 2023, when most temporary migrants are in their villages to harvest the *Boro* seasonal crops and plant the next *Aman* seasonal crops.

The survey was administered with the head of the household who is often the migrant member. We collect key demographic characteristics, e.g., age, gender, education, and occupation, labor participation at the origin, and detailed migration data for every member of the household. At the household level, we collect data about household's assets, agriculture farming, migrant networks, employment availability during the lean and normal periods, and season-wise income from farm and non-farm sources. During the survey, we referred to the past 12 months (August 2022- July 2023) for collecting time-variant data such as farming, migration, and income. To address individual migrant's perception about destination cities, we referred to their perception prior to making their first migration.

In the full dataset (n=878), 371 households (~42%) did not send any migrants for income. On the other hand, 330 households (~38%) sent exclusively temporary migrants, who migrated for a period of up to three months per episode and actively participated in the origin village's labor market upon every return. The dataset also contains 150 households (~17%) that sent exclusively longer-term migrants, and 27 households (~3%) sending both types of migrants simultaneously.

The original dataset includes 3,818 individuals from 878 households. As the destination choice is largely influenced by migrants' individual characteristics (Rana & Qaim, 2024; Regmi et al., 2019), we utilize the individual members' dataset here. From this dataset, we remove 44 individuals migrating for immediate non-income purposes, such as pursuing education. Moreover, 981 kids with age equal or less than 14 years are removed as they rarely migrate for income[1]. After removing these observations, we have a dataset of 2,793 individual members containing 385 members engaging exclusively in temporary migration (~14%), 220 members exclusively in longer-term migration (~8%), and the remaining 2,188 non-migrant members (~78%). Out of the 385 temporary migrants, 259 individuals (~67%) migrated to rural destinations, and 126 individuals (~33%) to urban destinations in their latest migration episode.

2.2 Model specifications

Households' participation in migration is self-selected. Similarly, the intra-household decision-making regarding a member's migration is also not random (Chiswick, 1999; Lee, 1966). Therefore, to understand temporary migrants' choice of destinations or the household-level income effects of different destination choices, it is crucial to correct for self-selection bias. Accordingly, we utilize a multi-step conditional regression analysis with subsamples, extending the Heckman selection model limited to two stages. In this approach, potential self-selection effects are estimated as the inverse Mills ratio (*imr*), following Heckman (1979). After estimating a binary outcome model, a probit model in our case, we predict the linear predictor for individual *i*'s participation (xb_i). This predictor is then used to calculate the inverse Mills ratio for individual *i* (imr_i), using equation (1) below, following Heckman (1979):

$$imr_i = \frac{\phi(xb_i)}{1 - \Phi(xb_i)} \quad (1)$$

where, $\phi(xb_i)$ and $\Phi(xb_i)$ are the probability density function (PDF) and the cumulative distribution function (CDF) of the standard normal distribution evaluated at xb_i, respectively.

[1] None of the excluded kids in our dataset engaged in migration.

This imr_i is then incorporated in the subsequent regression step to correct for potential self-selection bias. Our multi-step conditional regression models are specified in the following.

Modeling destination choices during temporary migration

For the first research objective, we utilize a three-step conditional probit selection model with subsample analysis. In the first-step, equation (2), we utilize the entire individual dataset of 2,793 observations to model the participation of individual *i* in migration versus non-migration (M_i). In the second-step, equation (3), we utilize the subsample of 605 individual migrants to model their participation in temporary versus longer-term migration (TM_i), incorporating their self-selection into migration ($imr1_i$), calculated from equation (2) based on equation (1). In the third-step, equation (4), we use only the subsample of 385 temporary migrants to model their choice of rural versus urban destinations (R_i), incorporating their self-selection into temporary migration ($imr2_i$), as calculated from equation (3). The three-step conditional probit equations are specified as below:

$$M_i = \alpha\ (x_{ij}, c_{jk}, ev_j) + u_i \tag{2}$$

$$TM_i = \beta\ (x_{ij}, c_{jk}, imr1_i) + e_i \tag{3}$$

$$R_i = \delta\ \left(v_i, c_{jk}, imr2_i\right) + \mu_i \tag{4}$$

In equation (2), we account for the characteristics of individual *i* and household *j* (x_{ij}) relevant for individual *i*'s participation in migration, as conceptualized in the literature (Rana et al., 2024; Stark & Bloom, 1985). This vector includes migrant *i*'s individual characteristics such as age, education, gender, and primary occupation type, and household *j*'s characteristics such as its experience of seasonal employment fluctuations, farm labor or family obligations[2], and the size of migrant networks at the origin. In this equation, we also account for relevant other controls for household *j* and village *k* (c_{jk}). They include household size, wealth, access to alternative livelihoods, and proximity to nearby migration hubs. Additionally, they include some relevant village-level controls such as, whether the village is in a flood-prone area, and village-level fixed effects. For consistent estimates, this vector of c_{jk} is controlled for in all subsequent equations.

Equation (3) models the individual migrant *i*'s selection into temporary versus longer-term migration (TM_i) by accounting for similar vectors of x_{ij} and c_{jk}, and the selection effects in migration- $imr1_i$, as calculated from equation (2). Since we use similar sets of explanatory variables in both equations (2) and (3), for a robust estimation of the selection effect- $imr1_i$, we utilize an exclusionary variable (ev_j) in equation (2), as suggested by Heckman (1979). We use households' experience of random economic shocks in their crops, livestock, and assets

[2]Farm labor obligations, particularly in labor-intensive livestock farming, and family obligations due to the presence of kids, distrusts of neighbors for family care during migration, and smaller household size with less member flexibility (see Rana et al., 2024 for more details).

in the past 12 months as the exclusionary variable. These idiosyncratic economic shocks can sometimes restrict their capability of sending migrants (Rana et al., 2024). However, these shocks do not affect households' choice between the physical labor-based temporary and longer-term migration, if they have already decided about migration (Rana et al., 2024)[3]. Table A1 in the Appendix confirms that the experience of random economic shocks differs significantly between migrant and non-migrants (M_i), but not between temporary and longer-term migrants (TM_i), confirming our hypothesis.

Finally, equation (4) models the temporary migrant's choice of rural versus urban destinations in their latest migration episode by correcting their self-selection in temporary migration ($imr2_i$). In this equation, we incorporate v_i as the vector of relevant explanatory variables for individual migrant *i*'s choice of destination, aligning with Rana & Qaim (2024). This vector includes migrant *i*'s individual characteristics- I_i, negative perception of urban areas- U_i, experience of the latest destination- D_i, migrant networks- N_i, and distance travelled in the latest migration episode- $Dist_i$. These variables are described in Table 1. The parameters to be estimated in the respective equations are represented by α, β, and δ, and the error term by u_i, e_i, and μ_i. Since equations (3) and (4) include distinct sets of explanatory variables relevant to their respective outcome variables, we do not introduce any additional exclusionary variable in equation (3), apart from the self-selection into migration ($imr1_i$).

Regarding individual characteristics (I_i), Rana & Qaim (2024) reveal that individuals with higher education are more prone to longer-term migration, or at least to urban destinations during temporary migration, as education rarely brings extra benefits in rural destinations. Educated individuals often possess increased life-skills making them confident about better opportunities in cities. Conversely, individuals with lower or no education often lack life-skills, leading to a preference for simpler settings like in rural destinations. For better estimates about the association of individuals' education with their destination choices, we also account for their skills (discussed in detail below) in this model.

Similarly, individuals engaged in agriculture at the origin may prefer agricultural jobs in rural destinations during temporary migration. We consider individuals' engagement in agricultural farming and farm labor sale at the origin as proxies (see Table 1). However, any physical sensitivity to agricultural jobs (e.g., cannot bend waist to harvest rice, among others) may discourage sensitive individuals from choosing rural destinations, which we control for in this model. Moreover, we account for other relevant factors at the individual (e.g., age) and household levels (e.g., household size, agricultural landholdings, family demographic shocks, and engagement in crop farming, livestock farming, business, safety-nets, and microcredit).

