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Rainfall variability and internal migration: the importance of agriculture linkage and gender inequality

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Abstract

This paper investigates the extent to which exposure to climate volatility can influence individual migration decisions in Vietnam, based on the historical rainfall data from 70 weather stations in Vietnam and the Vietnam Access to Resources Household Survey. Utilizing the exogenous variation in the rainfall deviation from the local norms within an individual fixed-effects framework, we uncover the negative association between rainfall and the probability of individual migration. Individual migration probability drops by 7.5 percentage points when the amount of rainfall relative to the long-run local average doubles. This reduction could potentially be driven by individuals who work in the agricultural sector and are less likely to migrate as more rainfall could increase their agricultural incomes. Furthermore, our heterogeneity analyses suggest that rainfall shocks could perpetuate gender inequality in Vietnam since women cannot cope with climatic shocks through migration. Policy-makers could shift their focus on flood control and water management in affected areas, where people's livelihoods depend on agriculture, to efficiently address issues related to climate-induced internal migration.

JEL codes: Q26, Q54, O15

Keywords: Climate change, Rainfall, Migration, Gender inequality, Vietnam.

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1 INTRODUCTION

Climate change has greatly affected precipitation patterns with the variance of rainfall rising significantly (Alexander 2016). Prior studies have shown that changing rainfall frequency has tremendous impacts on socio-economic outcomes. In particular, rainfall shocks are associated with more conflict and crime (e.g., Miguel et al. (2004); Sekhri & Storeygard (2014); Blakeslee & Fishman (2018)). Exposure to rainfall shocks can also reduce school enrollment (e.g., Björkman-Nyqvist (2013), Zimmermann (2020)) and worsen nutrition statuses for children (e.g., Jacoby et al. (2002)). Meanwhile, Maccini & Yang (2009) uncover a positive link between rainfall in early childhood and health, education, and socio-economic status for Indonesian women.

There are essentially five factors driving an individual's migration decision, whether domestically or internationally, including environmental, social, economic, demographic, and political factors (Black et al. 2011). Our project is motivated by the literature examining the relationship between economic drivers (e.g. incomes and wages), migration decisions, and the impact of climate change (environmental driver) on labour mobility within a country. We are interested in the intersection of these two drivers and the migration behaviours of individuals from affected areas (e.g., the Mekong Delta). Vietnam is one of the most vulnerable to climate change, due to the rise of globalisation and global warmings, such as floods, drought, cyclones, and saline intrusion. Chapman & Pham (2018) suggest that there is a migrant crisis from cities in the Mekong Delta region, which is one of the most critical rice production regions. Thus, climate change will affect not only people's lives in this region but also the Vietnamese national food security and other social imbalance issues.

Using Vietnam as a case study, this paper contributes to the growing branch of literature on the influence of climate variability on internal migration. First, we present a theoretical framework to formalize a testable hypothesis about the effects of rainfall on individual migration decisions. The framework helps to distinguish the effects on migrating for work, migrating for education and migrating for other reasons. Moreover, it predicts that the effects on migrating for work vary by gender, agriculture, and non-agriculture sectors. For the empirical estimation of the link between rainfall shocks and individual migration decisions, we employ the Vietnam Access to Resources Household Survey (VARHS henceforth) and climate data from 70 meteorological stations in Vietnam. The VARHS provides rich information on individual characteristics while the climate records from the meteorological stations help us construct district-level rainfall data. Utilizing the detailed spatial and temporal information from these datasets, we construct our main explanatory variable as the deviation of the 24-month rainfall from the long-run average of total rainfall during those 24 months for the individual's residential district.

There is a growing branch of literature evaluating the relationship between climate change and both international and internal migration[3] . Much research has been devoted to studying migration patterns and trends in developing countries that are vulnerable to the impacts of climate change, such as African nations (e.g., Henry et al. (2004), Dai (2011), Gray & Mueller (2012)), in South America (e.g., Mueller & Osgood (2009), Thiede et al. (2016)), and Indonesia (e.g., Gignoux & Menéndez (2016)). Yet, it is unclear how climate change induces migration. While some studies suggest that climate change influences international migration (Backhaus et al. (2015), Beine & Parsons (2017), Cattaneo & Peri (2016), Coniglio & Pesce (2015)) and internal migration (Bohra-Mishra et al. (2014), Dallmann & Millock (2017), Thiede et al. (2016)), others find little or no evidence at all (Beine & Parsons (2015), Gröschl & Steinwachs (2017), Ruyssen & Rayp (2014), Di Falco et al. (2012), Goldbach (2017), Gray & Bilsborrow (2013)).