[3]Another type of idiosyncratic shock includes the sudden death or severe accident of a working household member—family demographic shocks that may affect individual migrant's choice between temporary and longer-term migration due to increased family obligations (Rana & Qaim, 2024). We separate these shocks and use only economic shocks as the exclusionary variable here.

Table 1: Variables for analysing destination choices during temporary migration

Variables	Description	Expected sign in the model (Rural vs urban destination, R_i)
Individual characteristics (*I_i*)		
Education	Education in schooling years (1-14)	(-)
Occupation: Agriculture farming	Occupation being agricultural farming (1/0)	(+)
Agriculture labor sale	Engagement in agriculture labor sale at the origin (1/0)	(+)
Urban negativity (*U_i*)		
Prior negative perception of cities	Perception of 'difficulty' for living and earning in urban destinations before making the first migration (1/0).	(+)
Experience of destination characteristics (*D_i*)		
Income-to-cost ratio	Experience of the income-to-cost ratio at the latest destination (Likert scale of 1-10),	(+)
Physical comfort	Experience of physical comfort at the latest destination (Likert scale of 1-10),	(+)
Migrant networks (*N_i*)		
Rural-bound migrant kin	Have migrant kin or relatives migrating to rural destinations (1/0).	(+)
Migrant group size	Size of the migrant group in the latest migration episode.	(+)
Migration distance (*$Dist_i$*)		
Travel distance	Physical distance (km) between the migrant's origin and destination sub-districts.	(+/-)

Regarding urban negativity (U_i), Rana & Qaim (2024) observe that individuals with lower education or lacking skills beyond agriculture often view urban destinations as a difficult place for earning and living. This negative perception of cities often discourages aspiring migrants with lower education or skills from choosing urban destinations. Therefore, apart from education, we also account for migrants' lack of life-skills beyond agriculture.

For individual migrants' experiences at their latest destination (D_i), we collect their experience ratings on a 1-10 Likert scale, where 1 denotes 'worst' and 10 denotes 'best'. For example, a migrant rating 10 for income-to-cost ratio characteristic means they could save most of their daily earnings at the latest migration destination. This often occurs in rural destinations in Bangladesh, where employers frequently offer free accommodation and meals for migrant laborers (Rana & Qaim, 2024). Conversely, in urban destinations, around half of daily wages typically go toward accommodation and meal expenses (Rana & Qaim, 2024), shifting their income-to-cost experience closer to 'worst.' Therefore, although wage opportunities are higher in urban areas, rural destinations may offer greater psychological satisfaction from saving 'hard-earned' income, influencing poor migrant laborers' destination choices—a concept similar to 'loss-aversion'[4].

Similarly, while jobs in both types of destinations can be physically demanding, agricultural tasks in rural destinations may offer comparatively better physical comforts to the migrants from rural origins. In contrast, urban destinations often provide longer-duration wage opportunities than rural ones (Bryan et al., 2014; Rana & Qaim, 2024). This is particularly encouraging for temporary migrants from flood-prone villages, where lean periods are often prolonged due to weather extreme (Rana & Qaim, 2024; Rana et al., 2024). Therefore, we also account for migrants' experiences concerning wage opportunity duration at their latest migration destination, the geographic location of the village in flood-prone areas, and village fixed effects.

Regarding migrant networks (N_i), Rana & Qaim (2024) indicate that, in addition to the influence of migrant kin, the size of the migrant group from the origin plays a key role in choosing destinations. A larger group size reduces rural poor's risk-aversion toward migration and makes their migration pleasurable. Rural-bound migrants often travel in large groups, which is frequently required for employment in rural destinations. Employers in these areas tend to prefer hiring larger groups of migrant laborers to keep up with their crop calendar. Conversely, migration in larger groups raises competition for jobs at rickshaw garages or construction sites in urban destinations. Group migration, therefore, is more associated with rural-bound temporary migration, which may encourage risk-averse rural poor to prefer rural destinations. We collect data on group size from the migrant's latest migration episode, which we use here.

Regarding the implications of migration distance ($Dist_i$) for destination choices, earlier studies have found that longer-distance permanent migrations move towards urban centers (Lee, 1966). However, the relationship between distance and destination choices during temporary migration remains unclear, which we address here. We collect data on the destination sub-district for each migrant's latest migration episode. The physical distance in kilometer (km) between the origin and destination sub-districts is then calculated using a geo-referencing system. Here, we mainly use the bus-road distance, as buses are the common transport mode across the country. Moreover, we control for the proximity of individual migrant's household to the nearest migration hub, often the closest sub-district.

Due to the relatively large number of explanatory variables included in the model, we tested for multicollinearity by calculating the variance inflation factors for each equation. The results are shown in Table A2 in the Appendix. They do not indicate a high correlation among the explanatory variables and selection effects.

[4] Loss aversion concept suggests that 'losses' have greater influence on setting preferences than 'gains' (Tversky & Kahneman, 1991).

To check the robustness of our findings, we employ a system of simultaneous mixed-process equations using limited information maximum likelihood (LIML), following Roodman (2011). When multiple equations are mutually interdependent and deal with subsamples in different equations, as in our case, this analytical approach proves useful. For this analysis, we use the *cmp* command in Stata, incorporating equation (2), (3), and (4) while excluding their respective *imr*s. We skip the likelihood-ratio test, use five random draws for the Geweke-Hajivassiliou-Keane (GHK) simulator, and apply the Newton-Raphson method for optimization.

Modeling the income effects of different destination choices

For our second research objective, we utilize the same individual-level dataset to measure the income effects at intensive margins. We use the lean period income of household *j* (Inc_j) as the outcome variable in this analysis, as temporary migration takes place mainly during the lean period (Coffey et al., 2014; Khandker & Mahmud, 2012; Mobarak & Reimão, 2020). The income effects of the individual migrant *i*'s choice of rural versus urban destination during temporary migration (R_i) is captured in equation (5) below:

$$Inc_j = \theta\ (R_i, z_{jk}, imr3_i) + \varepsilon_i \qquad (5)$$

Studies have also shown that earning a lot of remittance is often not a priority for constrained poor temporary migrants (Banerjee & Duflo, 2007). Therefore, to better understand the income effects of destination choices during temporary migration, we use three indicators of income: i) household *j*'s total lean period income from all sources (tot_inc_j), ii) income earned exclusively from temporary migration remittances ($remit\_inc_j$), and iii) income from the origin's labor market ($loc\_inc_j = tot\_inc_j - remit\_inc_j$). Season- and source-wise income amount were collected in Bangladeshi Taka (BDT). We use the logarithmic transformation of income data in this analysis.

To obtain a more consistent estimate of the income effects, we control for certain relevant household and village characteristics for income (z_{jk}) in equation (5). These characteristics include the household head's age, education, and gender, household size, and experience of seasonal employment fluctuation, as well as some village-level factors, such as the location of the village in flood-prone areas, and village fixed effects. The parameters are represented by θ, and the error term by ε_i. From equation (5), we report the coefficient (θ) for choosing rural versus urban destinations (R_i) as the estimated effects on the households' lean period income (Inc_j).

In equation (5), we also account for the migrant's self-selection into destinations- $imr3_i$, which is calculated from equation (4) based on equation (1). However, $imr3_i$ appears insignificant in equation (5) for all indicators of income, as presented in Table A6 in the Appendix. This suggests that self-selection into destinations may not be a challenging issue when estimating the income effects of different destination choices. Nevertheless, we cannot entirely rule out the possibility of endogeneity in destination choice, particularly arising from unobserved heterogeneity. To address this challenge, we apply a control function approach, which is effective in correcting this type of endogeneity (Wooldridge, 2015).

In this approach, we calculate the control function or residuals (*res*) from equation (2), (3), and (4), and then incorporate them into the subsequent equations, instead of *imr*s. While *imr* is useful to correct self-selection bias, residuals account for the endogeneity arising from unobserved factors, mentioned above, by capturing the part of participation that is not explained by the controlled variables in the respective equation. To calculate residuals, after estimating a regression, we predict the probability of participation for individual *i* (p_i^*). Next, we calculate the residual for individual *i*'s participation (res_i) as the difference between the observed value of participation (p_i) and the predicted probability of participation (p_i^*), as outlined in equation (6) below:

$$res_i = p_i - p_i^* \quad (6)$$

In our multi-step control function analysis, we calculate $res1_i$ from equation (2) based on equation (6) and incorporate it into equation (3), replacing $imr1_i$. Similarly, $res2_i$ is calculated from equation (3) and used in equation (4). Finally, we calculate $res3_i$ from the destination choice equation (4) and incorporate it into the income effects equation (5). In this analysis, we use a similar exclusionary variable (ev_j) design, as discussed earlier in the multi-step conditional probit selection model.

Using control function approach, in equation (5), $res3_i$ appears significant sparsely for different income indicators, as shown in row (1) of Table 5 in the results section. Additionally, $res1_i$ and $res2_i$ appear significant in the respective equations, as presented in Table A7 in the Appendix.

To check robustness of our results from the multi-step control function analysis, we employ a similar approach of simultaneous mixed-process equations with LIML, as discussed earlier. Additionally, we use a two-stage least square (2sls) analysis with an instrumental variable (IV) design as an alternative strategy to further test the robustness of our findings. The general two-stage equations for this analysis are outlined in equation (7) and (8) below:

$$\text{First stage: } R_i^* = \delta\left(v_i, c_{jk}, z_{jk}, IV_i, imr2_i\right) + \mu_i \quad (7)$$
$$\text{Second stage: } Inc_j = \theta\left(R_i^*, v_i, c_{jk}, z_{jk}\right) + \varepsilon_i \quad (8)$$

where, R_i^* represents migrant *i*'s instrumented choice of rural versus urban destination, and IV_i denotes the instruments. We use the presence of rural-bound temporary migrant kin or relatives (see Table 1 for details) as an instrument here. This instrument is expected to influence migrant *i*'s choice of rural over urban destinations (R_i) through network effects, but not to directly affect household income. The first-stage regression results, presented in Table A9 in the Appendix, confirm the relevance of the instrument, with an F-statistic of 73.81 indicating its strength.

3. Empirical results

3.1 Descriptive statistics

Our data reveal that many migrations in northern rural Bangladesh are temporary and many of these temporary migrations follow rural destinations, as illustrated in Figure 1. Only some 3% of the migrants are female who migrate only to urban destinations, preferably to work in garments. We observe no female members migrating temporarily, as this migration involves higher social stigma for them, while garments offer better wage opportunities through longer-term migration.

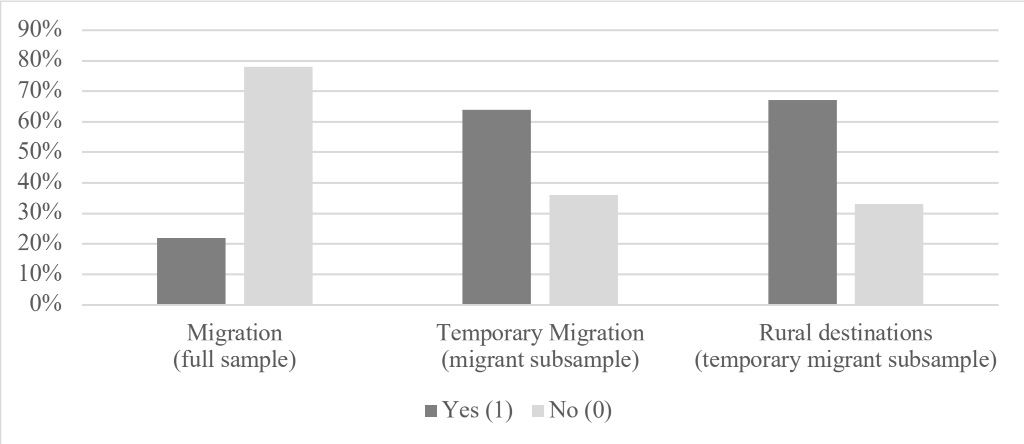


Figure 1: Migration and destination choice statistic

Among the 259 rural-bound temporary migrants in our sample, approximately 19% migrate to the Bogra district (~112 km from Rangpur city), 17% to the Tangail district (~218 km), 15% to the Comilla district (~402 km), and the rest to 26 other districts across the country. In contrast, Dhaka, the capital city of Bangladesh with the largest urban agglomeration, appears to be the most attractive destination for urban-bound temporary migrants. About 62% of them chose Dhaka (~296 km) in their latest migration episode, while the rest were almost evenly distributed among 21 other cities/towns across the country. A map showing the popular destinations for temporary migration is presented in Figure A1 in the Appendix.

Popular wage opportunities in rural destinations includes planting/harvesting rice, working in other crop fields and brick kilns, among others. About 85% of our rural-bound temporary migrants were engaged in rice planting/harvesting during their latest migration episode. In contrast, about 48% of our urban-bound temporary migrants worked in masonry/ construction sites, and around 39% in rickshaw-pulling in cities.

The summary statistics of the key explanatory variables for destination choices during temporary migration are presented in Table 2 below. A test of mean differences between rural- and urban-bound temporary migrants generally supports our hypothesized associations between destination choices and indicators of individual characteristics (I_i), urban negativity (U_i), experience of destination characteristics (D_i), and migrant networks (N_i). Additionally, migration distance ($Dist_i$) shows a significant negative association with the choice of rural destinations, aligning with the existing literature.

Table 2: Summary statistics of the key explanatory variables for destination choices

Variables	**(1) All observations (n=385)**	**(2) Rural-bound temporary migrants (n=259)**	**(3) Urban-bound temporary migrants (n=126)**	**(4) Mean difference (2-3)**
Individual characteristics (I_i)				
Education	3.42 (3.74)	2.66 (3.18)	4.97 (4.30)	-2.31*** [0.39]
Occupation: Agriculture farming	0.23 (0.42)	0.24 (0.43)	0.20 (0.40)	0.04 [0.05]
Agriculture labor sale	0.85 (0.36)	0.93 (0.25)	0.67 (0.47)	0.26*** [0.04]
Urban negativity (U_i)				
Prior negative perception of cities	0.34 (0.48)	0.49 (0.50)	0.03 (0.18)	0.46*** [0.05]
Experience of destination characteristics (D_i)				
Income-to-cost ratio	6.24 (3.14)	7.32 (2.93)	4.02 (2.26)	3.30*** [0.30]
Physical comfort	6.61 (3.24)	7.05 (3.23)	5.71 (3.09)	1.34*** [0.35]
Migrant networks (N_i)				
Rural-bound migrant kin	0.64 (0.48)	0.90 (0.30)	0.11 (0.32)	0.79*** [0.03]
Migrant group size	6.92 (5.04)	8.31 (5.06)	4.05 (3.59)	4.27*** [0.50]
Migration distance ($Dist_i$)				
Travel distance	274.82 (130.49)	251.58 (134.27)	322.60 (108.07)	-71.02*** [13.72]

Standard deviation in parentheses (); standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Regarding the second research objective, we observe an insignificant mean difference in the households' total income during the lean period (tot_inc_j) between rural- and urban-bound temporary migrant households, as presented in Table 3 below. However, the mean income from migration remittances ($remit\_inc_j$) and income from the local labor market (loc_inc_j) differ significantly between these two groups. Households sending temporary migrants to urban areas appear to receive larger remittances than those sending to rural areas. Conversely, rural-bound temporary migrant households tend to have higher income from the origin's local labor markets compared to those with urban-bound migrants.

One plausible mechanism for these effects could be the duration of temporary migration. Around 80% of our rural-bound temporary migrant samples stayed for a shorter duration of less than 30 days in their latest migration episode. In contrast, around 57% of our urban-bound migrants stayed for longer than 30 days during their temporary migration. This indicates that urban-bound temporary migrants tend to stay longer at their destinations, generating higher remittances. Conversely, rural-bound temporary migrants may already diversify their risks at the origin's labor market before making shorter duration migration to rural destinations. Table A3 in the Appendix presents that temporary migration for shorter duration of less than 30 days in an episode is significantly associated with lower remittances and higher income from the local labor market, which are plausible.