Among the most affected countries, Vietnam has emerged as a prime example to study the impacts of climate change. The relaxation of the household registration system (Ho-khau)

[3] For an in-depth survey of research on the impacts of climate change (whether slow-onset or sudden natural disasters) on international resettlement, please visit Belasen & Polachek (2013), Cavallo et al. (2011), Berlemann & Steinhardt (2017)

allowed people to move away from their local areas, especially as a result of natural disasters (Berlemann & Tran (2020)). The most affected regions were typically the poor areas with a high degree of income inequality (Arouri et al. 2015). Presumably, the more comprehensive study is by Nguyen (2021). While most studies focus on the push effect, Nguyen (2021) applies the gravity model to include the pull effect in his study. He finds that high rainfall encourages the out-migration of highly educated people (the push effect) but attracts the in-migration of the poorly educated (the pull effect). At the same time, the low temperature lowers the push effect and raises the pull effect as favourable weather improves both income and health of the residents. Our study provides consistent evidence. Low (high) levels of rainfall would push (pull) people out of (in) their regions because of the income reduction (rise). Climate-induced migration provides economic opportunities for migrants in other cities and thus allows them to send remittances to support their family in the home-sending cities. Nguyen et al. (2017) show that the remittances from migrants increase their household expenditures, especially on housing. These remittances also allow their family to move away from agriculture to non-farm sectors.

We contribute to the literature by providing new evidence of the impact of climate change on migration under different sectoral regimes. Cai et al. (2016) show a positive relationship between temperature and international migration in the most agriculture-dependent countries. We argue that this relationship is sensitive to the type of migration and the type of climate change. Indeed, our findings suggest working in the agricultural sector reduced the likelihood of *internal* migration when *rainfall* was unexpectedly high. Indeed, more rainfall can improve agricultural production. Consequently, individuals working in the agricultural sector are less likely to migrate within the country in response to high rainfall. We find evidence that the negative impact of rainfall on migration is more pronounced when the reason for migration is for working, as opposed to general migration. It suggests that the increased income due to rainfall for people working in the agricultural sector adds more reasons to stay in their local areas.

In addition, most of the studies mentioned above employed rapid onset events such as droughts, floods or short-run extreme rainfall. There is mixed evidence of whether these events are the main cause of migration, as opposed to slow-onset events such as saline intrusion. Koubi et al. (2016) suggest that the latter reduces movement because people learn how to adapt to these changes over time. We contribute to the discussion by providing evidence that slow-onset events play a more important role in this particular context. Indeed, while rapid-onset events affect the *current* living conditions, slow-onset events such as the changes in average long-run rainfall or saline intrusion result in changes in soil quality which is an important input in agricultural production. The affected income then leads to the migration decisions of the individuals.

To prove our hypothesis, we build a rainfall index which is the 24-month average of rainfall in each local authority. Our identification strategy is based on the assumption that the changes in rainfall only affect the soil quality in the long run. We then take advantage of the exogenous variation in the deviation of rainfall from the long-run local mean to which the individual was exposed 24 months leading up to the survey date. We reach the following findings. First, exposure to rainfall shocks reduces the probability of individual migration. Particularly, doubling the amount of rainfall relative to the long-run local average reduces the probability of migration by 7.5 percentage points. Second, according to our mechanism analyses, the impact of rainfall on migration decisions could potentially be driven by individuals working in the agricultural sector who are less likely to move due to higher agricultural income from more rainfall. Third, our heterogeneity analyses suggest that rainfall shocks could perpetuate gender inequality in Vietnam. The reason is that the female population cannot cope with climatic shocks, such as migration in response to the lack of rainfall. Finally, we conduct a battery of robustness checks to show that our findings are consistent across alternative measures of rainfall.

The remainder of the paper is organized as follows. Section 2 discusses the conceptual framework. Section 3 presents our data on rainfall and the Vietnam Access to Resources Household Survey (VARHS). Section 4 provides an overview of the empirical methodology and presents the main results. Section 5 discusses the mechanism to explain how weather influences migration, and robustness check, and section 6 concludes.

2 THEORY

To guide our empirical exercise, a conceptual framework is needed here. According to the seminal works of Roy (1951) and Borjas (1987), migration is considered as an investment activity. A rational individual will move to a new place if he/she can achieve higher earnings (after netting out the migration cost) than her current ones[4]. Our framework is based on the Roy model with the integration of a covariate climate risk. The framework helps to distinguish the effects of migrating for various reasons, be it working, education or other reasons.

In many studies in the literature, the choice of migration is usually adopted from the gravity model (Clement et al. 2022) where choice is proportional to the number of people migrating between origin and destination. The weakness of the gravity model is that it is not a model of individual behaviour. It does not describe the decision to migrate and climate shocks affect the choice of migration.

In this simple framework, we try to provide a mechanism for which people will take decisions on migration based on the impact of climate risk on their welfare. Prior studies have suggested that positive rainfall shocks can improve agricultural production; thus, raising agricultural income (e.g., Jayachandran 2006). We show here that the rainfall shocks prompt migration via the negative impacts on health or income.

[4] See Heckman & Honoré (1990) a discussion of the empirical content of the Roy model.

Suppose that the period utility of the agent h working in the agricultural sector is

$$U_{h,t} = w_{h,t} z_{h,t} L_{h,t} - D(L_{h,t}, R_{g,t}) \tag{1}$$

where $D(L_{h,t}, R_{g,t}) = \theta \frac{L^{1+\frac{1}{\varepsilon}}}{1+\frac{1}{\epsilon}} (R - R^*)^2$ is the labor dis-utility under rainfall $R_{g,t}$. An example of this is the health status (conditional on age and agent's characteristics) under climate risks. Alternatively, rainfall could lead to an income loss.

Given w and z, agent h maximizes her utility (1) by choosing the level of labour L. Hence,

$$wz = \frac{\partial D(L,R)}{\partial L} = \theta L^{\frac{1}{\varepsilon}} (R - R^*)^2 \tag{2}$$

Agent h working in the agricultural sector in location g at every period t has the choice of whether to migrate or not. If she migrates, she can choose to migrate for work, education, or other reasons. The return outcomes for these options, denoted by V^w, V^e and V^o, are measured in utility. She will choose the outcome that yields the highest utility:

$$\max \left\{ \underbrace{U(R_{g,t}, \Theta_{h,t})}_{\text{not migrate for any reason}}, \underbrace{V^w}_{\text{migrate for work}}, \underbrace{V^e}_{\text{migrate for education}}, \underbrace{V^o}_{\text{migrate for other reason}} \right\}.$$

Let denote $P_{h,g,g',t}$ the binary choice of agent h working in the agriculture sector in location g migrates to location g' for working or for any other reason. She will move if the utility derived from staying $U_{h,g,t}$ is lower than the utility of moving discounted by a one-time migration cost:

$$P_{h,g,g',t} = \begin{cases} 1 \text{ if } U_{h,g,t} - V^i_{h,g',t} + c_{h,g,g',t} < 0 \\ 0 \text{ if } U_{h,g,t} - V^i_{h,g',t} + c_{h,g,g',t} \geq 0 \end{cases}, i \in \{w, e, o\}.$$

Agent h in the agriculture sector decides to migrate from a province p to a province q for work if

$$\Delta(R_{p,t}, \Theta_{h,t}) = U_{h,p,t} - V^{w}_{h,q,t} + c^{w}_{h,p,q,t} < 0.$$

We can show that at least for the rainfalls below a certain level R^*, the probability of migrating falls with the level of rainfall. Indeed, we have:

$$\frac{\partial \Delta(R,\Theta)}{\partial R} = wz\frac{dL}{dR} - \frac{\partial D(L,R)}{\partial L}\frac{dL}{dR} - \frac{\partial D(L,R)}{\partial R}$$

From Equation 2, we then have:

$$\frac{\partial \Delta(R,\Theta)}{\partial R} = \theta \frac{L^{1+\frac{1}{\varepsilon}}}{1+\frac{1}{\epsilon}}(R^* - R) > 0$$

For the level of rainfall below some level R^*, more rainfall increases Δ and hence, enhances the probability of "stay" in the agricultural sector.

In our empirical exercise, we estimate $P_{h,g,g',t}$ as a function of $\Delta(R_{p,t}, \Theta_{h,t})$. We employ the reduced form of $\Delta(R,\Theta)$ as a function of rainfall, individual demographic characteristics, district, survey month, and survey year fixed effects.

3 DATA

3.1 Rainfall data

We obtain historical rainfall data for 70 weather stations across Vietnam from the Data Center of the National Hydro Meteorological Service of Vietnam, which belongs to the Ministry of Natural Resources and Environment. The data includes a pair of latitude and longitude to identify the location of each station. These stations also record the daily and monthly amounts of rainfall. We then assign the rainfall data to districts in VARHS based on the records from its closest station (measured by distance from the district centroid to the station). Figure 1 illustrates the distribution of rainfall stations (red dots) and districts (gray polygons) across Vietnam.

In examining the impacts of rainfall on migration, we calculate our main explanatory variable, rainfall shocks, as the deviation of the rainfall 24 months leading up to the survey time from the long-run average of the total rainfall during those 24 months for the individual's residential district. The 24-month long-run mean rainfall is calculated from 2002 to 2012 for each district. For example, for an individual surveyed in November 2008, we calculate the total rainfall in 24 months in the individual's district ($TR_{\text{Nov 06 - Oct 08}}$) by summing the monthly total rainfall from November 2006 to October 2008. Our explanatory variable, Rainfall Shocks ($RS_{\text{Nov 06 - Oct 08}}$), is then given by,

$$RS_{\text{Nov 06 - Oct 08}} = \frac{TR_{\text{Nov 06 - Oct 08}} - 2 \times LRTR_{\text{Nov - Oct}}}{2 \times LRTR_{\text{Nov - Oct}}}$$

where the 24-month long-run total rainfall $LRTR_{\text{Nov - Oct}}$ is two times the amount of the 2002-2012 average of total rainfall for November through October in the individual's district.