Table 3: Mean household income for different destination choices

Income variables (Inc_j)	(1) All observations (n=385)	(2) Rural-bound temporary migrants (n=259)	(3) Urban-bound temporary migrants (n=126)	(4) Mean difference (2-3)
Total income (*tot_inc*$_j$)	4.00 (0.65)	3.98 (0.64)	4.03 (0.67)	-0.05 [0.07]
Remittance income (*remit_inc*$_j$)	3.09 (0.92)	2.98 (0.86)	3.31 (1.00)	-0.34*** [0.10]
Local market income (*loc_inc*$_j$)	2.95 (1.34)	3.11 (1.23)	2.61 (1.49)	0.51*** [0.14]

Standard deviation in parentheses (); standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Local market income options include both on-farm and off-farm strategies. Table A4 in the Appendix presents the mean income differences from various local market sources between rural- and urban-bound temporary migrant groups. It shows that rural-bound temporary migrants have significantly higher income from livestock farming and selling labor at the origin. These income effects are further explained in the regression results sections.

3.2 Regression results

Here, we present and discuss the regression results. First, we discuss individual migrants' destination choices during their temporary migration (R_i). Next, we show the comparative effects of these destination choices (R_i) on households' lean period income (Inc_j).

Destination choices during temporary migration

As mentioned earlier, our three-step conditional probit selection model addresses three key questions: i) why the rural poor choose to migrate (M_i, eq. 2), ii) why they opt for temporary as opposed to longer-term migration (TM_i, eq. 3), and iii) why they prefer rural over urban destinations during their temporary migration (R_i, eq. 4). Results from equation (2) and (3) are presented in Table A5 in the Appendix[5]. The results from equation (4), which addresses our first research objective, are presented in column (1) of Table 4 below. Overall, most of our hypotheses on destination decision-making hold. These results here indicate associations only, not causal relationships.

[5] The choices of migration (equation 2) and temporary versus longer-term migration (equation 3) have already been studied in the literature, employing both qualitative and quantitative methodologies (Chen et al., 2019; Hu et al., 2011; Keshri & Bhagat, 2013; Rana & Qaim, 2024; Rana et al., 2024; Stark & Bloom, 1985; Todaro, 1969). In brief, existing studies find that households' poor earning at the origin and the presence of functional migration networks are important factors influencing the decision to migrate. Conversely, the presence of farm labor and family obligations discourages constrained households from migrating. However, even constrained poor households may migrate to diversify risks in their less-diversified economy. In such cases, they often prefer temporary migration, which maximizes their utility without exacerbating their constraints. Our regression results align with existing literature despite using different contexts and datasets.

Table 4: Factors for destination choices during temporary migration

Variables	**(1) Multi-step conditional probit selection model with subsamples**	**(2) Simultaneous mixed process equations using LIML**
	Rural vs urban destination choice (*R_i*)	Rural vs urban destination choice (*R_i*)
Individual characteristics (*I_i*)		
Education	-0.14** [0.06]	-0.09** [0.05]
Occupation: Agriculture farming	0.02 [0.30]	-0.14 [0.23]
Agriculture labor sale	1.08** [0.44]	0.90*** [0.32]
Relevant controls		
Physical sensitivity to agriculture	-1.10** [0.47]	-1.10*** [0.40]
Age	0.00 [0.01]	-0.00 [0.01]
Household size	-0.21* [0.11]	-0.16* [0.09]
Agricultural landholdings	0.01 [0.02]	0.01 [0.02]
Crop farming	-0.69** [0.35]	-0.67** [0.32]
Livestock farming	0.76** [0.32]	0.62** [0.24]
Family demographic shocks	-1.09** [0.52]	-0.77** [0.39]
Business	0.33 [0.34]	0.34 [0.35]
Social safety-nets	0.23 [0.32]	0.24 [0.26]
Microcredit memberships	-0.48* [0.29]	-0.46* [0.24]
Urban negativity (*U_i*)		
Prior negative perception of cities	1.09*** [0.34]	0.96*** [0.28]
Relevant controls		
Lack of skills beyond agriculture	0.77*** [0.26]	0.65*** [0.22]
Experience of destination characteristics (*D_i*)		
Income-to-cost ratio	0.36*** [0.06]	0.30*** [0.06]
Physical comfort	0.06 [0.05]	0.07* [0.04]
Relevant controls		
Daily wage opportunities	-0.21** [0.10]	-0.16** [0.08]
Flood vulnerability of the village	0.76 [0.72]	0.59 [0.50]
Village fixed effects	0.00 [0.00]	0.00 [0.00]
Migrant networks (*N_i*)		
Rural boundness of the closest migrant kin	3.02*** [0.45]	2.56*** [0.45]
Migrant group size	0.11*** [0.04]	0.08** [0.03]
Migration distance (*$Dist_i$*)		
Travel distance	-0.00*** [0.00]	-0.00*** [0.00]
Relevant controls		
Household distance to the nearby migration hub	-0.01 [0.01]	-0.01 [0.01]
imr2$_i$	-0.73** [0.32]	
Constant	1.10 [1.65]	-0.25 [1.09]
Wald chi2	153.03	834.14

N=2,793; robust standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Individual characteristics, such as migrant's low education and engagement in agricultural labor sale at the origin, are significantly associated with their preference for rural destinations during migration, as anticipated. Although individuals' engagement in farming does not seem to affect their destination choices, any physical sensitivity to farming discourages them from choosing rural destinations, which is plausible.

Negative perceptions of cities before the first migration, along with a lack of life-skills beyond agriculture, are significantly associated with choosing rural destinations, even in the latest migration episode. Moreover, a better daily wage compared to expenses (i.e., income-to-cost ratio) also influences migrants' preference for rural over urban destinations, though reverse causality is plausible here. While physical comforts at destinations do not show a strong association, wage opportunities are more closely linked to choosing urban destinations. Therefore, it is likely that rural poor who are unable to pursue longer-term migration due to household constraints, yet seek longer-duration wage opportunities, prefer to migrate to urban destinations.

Regarding migrant networks, the presence of migrant kin or relatives migrating to rural destinations affects aspiring migrant's destination preferences through network effects. Similarly, a larger migrant group size is strongly associated with choosing rural over urban destinations, as expected.

Similarly, distance is significantly associated with the destination choice. Our data reveal that rural-bound temporary migration is significantly more common over shorter distances, likely to minimize migration costs, which aligns with loss-aversion theory (Tversky & Kahneman, 1991) and classical migration theories (Lee, 1966). Additionally, shorter-distance migration can minimize the duration of migrants' separation from their left-behind families. This is crucial for rural-bound temporary migrant households, that often include greater labor constraints for livestock farming and labor sales, along with increased family obligations due to a less flexible member structure (Table 4).

Selection effects (*imr*) are significant at every stage of the model, as shown in Table 4 above and Table A5 in the Appendix, requiring their correction. The results from the simultaneous mixed process equations are presented in column (2) of Table 4. These results are consistent with those from our main model, demonstrating the model's robustness.

Income effects of the destination choice during temporary migration

Results from the multi-step control function analysis, showing the income effects of destination choices during temporary migration (equation 5), are summarized in row (1) of Table 5 below. Results from equations (2), (3), and (4) using this approach are presented in Table A7, and the full regression results for equation (5) are in Table A8 in the Appendix.

While temporary migration generally generates positive income gains for poorer households (Fabry & Maertens, 2024; Rana et al., 2024), we observe that the choice of rural over urban destinations during this migration does not affect the households' total income (*tot_inc*$_j$). While rural destinations are often associated with better income-to-cost ratio than urban ones (Table 4), urban-bound migration generates greater remittances (*remit_inc*$_j$). One plausible reason can be the longer duration of urban-bound temporary migration than rural-bound ones, as mentioned earlier.

Table 5: Income effects of the destination choice during temporary migration

Model	Variable	Total income (*tot_inc*$_j$)	Remittance income (*remit_inc*$_j$)	Local market income (*loc_inc*$_j$)
(1) Multi-step control function analysis with subsamples	Rural over urban destination choice (R_i)	-0.08 [0.08]	-0.39*** [0.12]	0.59*** [0.17]
	$res3_i$	0.28* [0.16]	0.41 [0.40]	-0.31 [0.43]
	Constant	3.92*** [0.28]	2.85*** [0.36]	2.63*** [0.45]
	Controls (z_i)	Yes	Yes	Yes
(2) Simultaneous mixed process equations using LIML	Rural over urban destination choice (R_i)	-0.10 [0.10]	-0.46*** [0.13]	0.65*** [0.22]
	Constant	4.02*** [0.30]	3.17*** [0.34]	2.48*** [0.45]
	Controls (z_i)	Yes	Yes	Yes
(3) Two-stage least square	Rural over urban destination choice (R_i)	-0.51*** [0.17]	-0.56** [0.25]	0.18 [0.30]
	Constant	4.15*** [0.47]	1.81*** [0.62]	2.97*** [0.86]
	Controls (z_i)	Yes	Yes	Yes

N=2,793; Income in Bangladeshi Taka (BDT) and transformed to log; $res3_i$- control function for individual migrant *i*'s participation in destinations; robust standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

One may wonder why many rural-bound temporary migrants prefer shorter migration durations with comparatively lower remittances. As we have seen from equation (3) (Table A5 in the Appendix), farm labor and family obligations are critical factors in choosing temporary over longer-term migration, which is also consistent with the existing literature (Banerjee & Duflo, 2007; Rana et al., 2024). Some of these households may have greater constraints that limit their migration duration. For these households, earning lot of remittances is often not a priority (Banerjee & Duflo, 2007), mentioned earlier. They rather prefer longer stays with their families by optimally diversifying their risks at the origin before migrating.

We have also demonstrated in equation (4) (Table 4) that households' engagement in livestock farming and selling labor at the origin is positively and significantly associated with their choice of rural over urban destinations. Similarly, rural-bound temporary migrants earn significantly more from these two sources (Table A4 in the Appendix). This explains the significantly higher income from the local labor market (*loc_inc*$_j$) for rural-bound temporary migrants, as presented in Table 5.

Some of these income options, particularly livestock farming, create significant labor constraints at the origin, prompting shorter-duration temporary migration, as also noted in the existing literature (Deshingkar & Start, 2003; Rana et al., 2024). For such short-duration migration, rural destinations with a more favorable income-to-cost ratio offer better utility maximization than urban ones. Conversely, utility maximization in urban destinations requires longer stays, which can be discouraging for households with farm labor or family constraints. In other words, urban-bound temporary migration with longer stays at destinations often limits scopes to diversify risks at the origin, relying primarily on remittances. This finding extends Rana & Qaim (2024)'s conclusion about the better income-to-cost ratio characteristic of rural destinations.

Results from the simultaneous mixed process equations, presented in row (2) of Table 5, are consistent with our main model. However, results from 2sls, presented in row (3) of Table 5, show that rural-bound temporary migration is associated with significantly lower total income, with the sign remaining consistent with our main model. Similarly, although 2sls does not find a significant association between rural-bound migration and household income from the local labor market, it suggests a positive relationship, again consistent with our main model.

4. Conclusion and policy recommendations

Given that urban destinations often offer greater wage opportunities than their rural counterparts, understanding why many rural poor prefer rural destinations during their income-driven temporary migration is crucial for identifying the motives behind this migration. Rana & Qaim (2024) provided valuable insights into such destination decision-making using an explorative qualitative methodology. However, certain aspects, such as the implications of migration distance and income effects of different destination choices, remain unclear. We employ a quantitative methodology to extend their qualitative findings and deepen our understanding of destination choices during temporary migration. We employ a multi-step conditional probit selection model with subsamples, extending on Heckman (1979), to analyze destination choices of temporary migrants from rural origins, correcting for their self-selection into migration and temporary migration. To address endogeneity in analyzing the income effects of different destination choices, we employ a multi-step control function approach with subsamples, extending on Wooldridge (2015).

Aligning with Rana & Qaim (2024), we find that the choice of destination for the temporary migrants from northern Bangladesh is strongly associated with their individual characteristics, prior perceptions and subsequent experiences of the destination, and the influence of migrant networks. Additionally, we find that longer-distance migration is often associated with urban destinations, consistent with existing literature (Lee, 1966). Although rural destinations often offer a better income-to-cost ratio than urban ones, which is plausible, they are not necessarily better than urban destinations to increase total household income, as we demonstrate. In contrast, urban-bound temporary migration generates higher remittances, partly because this group of migrants tend to stay longer at destinations to maximize their utility. However, constrained poor households often prioritize spending more time with their families by optimally diversifying their risks at the origin's labor markets, and then choose shorter migration duration. For such short-duration migration, rural destinations with more favorable income-to-cost ratio are better.

These findings are crucial for policies aimed at facilitating temporary migration for the rural poor. In particular, policies should support rural-bound temporary migration, as many poor temporary migrants prefer this strategy after optimally exploiting local labor markets. Many of these migrants are constrained by limited education and skills and hold negative perceptions of urban areas, which hinder rural-to-urban migration despite higher remittance potential. Furthermore, rural-to-rural migration is crucial to address farm labor shortages in destination rural areas, particularly in poor agrarian contexts like Bangladesh, where agriculture mechanization rates remain low (Rahman et al., 2021). In recent years, the shortage of local agricultural laborers has been a major challenge in regions of Bangladesh growing labor-intensive crops (Rahman et al., 2021). This was evident during the COVID-19 pandemic when the harvest of the main crop—rice—was severely affected by a shortage of migrant laborers (Rahman et al., 2022). Facilitating rural-bound temporary migration between early- and late-harvesting rural areas or between labor-short and labor-surplus regions could help address this issue, as experienced in Bangladesh during the pandemic. Such migration could be supported by policies through providing wage information, reducing search costs, and improving inter-district transportation networks.

Further research could explore the effects of temporary migrant laborers on crop production in destination rural areas. Additionally, examining how farm mechanization affects livelihoods of agriculture labor-dependent rural poor–who often rely on temporary migration as an important risk diversification strategy (Rana et al., 2024)–could be another important avenue for further research.

References

Asefawu, G. S., & Nedessa, K. G. (2022). Nature, patterns, and determinants of seasonal outmigration in the north-eastern part of Ethiopia. *Norwegian Journal of Geography*, *76*(3), 177–191. https://doi.org/10.1080/00291951.2022.2076610

Aydemir, A. B. & Duman, E. (2021). *Migrant networks and destination choice: Evidence from moves across Turkish provinces* (IZA discussion paper no. 14677). Institute of Labor Economics (IZA), Bonn. https://repec.iza.org/dp14677.pdf

Banerjee, A., & Duflo, E. (2007). The economic lives of the poor. *Journal of Economic Perspectives*, *21*(1), 141–167. https://doi.org/10.1257/jep.21.1.141

BBS. (2014). *Population and Housing Census 2011: Union Statistics (National Report, Volume 2)*. Bangladesh Bureau of Statistics (BBS), Dhaka.

BBS. (2022). *Agriculture Census 2019: Structure of Agricultural Holdings and Livestock & Fisheries* (*National Series, Volume 1)*. Bangladesh Bureau of Statistics (BBS), Dhaka.

Bryan, G., Chowdhury, S., & Mobarak, A. M. (2014). Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh. *Econometrica, 82*(5), 1671–1748. https://doi.org/10.3982/ecta10489

Chamberlin, J., Jayne, T. S., & Sitko, N. J. (2020). Rural in-migration and agricultural development: Evidence from Zambia. *Agricultural Economics*, *51*(4), 491–504. https://doi.org/10.1111/agec.12567

Chen, J., Kosec, K., & Mueller, V. (2019). Temporary and permanent migrant selection: Theory and evidence of ability-search cost dynamics. *Review of Development Economics*, *23*(4), 1477–1519. https://doi.org/10.1111/rode.12617

Chiswick, B.R. (1999). Are immigrants favorably self-selected? *American Economic Review* *89*(2), 181–185. https://doi.org/10.1257/aer.89.2.181

Christensen, Z. (2023). *Economic poverty trends: Global, regional and national*. Development Initiatives (DI), Bristol. https://devinit.org/resources/poverty-trends-global-regional-and-national/

Coffey, D., Papp, J., & Spears, D. (2014). Short-term labor migration from rural north India: Evidence from new survey data. *Population Research and Policy Review*, *34*(3), 361–380. https://doi.org/10.1007/s11113-014-9349-2

De Brauw, A., & Harigaya, T. (2007). Seasonal migration and improving living standards in Vietnam. *American Journal of Agricultural Economics* *89*(2), 430–447. http://www.jstor.org/stable/4492821

De Haas, H. (2021). A theory of migration: The aspirations-capabilities framework. *Comparative Migration Studies*, *9*(1). https://doi.org/10.1186/s40878-020-00210-4

De Weerdt, J., Christiaensen, L. & Kanbur, R. (2021). *When distance drives destination, towns can stimulate development* (IZA discussion paper no. 14157). Institute of Labor Economics (IZA), Bonn.