[Figure 1 here]

3.2 Migration data

Our second source of data is the Vietnam Access to Resources Household Survey (VARHS), carried out biannually from 2006 to 2014. The VARHS, a part of the UNU-WIDER's project on "*Structural transformation and inclusive growth in Vietnam*", is conducted by the Central Institute for Economic Management (CIEM) and the Vietnam Institute of Labour Science and Social Affairs (VILSSA). The VARHS surveys households from rural areas in 12 provinces, such as Dak Lak, Dak Nong, Dien Bien, Ha Tay [5], Khanh Hoa, Lai Chau, Lam Dong, Lao Cai, Long An, Nghe An, Phu Tho, and Quang Nam.

In this study, we exclude the VARHS in 2012 and 2014 due to the lack of similar migration

[5] Ha Tay has been merged to Ha Noi since 2008

variables as in previous years. Appending the remaining three waves of survey gives us an unbalanced panel data of rural households across 12 provinces of Vietnam. The sampling unit of VARHS is the household composed of members living together for more than six months. Socio-economic questions (e.g., age, gender, ethnicity, educational attainment, and marital status) employed in this study are defined consistently across all years of the survey. Moreover, the reference period in the survey always refers to the last 12 months. More importantly, the data allows us to identify whether an individual migrates in the last twelve months before the survey date. Therefore, we can construct our main outcome variable, migration status, as an indicator that takes a value of one if an individual migrated in the last twelve months, and zero otherwise.

Summary statistics of variables are provided in Table 1. Mean values and standard deviations (in the brackets) are calculated for the whole sample (Column 1) and disaggregated by migration status (Columns 2 and 3). Migration status takes the mean value of approximately 0.089 for the full sample, suggesting that 8.9% of observations in our sample migrated in the last 12 months.[6] Our main explanatory variable, Rainfall Shocks, take the mean value of -0.006 for the full sample. The mean is slightly lower for the migrant sample. It could be the case that these individuals migrate due to the lack of rainfall. However, a formal analysis as in Section 3 is required to make such a conclusion. The statistics of individual characteristics such as age, ethnicity, gender, education, and marital status are also provided.[7]

[Table 1 here]

[6] That means 8.9% of individuals left their current address in the last 12 months, and we do not have any information on whether this is a permanent or temporary migration.

[7] Being Minority, Being Male, Finished Primary School, and Being Married are dichotomous variables taking a value of one if an individual is classified as a minority, is male, completed primary school, and is married at the time of the survey.

4 EMPIRICAL METHODOLOGY AND MAIN RESULTS

4.1 Empirical Methodology

To examine the extent to which rainfall shock influences individual migration decisions, we start with the following model,

$$Y_{ismt} = \alpha_0 + \alpha_1 RS_{ismt} + \lambda_s + \delta_m + \mu_t + X'_{ismt}\Sigma + \varepsilon_{ismt} \tag{3}$$

where the subscripts i, s, m, and t refer to the individual, district, survey month, and survey year. The outcome variable Y_{ismt} represents individual migration status. Our main explanatory variable, RS_{ismt}, is the rainfall shocks 24 months prior to survey time, as defined in the previous section. Our coefficient of interest is α_1 summarizing the impact of rainfall shocks on individual migration decisions.

The terms λ_s, δ_m, and μ_t denote district, survey month, and survey year fixed effects. The vector X'_{ismt} is a covariate of demographic characteristics at the individual level, including age, age squared, ethnicity, gender, educational attainment, and marital status. Finally, ε_{ismt} stands for the error term. Standard errors throughout the paper are clustered at the individual level since the source of variation is within individuals.[8]

In the model given in Equation (1), our identification strategy relies on the variation in the exposure to rainfall shocks across individuals within the same district. However, this approach can bias our estimate if there exist unobserved individual characteristics that are correlated with both migration decision and rainfall shocks in the district. To deal with this issue, we employ the individual fixed effects model where the identifying variation comes

[8] Since households are primary survey units, we have clustered the standard errors at the household level and the results remain statistically unchanged. Also, since the weather information was obtained at the district and month level, we have clustered the standard errors at the district level and obtained similar results.

from the within-individual comparison in the exposure to rainfall shocks, given by,

$$Y_{ismt} = \beta_0 + \beta_1 RS_{ismt} + \gamma_i + \lambda_s + \delta_m + \mu_t + X'_{ismt}\Sigma + \varepsilon_{ismt} \tag{4}$$

where γ_i stands for individual fixed effects. Our coefficient of interest is now β_1 summarizing the impacts of exposure to rainfall shocks on individual migration decisions within the individual fixed effects model. Other notations are the same. This within-individual comparison strategy will absorb individual characteristics that cannot be observed, thus providing support to the internal validity of the estimates.

As one of the main disadvantages of the linear probability model is that the conditional probability could be greater than 1 or smaller than 0, we have also estimated the model using logistic regression to obtain odds ratios. Since we are interested in the direction of the relationship between the amount of rainfall and the probability of migrating and the main results remain consistent, we present the results for the linear probability model below and odds ratios obtained from logistic regression in Table 7-Table 9.

4.2 Main Results

We present our estimates of the impacts of rainfall shocks on individual migration status in Table 2. The structure is as follows. Column 1 provides our most parsimonious specification without any controls. In column 2, we introduce into our regression an exhaustive set of control variables, namely individual age, age squared, ethnicity, gender, educational attainment, and marital status. Next, we add district, month, and year fixed effects in Column 3. Finally, Column 4 reports our most extensive specification with individual fixed effects, district, month, and year fixed effects, and a full set of controls.

[Table 2 here]

Starting with the most parsimonious specification, we find that a 100 per cent increase in rainfall relative to the normal local average decreases the probability of migration by 5.3

percentage points (Column 1). Controlling for individual characteristics slightly increases the magnitude of our estimate while leaving the statistically significant level virtually unchanged (Column 2). Adding district, month, and year fixed effects raise our estimate from 5.5 to 6.1 percentage points, without changing the significant level. Finally, the estimated result from our most extensive specification with individual fixed effects (Column 4) suggests that doubling the amount of rainfall relative to the long-run local average reduces the probability of migration by 7.5 percentage points. All the estimates are statistically significant at the 0.01 level.

Overall, our conclusion is consonant with the works of Henry et al. (2004) and Gray & Mueller (2012) which also detect the negative effect of rainfall on migration decisions. We cannot, however, quantitatively compare our finding magnitudes to theirs since their main explanatory are indicators of the lack of rainfall (drought).

5 MECHANISM, HETEROGENEITY, AND ROBUSTNESS

5.1 Mechanism

Our theory in Section 2 suggests that positive rainfall shocks can improve agricultural production; thus, raising agricultural income. It also confirms the heterogenous effects of climate change on migration decisions. In this section, we will provide evidence to support this hypothesis.

To test the implication of this framework, we proceed as follows. First, we construct three binary indicators for whether individuals migrate for work, for getting educated, and for other reasons. We then use these three indicators as the dependent variables for our most extensive regression (similar to Column 4 of Table 2). The estimated results are reported in Columns 1, 2, and 3 of Table 3. We find that the negative effect of rainfall shocks on migration is primarily driven by migration for work. Doubling the amount of rainfall relative to the long-run local average reduces the probability of migration for working by

6.3 percentage points (Column 1). The estimate is statistically significant at a 1% level and much larger in magnitude compared to the other two.

Next, we split our sample into individuals working in the agricultural sector and non-agriculture. With these two new samples, we rerun the specification in Column 1 in which migration decision is the dependent variable. In Columns 4 and 5, we consider migration in general whereas in Columns 6 and 7, the reason for migration was for work. Two interesting results emerge from these Columns. First, people working in the agricultural sector were less likely to migrate after unexpectedly high rainfall. Indeed, high rainfall reduced the probability of migration for these people by 5.6 percentage points (Column 4). This reduction in likelihood is even more pronounced if the motives for migration were for work, from 5.6 to 7.9 percentage points (Column 6). It suggests that more rainfall would improve agricultural income, which makes migration for work less likely.

[Table 3 here]

5.2 Heterogeneity Analyses

In this section, we explore the heterogeneous effects of rainfall shocks on migration decisions along the lines of gender and ethnicity, using our most extensive specification (similar to Column 4 of Table 2). The estimated results are presented in Table 4. The dependent variable is the migration status of individuals, as in our main analysis. Each column represents a separate regression, and the column headings specify subgroup levels.

[Table 4 here]

We first examine whether the impacts of rainfall shocks differ by gender (Columns 1 and 2, Table 4). Interestingly, we find that men are more sensitive to rainfall shocks than women. A 100 per cent increase in rainfall relative to the normal local average decreases the probability of migration by 9.9 percentage points for men (Column 1) and 5.3 percentage points for women (Column 2). Admittedly, men have a higher tolerance to travel time and distance, thus they become more willing to migrate. Besides, women might face a higher mobility barrier than men due to job market discrimination or family ties. These factors could contribute to the differential effects of rainfall shocks on the migration decision.

Relative to the majority population (Kinh), the ethnic minority groups (non-Kinh) fall behind in various aspects, such as fewer employment opportunities, lower access to education, and lack of connection. Therefore, it is of interest to analyze the heterogeneous impacts of rainfall shocks along the lines of ethnicity. We provide the relationships of interest in Columns 3 and 4. Doubling the amount of rainfall relative to the long-run local average reduces the probability of migration by 7.5 and 7.7 percentage points for the Kinh and minority populations, respectively. Unlike other socio-economic aspects, we find that Kinh and the minority population are affected by rainfall shocks alike.