Deshingkar, P. & Start, D. (2003). *Seasonal migration for livelihoods in India: Coping, accumulation and exclusion* (Working paper no. 220). Overseas Development Institute, London. https://www.files.ethz.ch/isn/95707/wp220.pdf

Fabry, A., & Maertens, M. (2024). Temporary labor mobility to various geographical and sectoral destinations improves rural incomes − Insights from Peru. *World Development*, *185*, 106782. https://doi.org/10.1016/j.worlddev.2024.106782

Fafchamps, M., & Shilpi, F. (2012). Determinants of the choice of migration destination. *Oxford Bulletin of Economics and Statistics*, *75*(3), 388–409. https://doi.org/10.1111/j.1468-0084.2012.00706.x

Gill, G. J., Farrington, J., Anderson, E., et al. (2003). *Food security and the millennium development goal on hunger in Asia* (Working paper no. 231), Overseas Development Institute, London. https://www.files.ethz.ch/isn/22639/wp231_web.pdf

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153-161. https://doi.org/10.2307/1912352

Hossain, S. S., & Hossen, M. A. (2020). *Poverty Maps of Bangladesh 2016: Key Findings*. Bangladesh Bureau of Statistics (BBS), Dhaka.

Hu, F., Xu, Z., & Chen, Y. (2011). Circular migration, or permanent Stay? Evidence from China's rural–urban Migration. *China Economic Review, 22*(1), 64–74. https://doi.org/10.1016/j.chieco.2010.09.007

Keshri, K., & Bhagat, R. B. (2013). Socioeconomic determinants of temporary labour migration in India. *Asian Population Studies*, *9*(2), 175–195. https://doi.org/10.1080/17441730.2013.797294

Khandker, S. R. & Mahmud, W. (2012). *Seasonal Hunger and Public Policies: Evidence from Northwest Bangladesh*. The World Bank.

Khandker, S. R., Khalily, M. A. B., & Samad, H. A. (2012). Seasonal migration to mitigate income seasonality: Evidence from Bangladesh. *Journal of Development Studies*, *48*(8), 1063–1083. https://doi.org/10.1080/00220388.2011.561325

Kharel, A., Mobarak, A.M., Shenoy, A. & Vernot, C. (2021). *Seasonal poverty and the COVID-19 pandemic* (G²LM|LIC working paper no. 52). Gender, Growth, and Labour Markets in Low Income Countries Programme (G²LM|LIC), Institute of Labor Economics (IZA). https://g2lm-lic.iza.org/wp-content/uploads/2021/11/glmlic-wp052.pdf

Lagakos, D., Mobarak, A. M., & Waugh, M. E. (2023). The welfare effects of encouraging rural–urban migration. *Econometrica*, *91*(3), 803–837. https://doi.org/10.3982/ecta15962

Lee, E.S. (1966). A theory of migration. *Demography, 3*(1), 47–57. https://doi.org/10.2307/2060063

Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *Manchester School*, *22*(2), 139–191. https://doi.org/10.1111/j.1467-9957.1954.tb00021.x

Liu, Y., & Xu, W. (2015). Destination choices of permanent and temporary migrants in China, 1985–2005. *Population, Space and Place*, *23*(1). https://doi.org/10.1002/psp.1963

Lucas, R. E. B. (2015). *Internal migration in developing economies: An overview* (KNOMAD working paper no. 6). The Global Knowledge Partnership on Migration and Development (KNOMAD).

Meghir, C., Mobarak, A.M., Mommaerts, C., & Morten, M. (2022). Migration and informal insurance: Evidence from a randomized controlled trial and a structural model. *The Review of Economic Studies*, *89*(1), 452–480. https://doi.org/10.1093/restud/rdab021

Rahman, M. M., Ali, M. R., Oliver, M. M. H., et al. (2021). Farm mechanization in Bangladesh: A review of the status, roles, policy, and potentials. *Journal of Agriculture and Food Research*, *6*, 100225. https://doi.org/10.1016/j.jafr.2021.100225

Rahman, M. T., Akter, S., Rana, M. R., Sabuz, A. A., & Jubayer, M. F. (2022). How COVID-19 pandemic is affecting achieved food security in Bangladesh: A perspective with required policy interventions. *Journal of Agriculture and Food Research*, *7*. https://doi.org/10.1016/j.jafr.2021.100258

Rana, M. S., & Qaim, M. (2024). Patterns of temporary rural migration: A study in northern Bangladesh. *World Development*, *182*, 106718. https://doi.org/10.1016/j.worlddev.2024.106718

Rana, M. S., Faye, A. & Qaim, M. (2024). *Temporary migration decisions and effects on household income and diets in rural Bangladesh* (ZEF discussion papers no. 344). Center for Development Research (ZEF), University of Bonn, Germany. https://www.zef.de/fileadmin/webfiles/downloads/zef_dp/ZEF_DP_344.pdf

Regmi, M., Paudel, K. P., & Bhattarai, K. (2019). Migration decisions and destination choices. *Journal of the Asia Pacific Economy*, *25*(2), 197–226. https://doi.org/10.1080/13547860.2019.1643195

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal*, *11*(2), 159–206. https://doi.org/10.1177/1536867x1101100202

Shonchoy, A. S. (2015). Seasonal migration and microcredit during agricultural lean seasons: Evidence from northwest Bangladesh. *The Developing Economies* *53*(1), 1–26. https://doi.org/10.1111/deve.12063

Stark, O., & Bloom, D. E. (1985). The new economics of labor migration. *The American Economic Review* *75*(2), 173–178. https://www.jstor.org/stable/1805591

Thiede, B. C. (2023). *Climate variability and internal migration to urban and rural areas: Evidence from global microdata* (KNOMAD working paper no. 55), The Global Knowledge Partnership on Migration and Development (KNOMAD).

Tiwari, C., Bhattacharjee, S., Sethi, P., & Chakrabarti, D. (2022). Internal migration and rural inequalities in India. *Population Research and Policy Review*, *41*(4), 1673–1698. https://doi.org/10.1007/s11113-022-09707-5

Todaro, M. P. (1969). A model of labor migration and urban unemployment in less developed countries. *American Economic Review,* *59*(1), 138-148. https://www.jstor.org/stable/1811100

Tversky, A. & Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics, 106*(4), 1039–1061. https://doi.org/10.2307/2937956

Visaria, L., & Joshi, H. (2021). Seasonal sugarcane harvesters of Gujarat: Trapped in a cycle of poverty. *Journal of Social and Economic Development*, *23*(S1), 113–130. https://doi.org/10.1007/s40847-020-00120-2

Wang, C., Liu, X. & Yan, Z. (2021). Temporary versus permanent migration: The impact on expenditure patterns of households left behind. *Review of Economics of the Household 19*(3), 873-911. https://doi.org/10.1007/s11150-020-09505-y

Wang, Y., & Charles-Edwards, E. (2024). The ontology, measurement, and features of temporary internal migration in selected countries of Asia. *Asian Population Studies*, 1–20. https://doi.org/10.1080/17441730.2024.2363024

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources, 50*, 420-445. http://www.jstor.org/stable/24735991

Zug, S. (2006). Monga—Seasonal food insecurity in Bangladesh—Bringing the information together. *The Journal of Social Studies, 111*.