We further examine whether the effect of rainfall shocks is concentrated among different subpopulation groups, including males, minority (non-Kinh ethnicity), being the household head, and agricultural workers. Table 5 shows the results for interaction between aforemnetioned subpopulation groups and the rainfall shocks using our most preferred model specification. Our results suggest that rainfall shocks seem to homogeneously affect the decision to migrate between male and female, and between Kinh and other minority groups. As shown in Column 4, a household head is less likely to migrate compared to other family members. However, the effect of rainfall shocks does not make any migration more likely among household members.

[Table 5 here]

Table 5 suggests that even without the rainfall shocks, individuals working in the agricultural sector are 2.3 percentage points less likely to migrate than those working in non-Agriculture. However, the rainfall shocks reduce the probability of migration by another 8.3 percentage points among those who work in Agriculture. This is consistent with our results in Columns 4 and 5 in Table 5. Intuitively, more rainfalls contribute to the enrichment of fertile alluvial soils, which then result in the rise of income of residents. As a result, they are less likely to migrate to other areas.

5.3 Robustness Checks

In this section, we test for the robustness of our main results by constructing different measures for our key explanatory variable. The results of these robustness exercises come from our most extensive specification (similar to Column 4 in Table 2) and are presented in Table 5. Each column represents a separate regression. Recall that in Section 2, we define our key explanatory variable as the deviation of rainfall from the historical norms, computed as the differences of total rainfall in the individual district 24 months prior to the survey time and the district's long-run average of rainfall during those 24 months, divided by the long-run local average. In this section, we conduct robustness checks to investigate whether our results are sensitive to alternative measures.

[Table 6 here]

The first measure is Raw Rainfall $\times 10^{-3}$, which is simply the raw measure of rainfall (in mm) divided by 1,000. As shown in Column 1, a 1,000 mm increase in rainfall during the last 24-month period leads to a 1.7 percentage points decrease in migration decisions. Next, we take the natural log of the raw rainfall to have the second measure, namely Log Raw Rainfall. The estimated result in Column 2 suggests that a 1 percent increase in rainfall 24 months prior to the survey reduces the probability of migration by 7.5 percentage points. Since the survey only asks whether individuals moving away in the last 12 months, we do not know the exact month of moving. One might argue that migration could be the result of individual foreseeing future rainfall shocks (though very unlikely). Thus, we re-estimate our model with Rainfall Shocks, Raw Rainfall $\times 10^{-3}$, and Log Raw Rainfall from 13-24 months prior to the survey as our main explanatory variables. The period of 13-24 months prior to the survey date ensures that individuals always migrate after our measuring period. As shown in Columns 3, 4, and 5, while the magnitudes of our estimates are reduced, the significant levels remain virtually unchanged. The decreases in magnitudes are expected because we lower the period from 24 to 12 months.

6 CONCLUSIONS

Using Vietnam as a laboratory, this paper contributes to the growing branch of literature evaluating the impacts of rainfall variability by examining the extent to which rainfall shocks influence individual migration decisions. In our analysis, we rely on the Vietnam Access to Resources Household Survey for individual characteristics and the climate data from 70 meteorological stations across the country. Our identification strategy hinges upon the exogenous variation in the deviation of rainfall from the long-run local mean to which the individual was exposed 24 months before the survey date.

Our paper presents several interesting findings. We show that rainfall shocks make people likely to stay. Indeed, the probability of migration drops by 7.5 percentage points when the amount of rainfall relative to the long-run local average becomes twice as much. In addition, our mechanism analysis suggests that this impact is driven by individuals *working in the agricultural sector*. One possible reason for this result is that people working in the agricultural sector could gain more income as a result of more rainfall. Moreover, our heterogeneity analyses indicate that rainfall shocks could aggravate gender inequality in Vietnam; hence, it suggests that women in these areas are more vulnerable. We also conduct a series of robustness checks to show that our results are consistent with various specifications and measures of rainfall.

Among the findings in our paper, we want to emphasize an interesting result that rainfall shocks reduce the probability of out migration due to possible improved agricultural income from more rainfall. In other words, while floods due to heavy rainfalls might result in property loss which induces people to migrate, more rainfalls enhance the welfare of people working in the agricultural sector. This result can be used to implement evidence-based mitigation policies. For instance, it suggests that the government should implement a monitoring system that could predict floods to mitigate their impacts. The performance of such a system is now enhanced significantly with the development in machine learning (Choubin et al. 2019, Mosavi et al. 2018). Our results point out that people would move from regions with small amounts of rainfalls to the ones with higher amounts of rainfalls. As a result, the government should prepare the infrastructure in the latter, while ensuring the former does not lack a labour force. Finally, the result suggests that women are among people who are more likely to be affected by climate shocks. The results from our paper suggest more support targeted at these vulnerable individuals. These supports could include raising the awareness to climate change, providing peer-support groups, and making emergency funds more accessible to these individuals.