Appendix

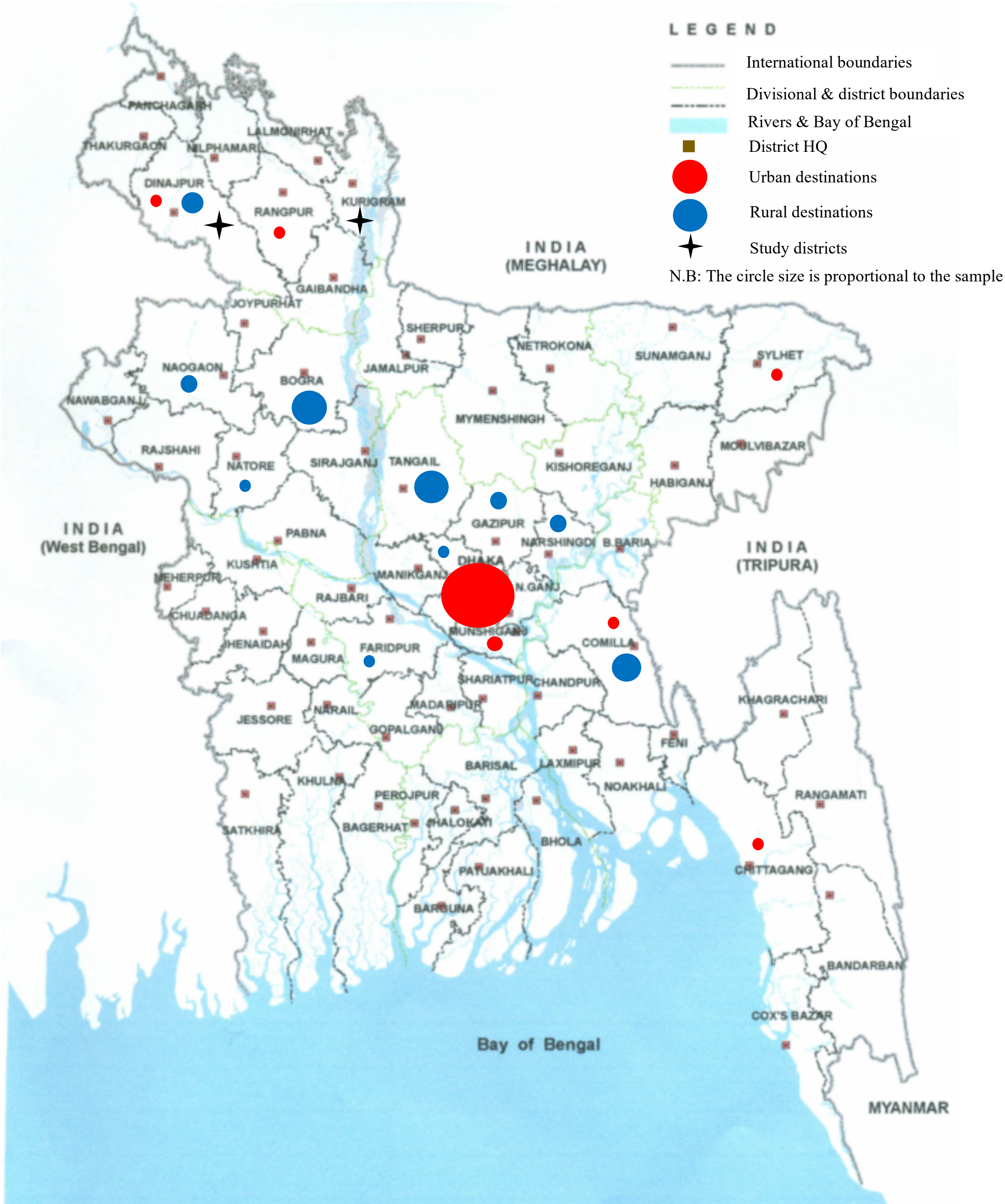
Table A1: Mean of household experience of idiosyncratic economic shocks in the past year

Using individual-level dataset (n=2,793)							
Variable	**(1) All observations (n=2,793)**	**(2) Migrants (n=605)**	**(3) Non-migrants (n=2,188)**	**(4) Mean difference (2-3)**	**(5) Temporary migrants (n=385)**	**(6) Longer-term migrants (n=220)**	**(7) Mean difference (5-6)**
Experience of random economic shocks (ev_j)	0.35 (0.48)	0.30 (0.46)	0.36 (0.48)	-0.06*** [0.02]	0.30 (0.46)	0.31 (0.46)	-0.01 [0.04]

Standard deviation in parentheses (); standard error in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Table A2: Collinearity tests for variables to explain temporary migrant's destination choices

Variables	Variance Inflation Factor (VIF)		
	Migration vs non-migration (M_i)	Temporary vs longer-term migration (TM_i)	Rural vs urban destination choice (R_i)
Individual characteristics *(I_i)*			
Education	1.81	1.79	1.76
Occupation: Agriculture farming	1.46	2.09	1.37
Agricultural labor sale			1.41
Relevant controls			
Physical sensitivity to agriculture			1.26
Age	1.86	2.57	1.58
Household size	1.40	1.50	1.21
Agricultural landholdings	1.24	1.28	1.31
Crop farming	1.21	1.77	1.30
Livestock farming	1.16	1.54	1.19
Family demographic shocks	1.01	1.07	1.07
Business	1.12	1.47	1.09
Social safety-nets	1.09	1.22	1.15
Microcredit memberships	1.06	1.05	1.12
Urban negativity *(U_i)*			
Prior negative perception of cities			1.44
Relevant controls			
Lack of skills beyond agriculture			1.42
Experience of destination characteristics *(D_i)*			
Income-to-cost ratio			1.39
Physical comfort			1.19
Relevant controls			
Daily wage opportunities			1.09
Flood vulnerability of the village	1.16	1.20	1.19
Village-level fixed effects	1.30	1.65	1.34
Migrant networks *(N_i)*			
Rural boundness of the closest migrant kin			1.63
Migrant group size			1.39
Migration distance *($Dist_i$)*			
Travel distance (km)			1.15
Relevant controls			
Household distance to the nearby migration hub	1.12	1.14	1.16
Other controls (X_i)			
Gender	1.55		
Occupation: Labor sales	1.60	3.94	
Seasonal employment fluctuation at the origin	1.14	1.16	
Children	1.18	1.31	
Elderly	1.31	1.24	
Distrust in neighbors	1.12	1.78	
Size of the migrant network	1.12	2.82	
Random economic shocks (ev_j)	1.05		
imr_i		7.59	2.38
Mean VIF	1.28	1.96	1.34
N	2,793	605	385



Map source: Author's construct on the free map from LGED Bangladesh

Figure A1: Popular destination districts among temporary migrants from northern Bangladesh

Table A3: Mean household income for different temporary migration duration

Income variables (Inc_j)	(1) All observations (n=385)	(2) <30 days duration in an episode (n=258)	(3) >30 days duration in an episode (n=127)	(4) Mean difference (2-3)
Total income (*tot_inc*$_j$)	4.00 (0.65)	3.97 (0.65)	4.06 (0.65)	-0.10 [0.07]
Remittance income (*remit_inc*$_j$)	3.09 (0.92)	2.91 (0.90)	3.45 (0.86)	-0.53*** [0.10]
Local market income (*loc_inc*$_j$)	2.95 (1.34)	3.09 (1.28)	2.65 (1.41)	0.45*** [0.14]

Standard deviation in parentheses (); standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Table A4: Mean differences of income from different local market sources

Income sources	(1) All observations (n=385)	(2) Rural-bound temporary migrants (n=259)	(3) Urban-bound temporary migrants (n=126)	(4) Mean difference (2-3)
Crop farming	0.37 (1.07)	0.42 (1.15)	0.27 (0.90)	0.15 [0.12]
Livestock farming	0.37 (1.06)	0.45 (1.14)	0.20 (0.83)	0.25** [0.11]
Labor sale	2.14 (1.49)	2.32 (1.42)	1.76 (1.57)	0.55*** [0.16]
Business	0.46 (1.19)	0.43 (1.16)	0.54 (1.24)	-0.11 [0.13]
Monthly fixed/service	0.27 (0.74)	0.23 (0.67)	0.35 (0.85)	-0.12 [0.08]
Seasonal safety-nets	0.32 (0.69)	0.33 (0.70)	0.30 (0.67)	0.03 [0.07]
Rents and assets	0.03 (0.34)	0.03 (0.38)	0.02 (0.25)	0.01 [0.04]
Others	0.01 (0.19)	0.01 (0.23)	0.00 (0.00)	0.01 [0.02]

Standard deviation in parentheses (); standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Table A5: Factors for migration and temporary migration by correcting self-selection (equation 2 and 3)

Variables	Migration vs non-migration (M_i)	Temporary vs longer-term migration (TM_i)
Age	-0.02*** [0.00]	0.03*** [0.01]
Education	-0.01 [0.01]	-0.05*** [0.02]
Occupation: Agriculture farming	0.31*** [0.11]	1.11*** [0.28]
Occupation: Labor sale	0.52*** [0.09]	0.57** [0.25]
Seasonal employment fluctuation at the origin	0.04 [0.07]	0.70*** [0.14]
Children	0.04 [0.07]	0.35** [0.16]
Elderly	-0.07 [0.08]	0.41** [0.18]
Distrust in neighbors	-0.84*** [0.10]	1.78*** [0.39]
Crop farming	-0.33*** [0.08]	0.53*** [0.18]
Livestock farming	-0.27*** [0.08]	0.58*** [0.17]
Family demographic shocks	-0.32 [0.29]	-0.46 [0.63]
Size of the migrant network	0.05*** [0.01]	0.02 [0.02]
Household size	0.00 [0.02]	-0.17*** [0.05]
Agricultural landholdings	-0.00 [0.00]	-0.01 [0.01]
Business	-0.35*** [0.09]	0.47** [0.19]
Social safety-nets	-0.14* [0.08]	0.01 [0.17]
Microcredit memberships	0.04 [0.08]	0.03 [0.16]
Household distance to the nearby migration hub	0.00 [0.00]	-0.01* [0.00]
Flood vulnerability of the village	-0.19 [0.12]	-0.38* [0.21]
Village-level fixed effects	0.00*** [0.00]	-0.00 [0.00]
Gender	2.00*** [0.12]	
Random economic shocks (ev_j)	-0.13* [0.07]	
imr_i		1.66*** [0.55]
Constant	-3.80*** [0.32]	-2.46*** [0.66]
Wald chi2	551.25	240.54
Observations	2,793	605

Robust standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Table A6: Income effects of destination choices by correcting self-selection bias (equation 5)

Model	Variable	Total income (tot_inc_j)	Remittance income ($remit\_inc_j$)	Local market income (loc_inc_j)
Multi-step conditional probit selection model with subsamples	Rural over urban destination choice (R_i)	0.06 [0.10]	-0.22 [0.18]	0.45* [0.23]
	$imr3_i$	-0.10 [0.08]	-0.11 [0.14]	0.09 [0.18]
	Constant	3.89*** [0.28]	2.80*** [0.36]	2.67*** [0.45]
	Controls (z_i)	Yes	Yes	Yes

Standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Table A7: Factors for migration, temporary migration, and destination choices employing multi-step control function approach (equation 2, 3, and 4)

Variables	Migration vs non-migration (M_i)	Temporary vs longer-term migration (TM_i)	Rural vs urban destination choice (R_i)
Individual characteristics *(I_i)*			
Education	-0.01 [0.01]	-0.05** [0.02]	-0.15*** [0.06]
Occupation: Agriculture farming	0.31*** [0.11]	0.82** [0.33]	-0.01 [0.29]
Agricultural labor sale			1.27*** [0.46]
Relevant controls			
Physical sensitivity to agriculture			-1.16** [0.45]
Age	-0.02*** [0.00]	0.05*** [0.01]	0.01 [0.01]
Household size	0.00 [0.02]	-0.18*** [0.05]	-0.26** [0.11]
Agricultural landholdings	-0.00 [0.00]	-0.01 [0.02]	0.02 [0.02]
Crop farming	-0.33*** [0.08]	0.79*** [0.26]	-0.80** [0.36]
Livestock farming	-0.27*** [0.08]	0.80*** [0.22]	0.76** [0.33]
Family demographic shocks	-0.32 [0.29]	-0.26 [0.71]	-1.02** [0.50]
Business	-0.35*** [0.09]	0.76*** [0.27]	0.33 [0.34]
Social safety-nets	-0.14* [0.08]	0.10 [0.19]	0.22 [0.32]
Microcredit memberships	0.04 [0.08]	0.00 [0.16]	-0.54* [0.30]
Urban negativity *(U_i)*			
Prior negative perception of cities			1.16*** [0.33]
Relevant controls			
Lack of skills beyond agriculture			0.69** [0.27]
Experience of destination characteristics *(D_i)*			
Income-to-cost ratio			0.38*** [0.07]
Physical comfort			0.07 [0.05]
Relevant controls			
Daily wage opportunities			-0.27** [0.11]
Flood vulnerability of the village	-0.19 [0.12]	-0.28 [0.23]	0.69 [0.71]
Village-level fixed effects	0.00*** [0.00]	-0.00* [0.00]	0.00 [0.00]
Migrant networks *(N_i)*			
Rural boundness of the closest migrant kin			3.15*** [0.48]
Migrant group size			0.11*** [0.04]
Migration distance *($Dist_i$)*			
Travel distance (km)			-0.00*** [0.00]
Relevant controls			
Household distance to the nearby migration hub	0.00 [0.00]	-0.01** [0.00]	-0.01 [0.01]
Other controls (X_i)			
Gender	2.00*** [0.12]		
Occupation: Labor sale	0.52*** [0.09]	0.14 [0.36]	
Seasonal employment fluctuation at the origin	0.04 [0.07]	0.67*** [0.14]	
Children	0.04 [0.07]	0.33** [0.16]	
Elderly	-0.07 [0.08]	0.51*** [0.19]	
Distrust in neighbors	-0.84*** [0.10]	2.54*** [0.57]	
Size of the migrant network	0.05*** [0.01]	-0.01 [0.04]	
Random economic shocks (ev_j)	-0.13* [0.07]		
res_i		-5.32*** [1.71]	2.57*** [0.97]
Constant	-3.80*** [0.32]	1.45 [0.97]	-0.01 [1.43]
Wald chi2	551.25	255.59	137.98
Observations	2,793	605	385

Standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Table A8: Full regression results from equation (5) using multi-step control function approach

Variable	Total income (tot_inc_j)	Remittance income ($remit\_inc_j$)	Local market income (loc_inc_j)
Rural over urban destination choice (R_i)	-0.08 [0.08]	-0.39*** [0.12]	0.59*** [0.17]
Age	-0.00 [0.00]	-0.00 [0.00]	0.00 [0.01]
Education	0.01 [0.01]	-0.00 [0.01]	0.00 [0.02]
Gender	0.26* [0.15]	0.10 [0.22]	-0.16 [0.24]
Household size	0.04 [0.03]	0.03 [0.04]	0.12*** [0.04]
Seasonal employment fluctuation at the origin	-0.13* [0.07]	0.18* [0.10]	-0.62*** [0.13]
Flood vulnerability of the village	0.09 [0.10]	0.17 [0.18]	0.06 [0.18]
Village-level fixed effects	-0.00 [0.00]	0.00* [0.00]	-0.00 [0.00]
$res3_i$	0.28* [0.16]	0.41 [0.40]	-0.31 [0.43]
Constant	3.92*** [0.28]	2.85*** [0.36]	2.63*** [0.45]

Standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01

Table A9: First-stage regression results summary from 2sls

Variables	Choice of rural versus urban destination (R_i)
Instrument: Rural-bound migrant kin (1/0)	0.54*** [0.05]
Constant	0.60*** [0.16]
F-statistics	73.81
Controls	Yes

Standard errors in square brackets []; *p<0.10, **p<0.05, ***p<0.01