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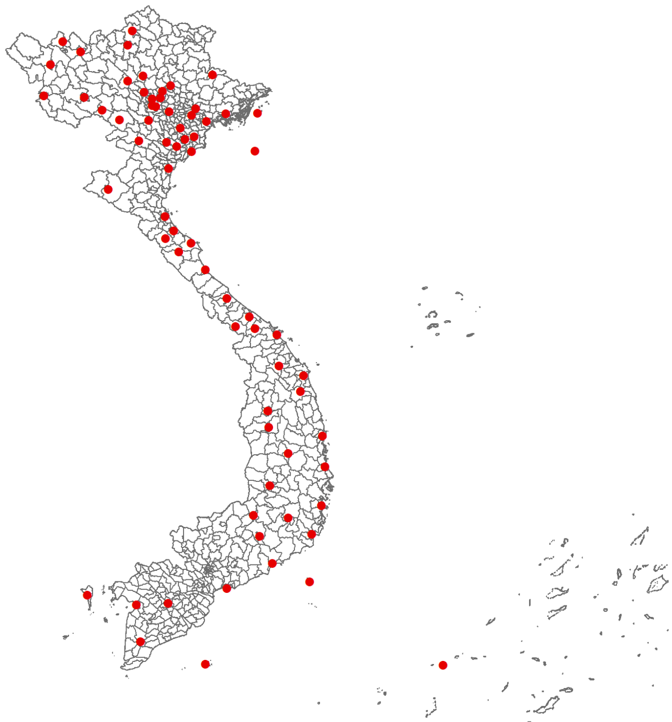
Figure 1: Geographic Distribution of Rainfall Stations across Vietnam



Note: Rainfall stations are illustrated by red dots. District boundaries are in gray.

Table 1: Summary Statistics

	All	Migrated	Not Migrated
	Mean (Standard Deviation)		
	(1)	(2)	(3)
Migration Status	0.089		
	(0.285)		
Rainfall Shocks	-0.006	-0.013	-0.006
	(0.106)	(0.111)	(0.106)
Age	42.98	30.91	44.17
	(16.59)	(13.11)	(16.42)
Being Minority	0.347	0.190	0.362
	(0.476)	(0.393)	(0.481)
Being Male	0.488	0.629	0.474
	(0.500)	(0.483)	(0.499)
Finished Primary School	0.654	0.898	0.631
	(0.476)	(0.303)	(0.483)
Being Married	0.750	0.391	0.785
	(0.434)	(0.488)	(0.410)
Observations	22,386	2,002	20,384

Note: Authors' calculations using VARHS 2006-2010.

Table 2: Impacts of Rainfall Shocks on Individual Migration Decision

	Y = Individual Migration Status			
	(1)	(2)	(3)	(4)
Rainfall Shocks	-0.053***	-0.055***	-0.061***	-0.075***
	(0.018)	(0.017)	(0.019)	(0.019)
Observations	22,386	22,386	22,386	22,386
Individual FE	·	·	·	✓
District, Month, Year FE	·	·	✓	✓
Individual Characteristics	·	✓	✓	✓

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each column represents coefficients in a separate regression. Individual characteristics include individual age, age squared, ethnicity, gender, educational attainment, and marital status. Robust standard errors are clustered at the individual level.

Table 3: Rainfall Shocks, Agricultural Employment Opportunity, and Migration

	Migration for Working	Migration for Education	Migration for Others	General migration		Migration for Working	
				Agriculture	Non-Agriculture	Agriculture	Non-Agriculture
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rainfall Shocks	-0.063***	-0.014	0.003	-0.056***	-0.070	-0.079***	-0.058
	(0.016)	(0.010)	(0.008)	(0.023)	(0.074)	(0.019)	(0.064)
Observations	22,386	22,386	22,386	15,798	1,994	15,798	1,994
Individual FE	✓	✓	✓	✓	✓	✓	✓
District, Month, Year FE	✓	✓	✓	✓	✓	✓	✓
Individual Characteristics	✓	✓	✓	✓	✓	✓	✓

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each column represents coefficients in a separate regression. Individual characteristics include individual age, age squared, ethnicity, gender, educational attainment, and marital status. Robust standard errors are clustered at the individual level.

Table 4: Migration Decision across Gender and Ethnicity

	Y = Individual Migration Status			
	Being Male (1)	Being Female (2)	Majority (Kinh) (3)	Minority (non-Kinh) (4)
Rainfall Shocks	-0.099***	-0.053**	-0.075***	-0.077*
	(0.032)	(0.021)	(0.022)	(0.040)
Observations	10,762	11,321	14,530	7,654
Individual FE	✓	✓	✓	✓
District, Month, Year FE	✓	✓	✓	✓
Individual Characteristics	✓	✓	✓	✓

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each column represents coefficients in a separate regression. Individual characteristics include individual age, age squared, ethnicity, gender, educational attainment, and marital status. Robust standard errors are clustered at the individual level.

Table 5: Decision to Migrate among Different Subpopulation Groups

	Y = Individual Migration Status			
	(1)	(2)	(3)	(4)
Rainfall Shocks	-0.069***	-0.073***	-0.081***	-0.134***
	(0.021)	(0.022)	(0.024)	(0.040)
Being Male	-0.020			
	(0.023)			
Rainfall Shocks x Being Male	-0.011			
	(0.034)			
Being Minority		0.021		
		(0.025)		
Rainfall Shocks x Being Minority		-0.010		
		(0.041)		
Being Household Head			-0.044**	
			(0.021)	
Rainfall Shocks x Being Household Head			0.016	
			(0.034)	
Working in Agriculture				-0.023***
				(0.006)
Rainfall Shocks x Working in Agriculture				-0.083*
				(0.047)
Observations	22,386	22,386	22,386	22,386
Individual FE	✓	✓	✓	✓
District, Month, Year FE	✓	✓	✓	✓
Individual Characteristics	✓	✓	✓	✓

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each column represents coefficients in a separate regression. Individual characteristics include individual age, age squared, ethnicity, gender, educational attainment, and marital status. Robust standard errors are clustered at the individual level.

Table 6: Robustness Checks - Different Categorization of Control Group

	Y = Individual Migration Status				
	(1)	(2)	(3)	(4)	(5)
Raw Rainfall $\times 10^{-3}$	-0.017***				
	(0.005)				
Log Raw Rainfall		-0.075***			
		(0.019)			
Rainfall Shocks			-0.037***		
(13-24 mths prior)			(0.012)		
Raw Rainfall $\times 10^{-3}$				-0.012**	
(13-24 mths prior)				(0.006)	
Log Raw Rainfall					-0.036***
(13-24 mths prior)					(0.011)
Observations	22,386	22,386	22,386	22,386	22,386
Individual FE	✓	✓	✓	✓	✓
District, Month, Year FE	✓	✓	✓	✓	✓
Individual Characteristics	✓	✓	✓	✓	✓

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each column represents coefficients in a separate regression. Individual characteristics include individual age, age squared, ethnicity, gender, educational attainment, and marital status. Robust standard errors are clustered at the individual level.

Table 7: Impacts of Rainfall Shocks on Individual Migration Decision - Odd Ratios

	Y = Individual Migration Status			
	(1)	(2)	(3)	(4)
Rainfall Shocks	0.520***	0.497***	0.524**	0.617*
	(0.112)	(0.113)	(0.125)	(0.147)
Observations	22,386	22,386	22,386	22,386
Controlled for:				
Individual ID number	·	·	·	✓
District, month, year dummy variables	·	·	✓	✓
Individual characteristics	·	✓	✓	✓

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each column represents odds ratios in the logistic regression. Individual characteristics include individual age, age squared, ethnicity, gender, educational attainment, and marital status. Robust standard errors are clustered at the individual level.

Table 8: Rainfall Shocks, Agricultural Employment Opportunity, and Migration - Odd Ratios

	Migration for Working	Migration for Education	Migration for Others	Migration for Working: Agriculture	Migration for Working: Non-Agriculture
	(1)	(2)	(3)	(4)	(5)
Rainfall Shocks	0.287***	1.074	1.499	0.182***	0.719
	(0.084)	(0.414)	(0.810)	(0.065)	(0.375)
Observations	22,386	22,386	22,386	17,476	4,910
Controlled for:					
District, month, year dummy variables	✓	✓	✓	✓	✓
Individual characteristics	✓	✓	✓	✓	✓

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each column represents odds ratios in the logistic regression. Individual characteristics include individual age, age squared, ethnicity, gender, educational attainment, and marital status. Robust standard errors are clustered at the individual level.

Table 9: Migration Decision across Gender and Ethnicity - Odd Ratios

	Y = Individual Migration Status			
	Being Male (1)	Being Female (2)	Majority (Kinh) (3)	Minority (non-Kinh) (4)
Rainfall Shocks	0.520***	0.497***	0.524***	0.617**
	(0.112)	(0.113)	(0.125)	(0.147)
Observations	10,762	11,321	14,530	7,654
Controlled for:				
District, month, year dummy variables	✓	✓	✓	✓
Individual characteristics	✓	✓	✓	✓

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each column represents odds ratios in the logistic regression. Individual characteristics include individual age, age squared, ethnicity, gender, educational attainment, and marital status. Robust standard errors are clustered at the individual level.